The Construction and Concept Validation of an Indian Financial Market Composite Risk Index (IFM: CRI): A Vibrant Risk Indicator to Retail Investors

Susmita Subba*[1], Muthu B. Pandian[2] and Ravi Shekhar Vishal[3]

Abstract

Financial market volatility has been a major interest to all the market stakeholders, especially retail investors, since 2020. Against this backdrop, the study is focused on constructing a Composite Risk Index (CRI) for the Indian Financial Market and examining the various methods of weighting as well as types of volatility captured in the construction of the Financial Market Composite Risk Index. The study intends to contribute to the methodological portion of the derivation of appropriate weights for each financial market segment. The study is based on the daily price series from 1st January 2020 to 31st March 2023. The research develops nine (09) different Composite Risk Index based on the types of volatility capture [Standard Deviation (SD), Autoregressive Conditional Heteroskedastic (ARCH), Generalised Autoregressive Conditional Heteroskedastic (GARCH)] and method of deriving the weights [Principal Component Analysis (PCA), Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA)] of various sub-markets [Equity, Commodity and Forex] and its segments [Spot and Derivatives]. The inter and intra-evaluation of nine CRI are carried out with the help of the nonparametric statistical tool Kruskal Wallis Test; further, the pair-wise comparation is also performed to analyse the homogeneity between the types of volatility capture and method of deriving the weights. The results reveal that the GARCH-based DEA Composite Risk Index better exhibits the volatility of the Indian financial markets compared to their counterpart CRI and also has a high co-movement with India VIX.

JEL: G1, G100, G110. G130, G190 **SDG:**

Keywords: Financial Market, Composite Risk Index, Risk Analysis, Spot & Futures Market, Others.

[1] Doctoral Research Scholar, School of Professional Studies, Sikkim (Central) University, Gangtok – 737102 Sikkim (East). *Corresponding author:. Email ID: subba14susmita@gmail.com
ORCID ID 0000-0003-0825-1915
[2] School of Professional Studies, Sikkim (Central) University, Gangtok – 737102 Sikkim (East). rishi2151@gmail.com / bmpandian@cus.ac.in. ORCID ID: 0000-0002-4523-9782
[3] School of Professional Studies, Sikkim (Central) University, Gangtok – 737 102 Sikkim (East) ravishekharvishal@gmail.com, rsvishal@cus.ac.in. ORCID ID: 0000-0002-4548-3312

1. INTRODUCTION

The Financial market is often regarded as an indicator of economic growth where other significant developments occur. Covid-19, also known as the SARS-CoV-2 virus, spread worldwide and caused disruptions, leading to slower development of the economy and impacting the financial market. In the financial sector, volatility is also referred to as risk and, in certain instances, (Gupta, 2009) states volatility as the "*rate and magnitude of changes in prices*". The value fluctuation of an asset over time is expressed as the variance or standard deviation of the asset's returns, which is regarded as an indicator of volatility. An asset's volatility increases as the standard deviation does. This also measures how risky an asset is since returns are more uncertain and there is more variation. Understanding the risk associated with any financial asset depends on tracking price fluctuations over time. (All about Volatility) the different types of measurement are historical (*realised*) volatility and implied volatility. (CBOE VIX Index) The S&P 500 Index call and put mid-quote prices are used in the VIX Index computation to generate an indication of the stock market's constant, 30-day projected volatility. VIX Index is one of the most renowned global forecasters of volatility, extensively monitored as a daily market indicator by a wide range of market experts. In India (National Stock Exchange), the volatility index measures the anticipation of short-term volatility in the market. The Volatility Index, based on the order book of the underlying index options, calculates the annualised volatility of an underlying index to determine how much it is projected to fluctuate in the near future. The India VIX is an indicator of volatility based on NIFTY measure option pricing. A volatility percentage that measures the projected market volatility over the following 30 calendar days is calculated using the best bid-ask prices of NIFTY Options contracts. Against this backdrop, the present study is focused on constructing a Composite Risk Index (CRI) based on the selection of the various *weighting methods* as well *types of volatility capture* from various sub-markets *[Equity, Commodity and Forex]* and its segments [*Spot and Derivatives*] as on the period from 2020. It purely represents the combined volatility or fluctuations of the various Indian financial submarkets.

The India VIX (Volatility Index) tracks the sole volatility of the Equity Market. The portrayal of the full extent of the Indian Financial Market volatility is not met. The Indian Market needs a representative of volatility in submarkets and their segments, along with the interactions of volatility between the submarkets and segments. Consequently, the study intends to gain insights into the combined risk that is useful for major decision-making among market stakeholders.

