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COMPARATIVE VOLATILITY STUDY ON INDIA VIX BY GARCH AND SHANNON'S ENTROPY FROM A BEHAVIOURAL FINANCE VIEWPOINT

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Abstract: India VIX was constructed in 2007 by CBOE, keeping CNX Nifty futures as underlying. This study has been constructed to observe the volatility levels during turmoil time zone from 2007-11 and relatively comfortable period 2012-16. From the zenith of late 2007 and early 2008, global indices nose-dived and stayed in low confidence zone for almost two years there before recovering in mid-2011.The cardinal reason of this study has been to check and test the reality of this so-called volatile time zone (2007-11) in comparison with the following time zone (2012-16). Apart from the familiar econometric tool of financial time series volatility testing GARCH (1, 1) interesting econophysics and information theory concept entropy, has been used here for this study too. The second objective of this study is to cross verify, whether entropy (Shannon's measurement) can capture the volatility of this stochastic time series or not. The last but not the least is the trace of behavioural finance in these two zones could prove, which of these can truly be predicted by the behavioural theories. Study reveals that entropy measures more accurately, during more frequent but lesser magnitude volatility.

Keywords: GARCH, Shannon' entropy, India VIX, Herd Behaviour, Cognitive bias, Heuristic simplification, Econometrics, Econophysics

JEL Classification: C5, C320

1. INTRODUCTION

In recent times, volatility has become a crucial topic in financial markets around the world. As a result, risk managers, portfolio managers, investors and academicians have shifted their focus to the accurate forecasting of volatility that is essential for asset and derivative pricing models and other financial applications (Minkah, 2007). Moreover, the 1996 and 1999 Basel Accord makes it compulsory for financial institutions to incorporate financial risk exposure in calculating the basic capital requirements (Pantelidis and Pittis, 2005). This makes volatility forecasting a mandatory task for all financial institutions.

According to Reider (2009), the three main purposes of forecasting volatility are for risk management, for asset allocation, and for taking bets on future volatility. In fact, estimates must be made of future volatilities and correlations in order to measure the potential future losses of any portfolio of assets (Goyal, 2000). As such, a number of time series models are used to forecast volatility and correlations.

A popular variant of models of changing volatility is typically the various forms of GARCH models. In these models, the volatility process is time varying and is modeled to be dependent upon both the past volatility and past innovations. Particularly, one aspect of GARCH models – GARCH (1, 1) is widely used when a model is estimated on various examples of realized stock market returns—market indices and individual stock issues (Ashley and Patterson, 2010).

In this paper, we focus on this familiar econometric tool of financial time series volatility testing - GARCH (1, 1) model - in order to observe the volatility levels during the financial crisis era and the post-crisis era. Additionally, the concept of entropy (Shannon's measurement) has been employed to examine whether the volatility of a stochastic time series can be captured or not. For this purpose, India VIX (volatility index), which is a key measure of market expectations of near-term volatility conveyed by NIFTY stock index option prices has been considered.

India VIX promised a clear measurement of volatility as its predecessor in the west (CBOE). Though as per methodology it has been taking just the short-term derivative contracts, yet due to the roll-over factor, long–term memory of investors could be well-tested too. At the same time, 2007 to 2010 was a gloomy and Dark Age in global investment banking scenario as the memory of banks falling down like nine-pins are still quite fresh in our memory. Moreover, sentiments were not so dented during the Brexit in 2014, China Slowdown in 2015 and Oil price avalanche breakdown in late 2015 to early 2016. Behavioural scientists were simply showing the HSBC performing manager's index movements; however, the truth was yet to be unearthed. Heuristic simplification always links Indian capital market with the US, rather than China and Brazil, though there is no such documentary evidence of the same. Econometrics experts generally predict and confirm the volatility of any stochastic time-series with its short-run as well as long-run memory to predict the evidence of persistent trace of volatility. Econophysics researchers on the other side, use the physical laws of nature, in the bourses as according to them, since everything is a part of nature, so the natural theories are good enough to define any such phenomena beneath the moon.

This paper has therefore been divided into the following parts: Section 2 focuses upon the Literature Review, wherein the concepts of risk index, econometric usage of it and the relationship of behavioral finance and physics in finance has been interrelated – thereby, identifying the gaps of the study topic. Section 3 discusses the research methodology, while Section 4 and Section 5 outline the results and interpretations of the results, respectively. Section 6 provides the concluding remarks for this study and Section 7, finally, highlight the scope of future research directions for this study.

