6th International Conference on Recent Trends in Engineering, Science & Management
Shri Guru Teg Bahadur Khalsa College Anandpur Sahib, Punjab (ICRTESM-17)
8th January 2017 , www.conferenceworld.in ISBN: 978-93-86171-21-4

A STUDY ON PURE WEATHER PORTFOLIOS WITH BANK'S RISK CAPITAL USING CONDITIONAL VAR

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ABSTRACT

The role played by weather data is crucial in estimating future prices of commodities specially Prices of Energy. Te present paper studies the portfolio Value at Risk for three metro cities based on their temperature studies. Historical and random values are used for conducting the study. Conditional VaR and GARCH model are also incorporated in the study.The analysis is conducted by using Spreadsheet. Due to the limitation of only three metro cities only few parameters are used. Banking Industry will be benefitted from this study in managing their investment portfolios and Mark to Market Trading Portfolios.

Keywords: GARCH Model, Conditional VaR, Mark to Market Trading Portfolios.

I.INTRODUCTION

Temperature variable is simple that most (nearly 90%) of existing weather related contracts (derivative contracts) worldwide are for utilities and these mainly require temperature as a measure for calculating risks.

VaR is the best approach so far in estimating the downside risks and this is equally useful from Agriculture industry point of view, Tarasov (2011).

The differences in the Portfolio VaR measures and Portfolio Risk capital as measured using Traffic signal Violations on temperature variables provide useful strategic understanding to the Indian stock market traders by shifting emphasis from traditional stock only set of trading assets into weather related contracts soon.

This study is based on temperature and performing GARCH 1, 1 modeling on tailed condition is by itself not found in empirical studies confining to India.

1.1Objective of The Study

To compare the performance of city-wise temperature performances.

1.2 Literature Review

Tarasov (2011) justified temperature variability as closely associated with global warming on one side improvement in technology to produce superior drought resistant crops on the other. Such contrasting scenario makes volatility of weather related phenomena's very dynamic and thus GARCH models seems relevant to occupy such changes.

Taylor and Buizza (2006) used an Ensemble prediction model by using scenarios placed with Probability density function. The resultant mean is considered as fair price of weather derivative and distribution around mean as risk for further use in VaR analysis. This paper explained the use of Value at risk on the Density

forecasts obtained by set of scenarios and taking mean of this as a payoff function. While using Atmospheric modeling, instead of simulation, a horizon based probability "bounds" are analyzed, that means what are the maximum fluctuations in the weather variables which can lead to an immediate energy demand-supply mismatch. However, in the article it is also revealed that since certain weather phenomena's like rainfall is highly localized and this confirm the need for index to be prepared from the same location and time. Feng (n.d.) stressed heavily on use of boot strap model to estimate Weather based portfolio VaR.

1.3 Broad Statistical framework

For the present research a careful selection of Bangalore, Mumbai and Chennai temperature are selected from 1996 to 2014 on monthly basis.

Further, to apply Value-at-risk model the following three approaches were utilized:

1.3.1 Non-parametric VaR: Use of historical temperature values and using the same to generate individual and pair-wise Portfolio VaR's for each of three temperature combinations. Bangalore-Chennai, Mumbai-Chennai and Bangalore-Mumbai respectively.

1.3.2 Parametric VaR: randomized series in replacement of historical values and using the same to generate individual and pair-wise Portfolio VaR's for each of three temperature combinations. Bangalore-Chennai, Mumbai-Chennai and Bangalore-Mumbai respectively.

1.3.3 Tailed VaR: Considering the maximum downside risk, out of the Non-parametric and parametric, whichever appear maximum on time series basis had been selected for further calculation? And this was further used for pair-wise Portfolio VaR's for each of three temperature combinations. Bangalore-Chennai, Mumbai-Chennai and Bangalore-Mumbai respectively.

The formula employed was

Tailed VaR**:** *=min (non-parametric VaR monthly, Parametric VaR monthly).*

For Portfolio VaR a formula used were as follows:

Portfolio risk = *under-root of ((product of squared Stdev temp variable 1* weight in portfolio (constant) of temp variable 1) + (product of squared Stdev temp variable 2* weight in portfolio (constant) of temp variable 2) +2 * weight in portfolio (constant) of temp variable 1)* weight in portfolio (constant) of temp variable 2)*Covariance of Temp variable 1 & 2.))*

Same used for three combinations of Mumbai, Chennai and Bangalore combinations.

Also, the Tailed Portfolio VaR = *Min (Non-parametric portfolio VaR, Parametric portfolio VaR)*

The time series modeling was done using GARCH 1, 1 Model where the estimate of α and β were based on Maximum likelihood function. For this each historical data value was converted into lagged return and lagged variance and then maximum likelihood function was applied on the historical series to generate the constant which were used with the formula to generate the GARCH based Standard deviations and Covariance's.