2. LITERATURE REVIEW

Paramanik and Singhal (2020) revealed that negative sentiment in the market causes large instability, and positive sentiment reduces volatility. Kumar and Gupta, (2009) examined the volatility and its pattern and concluded that economic events influencing the financial markets led to high volatility. The results contradicted the risk-return trade-off. Seth (2018) examines the inter-linkages prevailing in different financial markets (and concludes that inter-linkages in the foreign and stock exchange markets). Numerous Composite Index have been constructed, such as Krishnan's (2010) study is based on creating a socioeconomic index using standardisation procedures, (Vieira, Neto, Roque & Rocha, 2022) completed the construction of socioeconomic status indices (Social Vulnerability Index) for the area of the San Francisco River Basin in Brazil using Principal Component Analysis, the correlation matrix was used for the extraction of the principal components, (Boudt, d'Errico, Luu, & Pietrelli, 2022) Resilience Capacity Index has been constructed with the use of Principal Component Analysis to measure the resilience of food insecurity at the household level. Farrugia's (2007) study considers the various methods of constructing composite indices and also highlights the better criteria or conditions when constructing a composite index. (Gupte, Venkatarami & Gupta, 2012) study focuses on constructing a financial inclusion index for India. The index is based on the geometric mean of 4 Critical dimensions. A dimension-based index was computed, after which all the indices were combined to form the Financial Inclusion Index. financial index for the Indian setting is the main focus of the literature. The Financial Inclusion Index was created by first calculating a dimension-based index by taking the geometric mean of four important dimensions and then adding all of these indices together. Mazziotta and Pareto's (2016) study states that two conceptual approaches to the construction of composite indices are formative and Reflective Approaches. The Principal Components based index must be highly correlated indicators. Indicators with high correlation make up the major component-based index. Dharmawardena, Thattil, and Samita, (2015) focus on the Columbo district of Sri Lanka, and *Principal Component Analysis* (*PCA)* is used to produce composite indices, although this method eliminates natural variability. Dividing means making large modifications to change variables to unitless where the two alternatives are investigated. PCA and covariances matrices are not always appropriate due to their unpredictability. Mialou, Amidzic and Massara, (2017) aim to identify dimensions and assign weights and use a factor analysis to build a composite index for financial inclusion. The index assigns a ranking to countries placed in order according to the level of their financial inclusion. Roy, Biswas and Sinha (2015), the study intends to create the Financial Condition's Composite Indicator (FCCI) using principal component analysis (PCA) and analyse the connection between the economic activities and financial conditions in India from April 2003 to March 2014. Gerundo, Marra and Salvatore's (2020) study is based on the construction of a composite vulnerability index with the use of fuzzy logic focusing on the towns of Italy. The index is formed with the objective of identifying susceptible areas and measures of mitigation for the geographical areas that are in danger of deterioration. (Abeyasekera, 2005) The article states the importance of multivariate techniques in the construction of an index and its initial data exploration relating to the patterns and complex

relationships and reduction of data. using multivariate approaches for building an index is crucial, as is doing preliminary data exploration to find patterns and simplify complicated relationships. (Nardo, Saisana, Saltelli, & Tarantola, 2005)The article focuses on the construction of the composite indicators. It highlights the importance of determining steps such as theoretical framework identification of linkages, focuses on the variable's soundness and applicability to be measured, and emphasises the relevance of indicators and compensability in weighting and aggregation. (Joint Research Centre- European Commission, 2008) The construction of composite indicators is a complex process that requires careful evaluation of assumptions to avoid rigorous outcomes. It emphasises the importance of a conceptual framework and multivariate analysis before aggregating and examining the underlying assumptions in order to avoid the generation of erroneous findings. Prior to data aggregation, the articles highlight the importance of conceptual framework and multivariate analysis (Santos, Negas, & Santos, 2013). The DEA methodology enables the identification of both efficient and inefficient units within a framework that considers findings within their specific context. The use of this approach has mostly been directed towards evaluating the efficiency of non-profit organisations. The research also contrasts the efficiency boundaries of the Charnes, Cooper and Rhodes model (CCR) and the Bayesian Decision-Making (BCC) models. Fatehian and Fatehian, (2022) evaluate the efficiency of EN Bank branch networks. The authors concentrate on utilising the DEA model to assess bank branches' performance and determine the criteria for enhancing input or output. The bank branch's performance is benchmarked using a two-stage Data Envelopment Analysis technique. The efficiency of branches is determined by analysing inputs and outputs using CCR and BCC models. The primary rationale for employing a DEA model as opposed to alternative summary ratios/indices lies in the challenge of pre-determining appropriate weights for each efficiency component. A DEA model exhibits a robust capacity to choose weights objectively and produce a scalar-valued indicator objectively.