2. LITERATURE REVIEW

Need for a risk index

Risk avoidance is a cardinal element in accepted theories of asset pricing, contracts, decision sciences and insurance (Pratt, 1964; Arrow, 1965; Epstein and Zin, 1989 *et al.*). Investor's attitudes towards risks that are yielding potential gains may be quite distant from their attitudes toward risks yielding potential losses. In an unprecedented bull rally they might well be ready to invest in a stock with a beta of in excess of 2, however the similar kind of stock becomes virtually untouchable during a sluggish phase of the economy, thus behavioural finance can term this as cognitive bias linked with heuristic simplification (Kahneman and Tversky, 1979). Erudite scholars of behavioural finance also consider the volatility index as a principal indicator of investor confidence, and suggest that such an index can be benchmarked as a market indicator of the market cycle movement of the underlying index (Olsen, 1998).

Heterochthonous variations in risk avoidance, , have been utilised in academic research in order to delve in to the world of financial crisis of the late 1990s and to further annotate and enlighten the mechanisms that lead to financial fiasco(Kumar and Persaud, 2001).

Shefrin (2007) offered the dependence theory; this theory confirms that different market dynamics and changing scenarios do play a game in the minds of the investor just enough to convince him about the greed-fear mechanism, thus drifting away from the rationale.

Palaniswamy *et al.* (2013) have given a detailed methodology behind the construction and theoretical background of India VIX. The parent index was introduced way back in 1993, when Chicago Board of Options Exchange (CBOE) has modelled risk index for S&P 500. NSE launched it in early 2008 though the options were launched two years back itself. They have given details on the formula behind with the rationale of computation of the time to expiry, for those options under consideration. They have even offered detailed work on the calculation of volatility for the near month and next month options as well. Cognitive errors from behavioural finance and greed-fear mechanism were clearly spelt out in the outcome of their work, both in bullish as well as in bearish market. However they found that effective and large volume liquid trading in options segment can only make this VIX a true blue volatility measurement index.

Bagchi (2012) worked well in the Indian context to construct value-weighted portfolios based on market-to-book value, beta and market capitalisation indicators. This study thus finds a positive and notable association between the India VIX and the returns of the defined portfolios.

Econometric usage

Thenmozhi and Chandra (2015) in their NSE working paper series worked on asymmetric relationship between India VIX and CNX Nifty using various variant of the ARCH/GARCH family. They have considered NIFTY, India VIX, CBOEVIX, LVX, and showed the risk return relationship using the conditional volatility measures. Though they successfully struck many a chords related to this including trading strategy based on VIX but didn't test any time zone volatility whatsoever. Banerjee and Kumar (2011) from IIMC proposed a model that compares the performance of conditional volatility model (GARCH) and India VIX in predicting volatility in the underlying asset base i.e. CNX Nifty. Their outcome is quite interesting though. They found that if GARCH (1,1) is applied on CNX Nifty and error reduction becomes the cardinal goal, then India VIX reduces error such as (RMSE,MAE etc.) as a better method than the former. Several methodologies and distinctly different approaches (e.g., Corsi *et al*., 2008, Bandi and Russell, 2004, and Zhang *et al*. 2010) to estimate realized volatility were also been considered while measuring the performance of VIX and GARCH models are cross-checked with the error terms such as MAE, RMSE etc. in the above mentioned model (Banerjee *et al*. 2011).

Behavioural Finance Trail

A Chinese group consisting Leilei Shi, Yiwen Wang, Ding Chen, Liyan Han, Yan Piao, and Chengling Gou (2011) showed crowd learning and psychological behavioural pattern in Chinese stock markets from the point of view of high-frequency trading (HFT) data. They found significant herd behaviour in the expectancy of price momentum. Sewell (1992) suggested that behavioural finance is the body of research depicting the influence of psychology on the behaviour of financial market participants and the obvious effects on the bourses. According to him this can truly link the reality with the theoretical knowledge. Nowadays, behavioural finance has progressed in two aspects (Barberis and Thaler, 2003). Tversky and Kahneman (1979) confirmed that the normative and the descriptive observations cannot be reunited, and no theory of can follow both descriptive and normative at the same time. Based on this confirmation, Barberis and Thaler (2003) further demonstrated that normative approaches are likely to fail, because people in general make choice that do not follow normative or standardized pattern in dynamic scenarios. Soros (1987) contradicted and affirmed that economic phenomena cannot be justified by a complex equation involving high end mathematics as they tend to miss many parameters that may be time specific; as the rationale of thinking has a unseen hand of uncertainty in social science unlike in physical science.

