<u>Volatility study of French CAC 40 VIX (VCAC) - A review of GARCH and Information Entropy</u>

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INTRODUCTION-

Volatility is the measure of the dispersion from the actual returns. And volatility index (VIX) indicates the expected fluctuations in the underlying index for the near term. Both terms are very important in portfolio management as they capture the market risk and investor's behaviour. Therefore, this study aims to observe the volatility levels of the French CAC 40 VIX called VCAC during multiple time zones ranging from early 2005- early 2020 to determine the most volatile period by using econometric tool GARCH (1,1) and an econophysics tool Shannon entropy. This study will carry out a comparison between the two adopted methodologies to verify the most suitable tool for capturing the volatility by interpreting the similarity or the differences of the obtained results.

REVIEW OF LITERATURE –

This work focusses on various research conducted on measuring the volatility/ uncertainty in different indexes using tools from two diversified branches i.e. econometrics and econophysics. It includes researches from the year 1982 to 2020 to gain a deep understanding on the subject. The findings are as follows-

VIX was introduced in 1993 by the Chicago Board Options Exchange (CBOE) with the underlying S&P 500 index. VIX is an indicator of the expected changes in the underlying index for the near term. It perfectly captures the behavioural sentiments and psychological characteristics of the investors. Hence, an investor's decision on any investment in the near term can be indicated with the help of this instrument. VIX can be differentiated from the term volatility by the fact that the latter is just a measure of the changes in the returns of the security or index. Palaniswamy, and his colleagues have given insights on the computation of the VIX, time to expiry and near month and next month options as well. The outcome has also brought forward the bullish and bearish nature of the option in terms of VIX (Palaniswamy, Lakshminarayanan, & Venkatesh, 2013).

After the introduction of VIX other exchanges across the world introduced their respective volatility indices. On September 3, 2007 NYSE Euronext introduced three new volatility indices. They are AEX (Amsterdam Euronext) Volatility index, BEL 20 (Brussels Euronext) Volatility index, and CAC 40 (Paris Euronext) Volatility index. These indices were a modification of the VX1 and VX6 indices as they were developed by following the methodology of the newly introduced VIX by the CBOE.

Though these indices were introduced in Sep 2007 their daily historical prices are available from Jan 2000 (Siriopoulos & Fassas, 2011).

VOLATILTIY INDEX vs STOCK RETURNS

It had always been a matter of debate among the researchers about the relationship between the volatility index and the stock market returns. Mixed results had been obtained regarding the same.

Fleming Ostdiek & Whaley built a detailed methodology behind the construction of VIX and its examination over a specified time (Fleming, Ostdiek, & Whaley, 1995). Bart Frijns constructed implied VIX (AVX) using S&P/ASX 200 returns (Frijns, Tallau, & Rad-Touranni, 2010). Their work showed resemblance to the conclusion that VIX is a very suitable instrument for forecasting the volatility of the stock market. It also exhibits a temporal relationship with the stock market return. It is inversely proportional or negatively correlated with the index returns. Negative moves in the stock market are marked by large changes in the volatility than the positive moves, which define the asymmetric relationship between the two factors. Frijns and his colleagues also stated that AVX or in general volatility index contains important information relating to both in-sample and out-of-sample (Frijns et al., 2010). Dash and Moran in their study showed that the volatility index not only exhibits a negative correlation to hedge funds returns but also reveals asymmetric nature. At last, they concluded that it is beneficial to diversify the hedge fund portfolios by having allocations in volatility index, it downgrades the risk (Dash & T.Moron, 2005). The evidence for the negative and asymmetric association between the volatility index and the stock market return have been shown by many researchers in their respective studies. There is a negative and asymmetric association between FTSE/ ASE 20 index and the Greek volatility index (GVIX) (Skiadopoulos, 2004) and between the S&P100 and Nasdaq 100 indices returns and the respective volatility index VIX and VXN. Though he mentioned that the asymmetric property for Nasdaq 100 index is relatively weak (Giot, 2005). Though Dowling and Muthuswamy agreed on the negative correlation between the two parameters from the output of Australian stock market return and the volatility index (AVIX), they marked the absence of an asymmetric relation (Dowling & Muthuswamy, 2005). Shriya Janardan also tested the relationship of VIX for several G7 countries with the stock price and the bond yield (LBY). She used a Panel Data regression for the same. She concluded that both the chosen variables were able to forecast the fear index for the chosen countries. And both these variables have a negative correlation with the VIX, indicating an inversely proportional relationship between VIX and stock price as well as VIX and bond yield. However, the negative correlation has a higher impact on VIX than bond yield (Janardan, 2019). Contrary to the above outcomes, a positive correlation between the returns and the implied volatility was also found (Guo & F. Whitelaw, 2006). Bagchi considered Indian volatility index (India VIX) for his study, a recently introduced index by CBOE. His methodology was to construct a value-weighted portfolio based on the high-low beta, high-low market to book equity ratio and market capitalization. The above parameters were chosen because they are important traits of behavioural finance. A multiple regression model was used to reach the outcome. The study also founded that there existed a positive and remarkable association between VIX and the return of the above-specified portfolios (Bagchi, 2012).