3. DATA AND RESEARCH METHODOLOGY

The present study used the daily price series from various sub-markets *[Equity, Commodity and Forex]* and its segments [*Spot and Derivatives*] as of the period from 01st Jan 2020: 31st Mar 2023. The spot and futures segment of the Equity Market are represented by the NIFTY50 and NIFTY futures. The Foreign Exchange Market was represented by the USDINR reference rate and the USDINR Futures. Whereas in case of the commodity spot market, BCOMSP: IND disseminated by Bloomberg, commodity Futures is represented by the iComdex Composite index of the Multi Commodity Exchange. The daily price series are duly obtained from the respective official web sources from Financial Benchmark India Limited, National Stock Exchange, Multi Commodity Exchange, Investing.com and Reserve Bank of India. After data cleaning, for construction of the Composite Risk Index (CRI) based on the different ***types of volatility capture*** *[Standard Deviation (SD), Autoregressive Conditional Heteroskedastic (ARCH), and Generalised Autoregressive Conditional Heteroskedastic (GARCH)]* methods are used in the present research.

The formula for generating the returns series of the various financial submarkets and its segments is

$$Returns\ [r_t] = \frac{Today\ price\ [p_t]\ - Previous\ day\ price\ [p_{t-1}]}{Previous\ day\ price\ [p_{t-1]}}$$

Generating the different volatility series based on return has been constructed by using the electronic spreadsheet. The Standard Deviation (SD) volatility series is generated as follows.

$$Standard\ Deviation\ (\sigma) = \sqrt{\frac{(x_i\ -\ \mu)^2}{N}}$$

The Engle (1982) *Autoregressive Conditional Heteroskedastic* (ARCH) Model-based volatility series for the various financial submarkets and their segments follows the equation.

$$\sigma_t^2 = \alpha_0 + \alpha_1\ \varepsilon_{t-1}^2 + \ldots. + \alpha\ _p\varepsilon_{t-p}^2$$

With the presumption that the average of the return series is constant, the variance is treated as omega or unconditional variance (UV). The constant value is added to the daily return series to construct the Residual Series (RES). Square of the Residual Series $(RES)^2$ gives Squared Residual Series (S.res). To generate the delayed squared residual series, one period lag of the squared residual series is used (S.res n-1). The alpha value (α) is set to zero for the initial phase, and the *conditional variance* (C. Var) is computed as

$$Conditional\ Variance\ Series\ [C.Var] = UV + \alpha *\ S.res_{n-1}$$

To generate the log-likelihood series, the approach used [*LLS*] by

$$Likelihood\ [\mathrm{L}(\mu, \omega, \alpha)] = \log \left[\frac{1}{C.Var_t} \sqrt{2\pi * e^{\frac{-S.\mathrm{Res}_t^2}{2*C.Var_t^2}}} \right]$$

The log-likelihood function value equals $\sum Log\ Likelihood\ Series.$ To generate the realised Volatility Series. $\sqrt{S.Res}$. ARCH Volatility series is generated using the $\sqrt{C.Var}$. The Bollerslev (1986) established the *Generalised Autoregressive Conditional Heteroskedastic* (GARCH) Model, is as follows

$$GARCH(1986):\ \sigma_t^2 = \alpha + \alpha_1\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2$$

The GARCH (1,1) series follows a similar manner to the ARCH series. The average value, standard deviation and variance are computed together with the return series. The constant value equals the average value for the initial phase. The variance value is regarded as the omega or U*nconditional Variance* (UV). The alpha and beta values are set to zero before running the data solver function in the electronic spreadsheet.

The lag residual series and squared residual series are created. The data solver is used to optimise the parameters to modify the constant, alpha, and beta values in the GARCH volatility series and the alpha and constant in the ARCH volatility series. The volatility of the GARCH series is equal to the square root of the conditional variance series.

After duly generating the different types of volatility series, the researcher tries to identify the appropriate ***method of deriving the weights*** *[Principal Component Analysis (PCA), Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA)]* of various financial submarkets and its segment.