Physics in finance

Andreia Dionísio, Rui Menezes and Diana A. Mendes (2006) selected the daily closing prices of several stock market indexes such as ASE, CAC 40, DAX 30, FTSE, PSI 20, IBEX 35 and S&P 500, spanning over 1993 to 2002.They used mutual information and global coefficient or correlation based on Shannon's entropy. Sheraz (2014) in his dissertation linked GARCH model for financial volatility detection mathematically with four different types of entropy (Kaniadakis, Renyi, Shafee and Ubriaco) measures as an alternate methodology. Zhang, Huang (2010) have constructed a Quantum Physics based stock market prediction model. They have defined wave functions and operators of the bourses to establish the Schrödinger equation for the prediction of the stock market. They have considered an infinite quantum well where they used a cosine distribution to simulate the stock price under a state of equilibrium. Sitabhra Sinha (2010) in his innovative attempt showed that complex market structures are unstable (following May-Wigner theorem) so network patterns have to be chosen in the arrangement of their interactions in order to predict the interdependency and systemic risk of the bilateral exposure of US and European Banks. Sitabhra Sinha and Bikas K Chakrabarti (2009) took reference from Nobel Laureate Robert Lucas (2003) that "the central problem of depression prevention has been solved, for all practical purposes" and provided a deep understanding and application base of econophysics for social science especially for investment finance. They showed how the model made of complex networks with positive and negative degree assortative be used can be replicated in stock markets. The most interesting network fact that comes out of their work is that even if two or more networks have identical local as well as global properties, still they could have completely different behavioural pattern depending upon the different intermediate level or mesoscopic properties that is defined by sub-group of agents with their various and dynamic interaction level. This study was a melting pot of four independent disciplines such as, physics, econometrics, economics and finance.

Gaps identified

After an extensive literature review, certain gaps pave the way for further research (this study). India VIX has not been regressed with its own Lag using GARCH (1, 1) model. Being evident about the fact that it carries its own footstep with an autoregressive coefficients the natural tendency is for the above mentioned study. Time zone study has been given a miss by researchers as far as India VIX is concerned. However such study can truly unearth hidden truth and may break certain age-old myths. Entropy though has been quite a favourite for econophysics researchers in the domain of volatility study for a stochastic series; however time-zone based study and comparative study with an apt econometric tool such as GARCH (1, 1) has yet to be done. This very study has been designed for filling all these gaps.

3. DATA AND METHODOLOGY

India VIX daily closing from 3rd May 2007 to 31st March 2016 has been considered. Then two clusters have been made. The first phase is from 2007 to 2011 end (data set 1157) and the second phase is from 2012 beginning to 2016 fiscal end (data set 1052). First phase is a complete bubble set up from the formation stage in 2007 and till the collapse in early 2009 followed an extremely volatile but short span of time. The second phase is also having small crisis period (2013 August, India's credit rating downgrade and rupee depreciation against dollar followed by Crude Oil price fall for a relatively large period of time) but overall it is cyclical in nature without any huge global financial tsunami.

GARCH, a standard tool to measure volatility and its nature as well has been put into use here. Entropy, on the other hand depicts complexity and randomness in a stochastic series as described by Kristoufek and Vosvrda (2014). Zunino *et al* (2010) compared long term memory of markets against entropy measurement. In the current work, the researchers have used the presentation of entropy as deûned in information theory, since price discovery of a stock or an index processes are found to be primarily information generating processes. Stock price movement has been a random or stochastic process for each and every stock in a stock market. Certain trading days, the opening and closing prices are found to be different from previous closing and on certain occasions they are found to be same as well. However, this finding same value or different value of the stocks, or the index on a daily basis is random itself. This proposition could fail, if information becomes static and repetitive each trading day. Similar concept has been used by Pawel Fiedor (2015), in his quest for finding maximum entropy production function for stock returns.

Both GARCH of order one and Shannon's entropy measure have been in use for these two specific periods. The output of GARCH and entropy is finally compared to check, which phase is relatively more volatile. From cognitive error and bias point of view it could be concluded that the first phase seemed more volatile, however post the econometric and econophysical checks it would be having conclusive evidence either in its favour or in it's against. EViews was used for GARCH (1,1) and MATLAB was used for Shannon's entropy calculations.

Shannon's entropy and GARCH (1, 1) measures are detailed below:

3.1. Shannon's entropy

Shannon's entropy

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

$$S(x_i) = -\Sigma_{i=1}^{n} P_i \log(P_i) \quad (1)$$

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").