BEHAVIOURAL FINANCE-

Leilei Shi along with his colleagues focussed on the crowd learning using high trading frequency in the Chinese stock market. They tested for the correlation between the rate of price volatility and the change in trading frequency and found that there is a positive correlation between the two. There is a strong relationship between herd behaviour and the expectation of price momentum. They also stated that the behavioural finance models are narrow as they do not capture completely about investor's belief, preference, or limits to arbitrage (Shi et al., 2012). The behavioural finance field has two categories- first is the limit to arbitrage while the second is the psychology which records the types of deviations from rationality an investor wants to experience. This can be named in a general term as normative and descriptive models (Barberis & Thaler, 2002). According to Kahneman and Tversky, expected utility theory has been accepted as a normative model which quite often is also used as a descriptive model in the decision-making process violating the principle of the theory. Therefore, the authors have developed a prospect model as an alternative for decision making under risk. Hence it can be concluded that both the descriptive and the normative model cannot be used simultaneously for the choice under risk (KAHNEM & TVERSKY, 1979). Based on this, it was proposed that a financial phenomenon can be better understood when people do not have a normative approach i.e., they tend to violate from the principle of Expected utility theory. Hence, it was concluded that the theories based on normative scenarios are not competent (Barberis & Thaler, 2002).

ARCH/GARCH-

Nobel laureate Robert F Engle came up with a new econometric tool called Autoregressive Conditional Heteroskedasticity (ARCH) to measure the mean and variances of inflation in the U.K. The properties of this model are that it is a zero-mean, serially uncorrelated with constant unconditional variance. A regression model was further introduced following the ARCH process. A Lagrange multiplier model was applied to know whether or not the disturbances follow an ARCH (Engle, 1982). Tim Bollerslev, extended the ARCH model introduced by Engle to build a more generalised one known as the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) which is quite similar to the ARCH but with the difference that the former provides with more flexible lag structure and long memory. He also stated that the autocorrelation and partial autocorrelation for the squared process seems to help identify and check GARCH behaviour in the conditional variance equation. He further explained the GARCH (1,1) model, developed a regression model, and gave its application by explaining the uncertainty of the inflation rate (T Bollerslev, 1986). Robert F Engle explained the edge of using an ARCH/GARCH model to measure the volatility in place of any traditional model. He mentioned that the ARCH/GARCH model takes into account the heteroskedasticity of time-series data. He explained the GARCH (1,1) model and highlighted its application to estimate the value at risk. i.e., using the GARCH (1,1) model to calculate the risk in the portfolio. He also mentioned various other forms of the GARCH model (Engle, 2001). Bollerslev and Bera took the study on the ARCH model one step ahead by marking the importance of volatility in the determination of asset pricing, hedging, estimating volatility for market efficiency and deciding option prices and described the ARCH model and various other processes in the ARCH family as an effective tool along the above-stated dimensions (Bera & Higgins, 1993; Tim Bollerslev, Chou, & Kroner, 1992). Another application of ARCH model was studied by Swarna Lakshmi P. She used ARCH model to capture the volatility in the Indian stock market pre and post period of the introduction of Securities borrowing and lending scheme. The main theme was to check the viability of the newly introduced scheme on the basis of volatility estimate. If the volatility measured after the introduction of the scheme increased, it stated that more lending and borrowing is happening and vice-versa. But her study concluded that, the volatility measure decreased and hence, the scheme did not get much attraction from the investors (Lakshmi, 2014). Rob Reider had also explained the need for volatility forecasting like the others. And further described some properties of the volatility which is positive autocorrelation of the squared returns, the asymmetric variations. He told the process of estimating the parameters using maximum likelihood by forming a likelihood function (joint probability density function) and considering it as a function of the parameters given the data. He also described which GARCH model should be used under which condition and how a model can be chosen as a better fit to the data (Reider, 2009). In order to decide which version of GARCH model is suitable for predicting the volatility under the error distributions viz, normal distribution and student-t distribution, Wei Jiang used the root mean square error (RMSE) approach. He selected different market indices viz, NASDAQ's daily index, Standard and Poor's 500 daily index, FTSE100 daily index, HANG SENG daily index and NIKKEI daily index for the same. He found different GARCH models under normal distribution were suitable for different indices. E.g., the GARCH (1, 1) model under normal distribution has the smallest RMSE for HANG SENG stock return, therefore, it will forecast volatility better than other models (Jiang, 2012). Certain studies were also done to check the compatibility of the GARCH model with the traditional method of calculating volatility i.e. using the daily stock returns. Amit Goyal in his study found that GARCH is not a superior method of forecasting volatility over the traditional one, but concluded that the volatility forecasting ability of this model cannot be completely neglected (Goyal, 2000). A new dimension to the earlier study was given by Pantelidis and Pittis, who took root mean squared forecast errors (RMSFE) as an indicator to test the accuracy of the model over the model that assumes homoskedasticity. He concluded that the GARCH model does not outperform the traditional model and hence is not a superior model for forecasting volatility by making a call on the argument made that using squared errors in the place of unobserved conditional variance inflates the RMSFE. He further stated that for one period ahead forecasts GARCH is better than the traditional method when compared with long horizons and supported it by measuring the volatility of exchange rates for the US Dollar (Pantelidis & Pittis, 2006). Richard Minkah performed in-sample and out-of-sample tests and went ahead to state that for in-sample tests, GARCH is an accurate model as the RMSFE is very low, but for out-of-sample tests, GARCH is a favourable model only for shorter forecasting period and not for long forecasts horizons due to the introduction of errors in the model which runs the forecasting (Minkah, 2007). Therefore it can be said that GARCH as a forecast model cannot be completely ignored for its process and can be used for predicting volatility of the time-series data as it considers the heteroscedastic characteristics of the time-series data which is not considered in the normal process which calculates volatility using the daily stock returns.