Standard deviation at nth variable**:** *under-root of ((squared stdev of n-1 variable+ β+W (long term weight*v (long term volatility) +squared return of n-1 temp variable* α))*

Here, W (long term weight*v (long term volatility) had been kept 0.

Similarly, for Covariance between the set of two temperature variables the formula used was:

Covariance Temp var 1 and 2 at nth variable: (*Covariance for n-1 variable * β + return of n-1 temperature variable 1 *return of n-1 temp variable 2* α+ W (long term weight*v (long term volatility)*

Here, W (long term weight*v (long term volatility) had been kept 0.

Once the temperature VaR and Portfolio VaR are so generated based on 3 combinations for non-parametric, parametric and Conditional basis. The next step was to calculate the average Portfolio VaR which was simply calculated by taking the average of 191 months Portfolio VaR.

This is further exhibited in the charts and tables below which are primarily used for further analysis.

The other important feature of the Portfolio model was to gather Portfolio risk capital based on three pair-wise temperature portfolios.

For this two methods were employed. ***Point backtest***, where the limits for 191 months based at different time intervals were generated. The details of each limit are explained below. These limits were used to test the VaR breaches and acceptances on one side and confirmation of non-normality condition on the other.

For 191 months the ranges as per point backtest rule are as follows:

For 90% confidence level lower limit is 12 maximum limit of breaches is 26

For 95% confidence level lower limit is 4 maximum limit of breaches is 16

For 98% confidence level lower limit is 0 maximum limit of breaches is 8

For 99% confidence level lower limit is 0 maximum limit of breaches is 5

Use of Traffic signal violations:

To estimate the risk capital based on Point backtest values, the following formula is employed:

Risk capital = *min (VaR 191th month, S (Factor of 3, 3+ (5-x)*0.2 or 4) multiplied by Average of 191 month VaR values)*

Thus, for 191 month horizon, the individual VaR Risk capital and Portfolio risk capital estimates were calculated and used further in the study. Portfolio Risk capital is calculated for all three VaR values i.e. Parametric, Non-Parametric and Tailed basis.

The result of Portfolio risk and Portfolio risk capital are now analyzed

Dirty back testing is employed here means the weights of the portfolio are assumed to be unchanged throughout the 191 months period.

II. ANALYSIS & MAJOR FINDINGS

After calculating the Portfolio VaR by multiplying Portfolio Standard deviations with the dirty weights of each of two sets of temperature trading variable. The following Portfolio VaR's will be obtained and there time-series are displayed and explained below.

Analysing the three combinations, reason of choosing a Tailed Portfolio VaR combination. In all three combinations, the downside risk is fully covered by Tailed component. Mumbai-Chennai seems better as the range of minimum loss is visibly small compare to that appearing in Bangalore and Chennai temperature combinations. While for Bangalore-Chennai and Mumbai-Bangalore it is ranging between 0-(20000) Rupees, the same is usually under 0 to -4000 in case of Mumbai-Chennai combination.

In comparision to the previous one, the patterns of portfolio VaR is significantly different from Non-parametric and Parametric Portfolo VaR's

In all the three combinations, Mumbai chennai is not visible, i.e. there risks are comparatively lower in comparison to the two combination occupying Bangalore. Which chiefly relates to the fact that the volatility in Bangalore temperature was found more in comparison to other two cities. Also, from diversification point of view, including Bangalore will be more sound compare to other combinations. In case of Parametric Portfolio VaR downside volatilities are less compare to the upside volatilities. What this means is that GARCH model had been able to capture upside volatility clustering more oflen than downside volatility clustering. The same however, is not revealed in either of the two combinations.

Table 1 : Average Portfolio Value-At-Risk Measures With Generalized Autoregressive Heteroskadicity Model (GARCH 1,1)

(1996-97 to 2013-2014)

Portfolio VaR using GARCH 1,1 Model (All figures are in Rupees)							
Scenario Description							
Bangalore Chennai	90-%	95-%	98-%	99-%	STDEV	AVG	CV=stdev/avg
AVG Non-Parametric							
AVG Parametric	354	428	512	555	91.52	464.75	0.18
AVG Tailed	1180	1403	1677	1857	298.42	1529.27	0.20
Mumbai Bangalore	(1147)	(1364)	(1630)	(1805)	290.00	(1486.50)	(0.20)
AVG Non-Parametric							
AVG Parametric	337	401	480	530	87	436.75	0.18
AVG Tailed	6303	7494	8843	9915	1591.89	8166.50	0.18
Mumbai Chennai	(1195)	(1413)	(1680)	(1881)	300.56	(1542.27)	(0.18)
AVG Non-Parametric							
AVG Parametric	21	27	30	33	5.32	27.27	0.20
AVG Tailed	42	50	59	66	10.47	55	0.18
	(208)	(243)	(286	(327)	51.68	(266.00)	(0.18)