Principal Component Analysis (PCA) is a statistical method that identifies the underlying factors or components driving the variation in a dataset. The explained variance ratios from the Rotated Components' Matrix (RCM) help in understanding the relative importance of each component in capturing the overall variability of the data. To determine the weights using different generated SD, ARCH, and GARCH Volatility Series of various sub-markets *[Equity, Commodity and Forex]* and its segments [*Spot and Derivatives*] has been used for obtaining Rotated Component Matrix, which was created using the Principal Component Approach. Further, the Excel spreadsheet is used for computing the *higher explained variance ratios*, indicating a more significant impact on the overall variance and should consider more domineering when determining the weights for the composite index. The sum and the cumulative percentage of explained variance are used to compute the factor weights. In order to generate new weights for each variable based on the values of the rotated component matrix, the sum of the new weights must be equal to 1 or 100. The weights have been determined using the formula

$$Component\ Weight\ (CW_i^{PCA}) = \left(\frac{100}{\sum Factor\ Weights}\right) \times Rotated\ Compnent\ Matrix$$

(Passage Technology) Thomas L. Saaty (*1970*) developed the *Analytic Hierarchy Process* (AHP), which offers a cohesive framework for a necessary decision by measuring its criteria, comparing its options, and connecting the elements to the main goal. The relevance of different criteria is compared side by side by stakeholders using pair wise comparisons. It represents an accurate approach to quantifying the weights of decision criteria. The AHP method determines the important factor according to pair-wise comparisons of stakeholders involved in the decision-making process. In the secondary data analysis, creating pair-wise comparisons of stakeholders is impossible; therefore, we use the correlation matrix of the respective variable as the proxy of the pair-wise stakeholder comparison table. The present research process uses the AHP process to determine the *Prioritization Matrix* to obtain the weight to the respective SD, ARCH, GARCH Volatility Series of various sub-markets *[Equity, Commodity and Forex]* and its segments [*Spot and Derivatives*]. Based on the correlation matrix column (j) component-wise total, we compute the priority value of each component on the basis of the proportion to the total of the respective component. The priority table is

$$\text{Priority Value } (PV_{ij}) = \frac{Pairwise\ Correlation_{ij}}{Sum\ of\ Pairwise\ Correlarion_j}$$

Further, the component column total of the respective priority values should be equal to 1; then, proceed to compute the criteria weight by using the following process.

$$\text{Criteria Weights } (W_i^{AHP}) = \frac{Sum\ of\ teh\ priority\ Value\ _i}{Total\ No.\ of\ Components\ (n)}$$

If the component column total of the respective priority values is not equal to 1; then continue the standardisation process to revise the Priority Value (PV_{ij}) to achieve the constraint. The component column total of the respective priority values should be equal to 1. Then, finally, calculate the criteria weights.

Data Envelopment Analysis (DEA is also regarded as Frontier Analysis, was presented by Charnes, Cooper and Rhodes (*1978*). DEA is a linear programming approach that, through experimentation, examines the effectiveness of a number of comparable entities or Decision-Making Units (*DMU*) (Malik, Efendi, & Zarlis, 2018). DMUs on DEA are components of groups that use inputs to produce outputs in the way entities are described. A matrix consisting of the inputs, outputs and complementary components of the DMU is required to conduct a *Data Envelopment Analysis*.

For generating the weights under the DEA method, the average values of different *volatility series [i]* (*SD, ARCH, GARCH*) have been bifurcated on the basis of SENSEX rallies of above 40,000 and above 50,000 separately. The *DEA Solver Learner Version 8* has been used to measure the market-wise weight of the various volatility series by using *Charnes, Cooper, and Rhodes* (CCR) approach on the basis of average value of various types of volatility series in two different rallies as output variable and the complete average value of price of the different ***segments (s)*** of the market as input variable and the same process will be repeated to all other financial ***submarkets (m)*** to capture the score based on input and output by running the DEA Solver. The market-wise DEA input and output ratio scores are converted into 100 by using the weighted proportion.

$$\text{Market Segement} - \text{wise Weight } (\text{MSW}_s^m) = \frac{100}{\sum I/O\ based\ Score\ _s} * respective\ Score\ of\ {}^m_s$$

Finally, based on the market-wise weight, the aggregated market weight of three different ***submarkets(m)*** is converted into 300 by using the following formula.

$$\text{Aggregated Market Weight } (\text{AW}_s^m) = \frac{300}{\sum w_s^m} * respective\ weight\ of\ {}^m_s$$