VOLATILITY FORECASTING-

Poon and Granger**,** have conducted a radical study on the volatility forecasting domain. They described both the time series model and option-implied standard deviation methods of forecasting volatility (Poon & W.J.Granger, 2003). VIX, CBOE VIX, ARCH/GARCH, LVX were considered to measure the volatility of the return (Chandra & Thenmozhi, 2015). S.S.S. Kumar**,** Chandra and Thenmozhi outlined the negative association between VIX and the Nifty returns, however, they stated that VIX is a remarkable tool that an investor must consider to get a positive return from their portfolios. VIX is a suitable measure for realised volatility, better than the standard deviation of returns, daily variance estimates, or monthly sum of squared returns (Chandra & Thenmozhi, 2015; Kumar, 2012). Maghrebi along with his colleagues constructed a volatility index for the Korean stock market and referred it as an indicator of implied volatility concluding that KOSPI 200 implied volatility index contains useful information for predicting future volatility (Maghrebi, Kim, & Nishina, 2007). A comparison between India VIX and econometric tool GARCH was performed by Banerjee and Kumar in his study to decide a suitable tool for forecasting the volatility in the underlying index NIFTY 50. They used India VIX as an indicator of implied volatility in measuring the volatility of the index, because it being a model-free estimate, is free from any model error. They revealed that if the volatility of an underlying index like NIFTY has to be calculated, VIX is a superior tool than the conditional volatility model as the forecast error (RMSE, MAE) is minimum for the former tool (Banerjee & Kumar, 2011). This was also made evident by Corrado and Miller, who stated that CBOE implied volatility index like VIX, VXO, VXN provide a better estimate of predicting future price volatility for S&P 500, S&P100 and Nasdaq 100 respectively (Corrado & Miller, 2005). Banerjee and Kumar also estimated realised volatility by doing the summation of intra-day squared returns (Banerjee & Kumar, 2011). Various approaches and different styles to calculate realised volatility had been considered while doing a comparison between GARCH and VIX (Bandi & Russell, 2008; Zhang & Huang, 2010).

ECONOPHYSICS-

The concept of quantum physics had been used to build a model for forecasting the stock market. The scholars used wave functions and operators of the stock market to construct a Schrodinger equation for the stock price prediction. They have studied an infinite quantum well based on the theoretical bodywork, using a cosine distribution to reproduce the stock price in equilibrium (Zhang & Huang, 2010).