3.2. GARCH

Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH)

Here GARCH (1, 1) is used, the formula is

$$h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} \quad (2)$$

Where h_t is the time series, α_1 and β_1 are the coefficients coming out from error and lag of one order i.e. h_{t-1} and lag of one variance could define the volatility, when the coefficients of short run effect and the long run effects add up to a figure approaching 1, confirms a persistent volatility in the market.

4. EMPIRICAL STUDY OUTPUT

Table 1
Phase I (2007 to 2011) stochastic outputs

GARCH

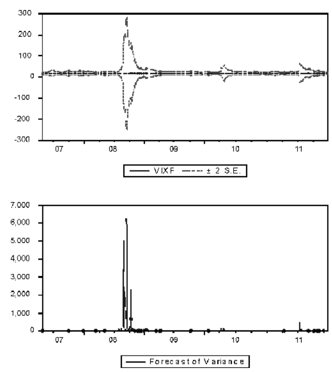
Dependent Variable: VIX
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 1156 after adjustments
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(1)^2 + C(5)*GARCH(1) + C(6)*VIX + C(7) *VIX(1)

Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
C	0.481486	0.149874	3.21261	0.0013
VIX (1)	0.96719	0.006448	149.993	0.0000

Variance Equation

C	-0.09481	0.052449	-1.807684	0.0707
RESID (1)^2	0.068741	0.009658	7.117522	0.0000
GARCH (1)	0.872065	0.013411	65.02732	0.0000
VIX	0.354777	0.001078	328.9614	0.0000
VIX (1)	-0.34444	0.003884	-88.6728	0.0000

R-squared	0.946216	Mean dependent var	26.94559
Adjusted R-squared	0.946169	S.D. dependent var	10.95572
S.E. of regression	2.541883	Akaike info criter	3.877302
Sum squared resid	7456.19	Schwarz criterion	3.907898
Log likelihood	-2234.08	Hannan-Quinn	3.888849
Durbin-Watson stat	2.21694		



Forecast: VIXF	
Actual: VIX	
Forecast sample: 5/03/2007 12/30/2011	
Adjusted sample: 5/04/2007 12/30/2011	
Included observations: 1156	
Root Mean Squared Error	14.40689
Mean Absolute Error	9.617917
Mean Abs. Percent Error	28.35120
Theil Inequality Coefficient	0.308839
Bias Proportion	0.424222
Variance Proportion	0.562435
Covariance Proportion	0.013343

Table 1.1
Entropy details for Phase I (2007 to 2011)

Shannon's entropy:	
	6.983135
Normalized Shannon's entropy:	
	0.991012

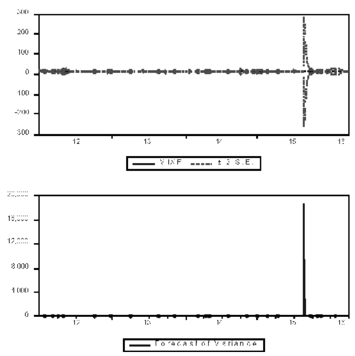
Table 1.2
Phase II (2012 to 2016) stochastic outputs

GARCH

Dependent Variable: VIX
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 1051 after adjustments
Convergence achieved after 23 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(1)^2 + C(5)*GARCH(1) + C(6)*VIX + C(7) *VIX(1)

Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
C	1.042915	0.176347	5.913986	0
VIX (1)	0.9138	0.011439	79.88575	0
Variance Equation				
C	-0.082544	0.020244	-4.077435	0
RESID (1)^2	0.045118	0.01013	4.453775	0
GARCH (1)	0.848704	0.026317	32.24931	0
VIX	0.323584	0.002817	114.8795	0
VIX (1)	-0.310666	0.000345	-899.9582	0

R-squared	0.85437	Mean dependent var	15.91792
Adjusted R-squared	0.854232	S.D. dependent var	3.555208
S.E. of regression	1.357365	Akaike info criter	2.899313
Sum squared resid	1932.719	Schwarz criterion	2.932332
Log likelihood	-1516.589	Hannan-Quinn	2.911832
Durbin-Watson stat	1.793708		



Forecast: VIXF
Actual: VIX
Forecast sample: 1/02/2012 3/31/2016
Adjusted sample: 1/03/2012 3/31/2016
Included observations: 1051

Root Mean Squared Error	4.656081
Mean Absolute Error	3.239187
Mean Abs. Percent Error	17.49899
Theil Inequality Coefficient	0.159413
Bias Proportion	0.421536
Variance Proportion	0.495797
Covariance Proportion	0.082668

Table 1.3
Entropy details for Phase II (2012 to 2016)

Shannon's entropy:	
	6.935561
Normalized Shannon's entropy:	
	0.996

5. INTERPRETATION

The Phase I (2007 to 2011)