In Table 1, we can see that starting from 90% to 99% the change on average non-parametric VaR was 354 Rs per month, this was more than two times in case of parametric VaR. But both parametric and non-parametric VaR failed to account for downside risk on the average value basis. Contrary to this, Tailed VaR in case of Bangalore-Chennai had revealed far appealing figures. It can be seen that the coherency of VaR had increased with increase in confidence intervals. The average portfolio tailed VaR stood at negative 1486.5 Rs.

For Mumbai-Bangalore , the figures on Non-parametric VaR front were little down starting at 90% at 337 Rs/month at upside level it improved to 530 Rs. But volatility seems maximum with Parametric value as it averaged at wooping 8166.5 Rs per month ehile for Tailed VaR too it stood at negative 1542.5 Rs respectively.

Contrary to the above two tempeature portfolios, Mumbai-Chennai had remained more conservative, and upside and downside risk had remained relatively very low. Average portfolio VaR for non-parametric case was as low

as 27.27 Rs while for parametric it was 55 Rs. Non only this tailed VaR too was closed at as low as negative 266 Rs month. Almost 6 to 7 times lower than the last two tailed VaR combinations.

Hence, from hedging point of view, Mumbai-Chennai portfolio seems a better preposition, but for high risk high return perspective, Bangalore based combinations can be picked up.

Table 2 : "191-Month Horizon Portfolio Risk Capital"

Based On Traffic Signal Violations Approach With Generalized Autoregressive Heteroskadicity Model (GARCH 1,1)

(1996-97 To 2013-2014)

Portfolio Risk Capital using GARCH 1,1 Model (All figures are in Rupees)							
Scenario Description	90-%	95-%	98-%	99-%	STDEV	AVG	CV=stdev/avg
Bangalore Chennai							
Portfolio Risk Capital Non-Parametric	1418	1686	2014	2231	358.20	1837.27	0.18
Portfolio Risk Capital Parametric	(1540)	(1831)	(2188)	(2423)	389.17	(1995.50)	(0.20)
Portfolio Risk Capital Tailed	(4578)	(5441)	(6502)	(7202)	1156.46	(5930.75)	(0.18)
Mumbai Bangalore							
Portfolio Risk Capital Non-Parametric	1332	1584	1893	2096	336.74	1726.27	0.20
Portfolio Risk Capital Parametric	(1369)	(1627)	(1945)	(2153)	345.69	(1773.50)	(0.18)
Portfolio Risk Capital Tailed	(4750)	(5612)	(6749)	(7473)	1205.34	(6146.00)	(0.20)
Mumbai Chennai							
Portfolio Risk Capital Non-Parametric	89	106	127	140	22.55	115.50	0.20
Portfolio Risk Capital Parametric	(480)	(571)	(682)	(755)	121.18	(622.00)	(0.18)
Portfolio Risk Capital Tailed	(831)	(971)	(11440	(1307)	206.87	(1063.27)	(0.18)

Continuing with the explanation of portfolio VaRs, let us focus on how much amont of risk capital one has to account for which considering portfolio's of three tempeature variables.

The negative portfolio capital is more of a concern, on an average while for Bangalore-chennai a parametric portfolio risk capital improved from 1540 Rs to 2423 Rs , it averaged at 1995 Rs or approximately 2 % of the initial Mark-to-market value. This is comparatively very low when it come to Tailed compoenent which stood at 5930 Rs roughly 6% on monthly basis. However, for Mumbai –Bangalore the value peaked at 6146 Rs a month. As usual, just like Portfolio VaR the figures of risk capital were also too low in case of Mumbai –Chennai combination, it averaged at just 1063.27 Rs a month.

III. CONCLUSION

Temperature volatilities have impact on utilities prices and thus on economy. Agrarian Economy of India largely needs a mechanism to monitor the financial institutions preparedness by taking volatilities of such fundamental factors into account.

Temperature patterns vary according to location and hence micro level risk assessment of weather related investments is the order of the day. Much is needed in this direction from Indian perspective. There is a possibility that prices of essential food grains which are reflected in inflation can be linked to how far we can gauge the performance of temperature and other weather patterns with predominately GARCH type analysis as revealed earlier.

Banks extending major credit to agriculture industry must be allowed to manage their capital adequacy requirements on geographical basis and thus will put lesser load on risk capital requirements.

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