AN ENTROPIC APPROACH –

Many researchers in their respective studies marked the importance of calculating the uncertainty in the domain of portfolio management, asset pricing, etc. But they all criticised the traditional method of estimating volatility of the stock returns. The traditional method is the variance or standard deviation approach of predicting the future. They underlined certain disadvantages related to the traditional approach i.e. consideration of only linear characteristics of the time series data, treating variation of different periods as equal because of its time-invariant property, and due to the square of the difference between mean and the observation, the effect of the outliers gets accentuated (Dionisio, Menezes, & Mendes, 2006; Ruiz, Guillamón, & Gabaldón, 2012; Tran Thi Tuan Anh, 2017). To address these disadvantages, many researchers came forward and applied many new and different approaches in this particular domain. The most prominent is the use of physics in finance. Dionisio and Carmen Ruiz along with his colleagues described the correlation between physics and financial theory. The tool to measure uncertainty in the stock market and avoid the demerits of the traditional variance approach is the use of entropy (Dionisio et al., 2006; Ruiz et al., 2012). Entropy is a thermodynamics concept introduced by Rudolf Clausius in 1870. The use of this concept in the financial domain was made evident by Dionisio and his co-researchers. They used the Shannon entropy approach to measure the uncertainty in the Portuguese stock market. They described entropy as a measure of uncertainty, diversification, dispersion, and disorder (Dionisio et al., 2006). Entropy is the estimate of uncertainty in the market, greater the uncertainty lesser is the predictability. Hence, entropy can be used as a measure to analyse if new information can help traders predict changes in the price (Liu, Chen, Yang, & Hawkes, n.d.). Kristoufek & Vosvrda, in their study stated that entropy signifies the complexity and randomness of the data series. They went ahead and described entropy in absolute terms. They mentioned that a data series can be characterised as random when the value of entropy is high (meaning data series carrying no information) while that with a low entropy value can be characterised as deterministic. They further described Capital market efficiency in terms of entropy. The higher the value of entropy, the more efficient is the market and vice-versa (Kristoufek & Vosvrda, 2014). Nicolas Navet and Shu-Heng Chen, defined entropy as a measure of uncertainty which is contained in the next information produced by the process, containing all the information from the past. They used the concept of entropy to measure the predictability and any temporal dependence in the time-series data. For the same they used the end of the day price of the stock in the NYSE US 100 index from a period ranging between 2000-2006. They concluded that some of the stocks included in the index showed the evidence of temporal dependency in the time-series data (Navet & Chen, 2008). While Bikramaditya Ghosh and his co-scholars took a different note to explain the term Shannon's entropy in their recent study and defined it as a tool to quantify the uncertainty in the information. They expressed the Shannon entropy in terms of crisis by specifying that if the value of Shannon entropy is greater than 3.5, the uncertainty of information is beyond control, signalling that the crisis is obvious, while if the value of Shannon's entropy is below 3.5, the uncertainty is low and within control. They applied the concept of Shannon's entropy to recognise any herding likelihood and the corresponding bubble information to understand the momentum of the market. Dionisio, Menezes, and Mendes used Shannon entropy for their study and ranked the former above the standard deviation based on certain advantages like- the former considers the high order moments of probability distribution and concluded by the statement that the use of entropy can be used as an alternative approach to the traditional one (Ghosh, Le Roux, & Verma, 2020). One more evidence of this was presented by Bentes and his colleagues, also used an entropic approach (Shannon entropy and Tsallis entropy) to estimate the uncertainty in the stock market. They considered data of seven countries which included CAC 40 (France), MIB 30 (Italy), NIKKEI 225 (Japan), PSI 20 (Portugal) IBEX 35 (Spain), FTSE 100 (UK) and SP 500 (USA) to measure the uncertainty and rank the chosen indices accordingly. They also compared the results obtained from the standard deviation method and the entropy method and concluded that there is a difference between the results obtained from the applied methods. Though the overall result i.e. CAC 40 and NIKKEI 225 being the most volatile indices remains the same no matter which method is used. However, they stated that the entropic approach has an edge over the traditional methods on account of considering the uncertainty and disorder in data series without putting any restriction on probability distribution (Sonia R. Bentes & Menezes, 2012). The use of Shannon entropy to estimate the uncertainty was further extended in the study done by Tran Thi Tuan Anh. He chose Vietnamese stock market in addition to other ASEAN countries like Thailand, Singapore, Philippines, Malaysia, and Indonesia. He also did a comparative study between the traditional approach and the entropy approach to calculate the volatility. He ranked the countries index on the basis of volatility separately for both the methods and the result obtained were quite different i.e. the ranking order obtained were different. He explained this difference based on the fact that entropy uses more information than standard deviation and the former doesn't require the assumption of the normal and symmetric distribution of return series. He thus concluded that the use of entropy in respect of finance can be regarded as an augmentation of information entropy and probability theory. His study was in tune with the results obtained by Bentes and Rui Menezes (Tran Thi Tuan Anh, 2017). Mrs. Muskan Karamchandani1, Ms. Shubhra Mohadikar2, Ms. Savera Jain, also used the concept of Shannon entropy in their study to measure the volatility in the major stock indices of BRIC economies over the standard deviation method because the former considers for both linear and non-linear nature of the time series data and ignore the loophole of the latter. They found that not much research had been done in emerging countries and thus extended his study in that particular domain by choosing BRIC economies. They concluded that India (Sensex) was the least volatile while the Russian market was the most volatile market. Hence, they stated that investing in the Indian market would be feasible to low-risk appetite individuals. But an interesting result of their study was that both the Shannon entropy and Standard deviation methods gave the same output which is contrary to that observed by Tran Thi Tuan Anh and Bentes-Rui Menezes in their respective studies (Karamchandani, Mohadikar, & Jain, 2014). Muhammad, Dedub and Preda, also used the concept of Shannon entropy along with other entropy measures to assess the most volatile indices by taking the weekly and monthly closing prices of CAC 40 (Paris Index), Hang-Seng (Hong Kong Index), FTSCST China (Singapore Index) and FTSE.MI (Milan Index) from 2000-2012. They highlighted the non-linear nature of data series by the fact that the computed entropy is positive. They found that the calculated value of entropy was highest for the Paris index (CAC 40), hence, it is the most volatile among the chosen indices while Milan Index is the least volatile (Sheraz, Dedu, & Preda, 2015).