GARCH (1, 1) shows that VIX can be predicted well within the permissible limits with the effective use of VIX (-1), which is the Lag of VIX to order of 1, though the relationship is mildly inverse in nature. The Auto regressive Coefficient generated from the GARCH (1) does predict the VIX with firm positive relationship. R Squared is well over 94% signifies the strength of the work. Akaike Info Criterion and Schwarz Criterion too are quite low thus ensuring the stability in the work. Durbin-Watson is marginally over 2, signifying feeble trace of negative auto-correlation. Sum of Coefficients in GARCH (1, 1) are close to 1, hinting at presence of persisting volatility. Shannon's entropy too is very close to 1. This econophysics tool too hints at presence of persisting volatility.

The Phase II (2012 to 2016)

GARCH (1, 1) shows that VIX can be predicted well within the permissible limits with the effective use of VIX (-1), which is the Lag of VIX to order of 1, though the relationship is mildly inverse in nature. The Auto regressive Coefficient generated from the GARCH (1) does predict the VIX with firm positive relationship. R Squared is well over 85% signifies the strength of the work. Akaike Info Criterion and Schwarz Criterion too are quite low thus ensuring the stability in the work. Durbin-Watson is marginally below 2, signifying feeble trace of positive auto-correlation. Sum of Coefficients in GARCH (1, 1) are close to 1, hinting at presence of persisting volatility. Shannon's entropy too is very close to 1. This econophysics tool too hints at presence of persisting volatility.

Table 1.4
Comparative Chart of Shannon's entropy and GARCH (1, 1)

	Normalized Shannon's entropy (NSE)	*Sum of Coeff. In GARCH (SCG)*
2007-11	0.991	0.856
2012-16	0.996	0.824

Interesting thing to note here it that the NSE and SCG both are showing clear footprints of persisting volatility yet, the direction is reverse, in a mild way though. So, according to SCG 2007 to 2011 was more volatile and according to NSE 2012-2016 phase is more volatile. Also, NSE values are closer to 1, when in comparison with SCG values depicting that NSE predicts more volatility than SCG. Another interesting observation tells us that RMSE (error during prediction) during the first phase was 14.4 and the same came down to 4.56 during the second phase hinting that whether volatility has gone up (as per NSE) or come down (as per SCG) the prediction accuracy has increased by leaps and bounds. In simple terms, Phase I could be predicted 95% (approx.) times but with higher error in the predicted value of Ind VIX and Phase II can be predicted 85% (approx.) but with significantly less error for the same cause.

6. CONCLUSION

This study is quite unique in its own as it's a perfect melting pot of four disciplines of very little commonality in between them. Generally bubbles or for that matter stochastic volatilities are found to be of two types. Infrequent but high impact stages are present alongside more frequent variations with lesser amplitude. The cardinal question, to be answered here is "which one of them is more volatile in nature".

The econometric tool, GARCH (1, 1) depicted evidence of more volatility in the first zone, compared to the second one. The first zone had infrequent however substantially larger amplitude stochastic movements.

On the other hand the Econophysics tool Shannon's entropy predicted marginally higher volatility during the second zone (having Oil Price avalanche breakdown, Brexit, India Credit rating downgrade, China slowdown etc.).

Hence, in the hindsight it could well be commented that in econometric method a large global event having mammoth proportion with low frequency has been given precedence, while in econophysics method gives more impetus to relatively low-amplitude but high-frequency global events.

Though, concrete evidence is missing for herd behaviour or any other cognitive biases, in both the results, yet, as the financial literacy in India is on the lower side, so a gigantic worldwide financial fiasco would attract irrational behaviour.

So this innovative and multi-dimensional study does validate the outcome of Darbellay and Wuertz (2000) study on proving that entropy is an apt measurement in estimating the volatility factor in financial time series.

7. FURTHER SCOPE OF RESEARCH

This research has been a true melting pot of traditional finance, behavioural finance, financial econometrics and lastly econophysics. So, the overlapping zone of four domains has been captured. Automatically, similar studies could be done by adding a new frontier or omitting one from the considered ones. GARCH (1, 1) constructive models in general are not quite robust when we come across structural break in the data (so, GARCH is only recommended for continuous data set without any structural break), so to counter such a deficiency stochastic volatility models with Markov regime switching has been introduced lately. Those can be used instead of GARCH for similar kind of study. Tsallis and Kaniadakis entropies could replace Shannon's entropy. The entire study can be done in a different event zone as well as time zone, also in a completely new economic zone too.

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