Not only Shannon entropy but other variants of entropy can also be helpful in the uncertainty estimation. Permutation, topological, and modified permutation has also been found successful to measure the volatility. Hence, it was made evident that entropy is a fine measure to quantify randomness, uncertainty, and determinism of time series data to estimate volatility. Further, the non-linear characteristics of the time series data can be considered in the process (Ruiz et al., 2012).

Bentes, Menezes and Mendes, in their study got into to measure the volatility of the SP 500, NASDAQ 100, and Stoxx 50 indexes. They adopted a comparative approach for the same and hence used the traditional method of measuring volatility i.e. GARCH and another approach quite different from the traditional one that is the concept of entropy. In the former approach they used GARCH (1,1), IGARCH (1,1), and FIGARCH (1, d,1) while in the latter they used the Shannon, Renyi, and Tsallis measures. They concluded that the output obtained from both the methods validate the presence of the non-linear characteristics of the volatility in the above-specified indexes. Hence, both the measures can be regarded as complementary to each other. Although, in case of analysing the stock market returns entropy outperforms the ARCH/GARCH model because the latter considers that the time-series data is independently and identically distributed (i.i.d) which is not the case. The volatility clustering and long-memory effects can be attributed by examining the entropy value for equally spaced sub-periods (Sónia R. Bentes, Menezes, & Mendes, 2008). Bikramaditya Ghosh and Nabila Nisha, further extended this by doing a comparative study to validate the volatility levels of the so-called most volatile time-zone ranging between (2007-2011) with that to a relatively lower volatile zone i.e. ranging between 2012-2016. They used the not so old volatility index i.e. India VIX for the measurement of the volatility levels. The tool used by them for the process is GARCH (1,1)- an econometric tool. In addition to this, they also involved the concept of econophysics in their study by using an information theory concept called entropy (particularly Shannon entropy) to measure the volatility levels for the specified time-zone and to verify whether or not this tool is competent enough to record the volatility of the considered data series. They mildly touched upon the theory of behavioural finance to examine if the theory can explain the volatility between the two time zones mentioned above. They concluded by stating that GARCH (1,1) indicated higher volatility for the first time-zone on the basis that the variation is less frequent but larger movements in the time series data while entropy defined the second zone as more volatile. However, they stated that entropy is an outperformer for volatility measurement in case of the more frequent and lower amplitude of volatility (Ghosh & Nisha, 2018).

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