T*able 1* exhibits the weights derived from the ***various methods [n]*** (*i.e., PCA, AHP and DEA*) based on the different ***types of volatility series[i]*** (i.e., *SD, ARCH, GARCH*) for the different financial ***Submarkets [m]*** (i.e., Equity*, Commodity and Forex*) & its ***Segments [s]*** (i.e., *Spot &Futures*). With regard to the weights based on the SD volatility series, the higher contribution of weights is constituted from DEA-based Commodity Spot volatility series (31.86), AHP & PCA based Equity Spot (18.11 & 18.21), whereas, in ARCH Volatility series where a higher weight is found in Equity Spot Market based on PCA & AHP (17.73 & 18.27), and Commodity Spot Market in the DEA based weight (32.01). In the case of the GARCH volatility series, the higher contribution of weights from PCA is from the Forex Spot Market (18.31), Equity Futures Market (17.80) on weights based on AHP and Commodity Spot from DEA (31.97).

Table 1: Comparation of weights computed by various methods on the basis of different types of volatility series for the different financial submarkets & their segments.

Particulars		SD			ARCH			GARCH		
		PCA	AHP	DEA	PCA	AHP	DEA	PCA	AHP	DEA
Equity Market	*Spot*	18.21	18.11	16.51	17.73	18.27	16.64	16.76	17.71	16.38
	Futures	18.20	18.03	16.81	17.71	18.22	16.68	16.23	17.80	16.94
Commodity Market	*Spot*	16.49	15.61	31.86	16.57	15.23	32.01	16.19	15.80	31.97
	Futures	16.32	16.11	1.472	16.14	16.45	1.322	14.48	16.51	1.356
Forex Market	*Spot*	16.41	15.40	16.50	16.36	15.26	16.17	18.31	15.65	16.28
	Futures	14.35	16.74	16.82	15.46	16.56	17.16	17.99	16.54	17.04

Computed and Compiled by the Authors

After identifying the appropriate weight under the various ***methods of weight derivation (n)*** based on the different ***types of volatility series (i)***, the weighted score of the composite volatility (WSCV) series is computed using the following formula.

$$WSCV_i^n = \sum_{s=2}^{m=3} (Volatility_s^m * Weight_s^m)$$

Where, i = Types of Volatility Series; n = Method of Weights derivation; m = financial submarkets; s = segment of the market.

Finally, the Indian Financial Market Composite Risk Index (IFM: CRI) is calculated based on the weighted score of composite volatility as follows: the base value for the weighted score of composite volatility is considered as 100.

$$\text{IFM: CRI}_i^n = \left(\frac{Current\ Value\ of\ WSCV\ \times\ 100}{Base\ Value\ of\ WSCV}\right)$$

Based on the above computational procedures, there are nine (09) different types of Indian Financial Market Composite Risk Index (IFM: CRI) series are generated on the basis of (03) types of volatility series and (03) method of weight derivation.

4. DATA INTERPRETATION AND RESULTS

The different types of Indian Financial Market Composite Risk Index (IFM: CRI) series are based on different methods of derivation of weights and using the different types of volatility series. The basic data profiling of the above index series exhibits the portrayal of the different composite risk indexes. It helps to understand the performance of the series and efficiently organises and exhibits data from an enormous dataset into a form that is swiftly utilised to derive conclusions and contributes to decision-making.

Based on *Table 2* of the descriptive statistics, all the various types of composite risk indexes are on the basis of different methods of weight derivation and types of volatility series along with India VIX. The values of India VIX fluctuate from a range of 0 to 100, with the mean for India VIX is 20.82 ± 8.679 during the study period. Meanwhile, in the remaining, the Composite Risk Indexes have a base value of 100. The SD-based CRI Indexes capture the minimum of 14.70, 14.95 and 11.55 with a maximum of 915.30, 923.93 and 923.77, respectively, whereas in the case of ARCH and GARCH-based CRI Indexes record parades with a range of 92 to 451.12 and 546.64 ARCH and GARCH based CRI respectively.

Table 2: Table for Data Profiling of the India VIX and Various Composite Risk Index

Method	Type	Min	Mean	SD	Max	Skewness	Kurtosis	JB
VIX		11.49	20.82	8.679	83.60	14.92	3.315	8324.50***
[1]. Principal Component Analysis	**[1.1]. SD**	14.70	114.40	90.35	915.3	3.367	18.58	12201.48***
	[1.2]. ARCH	92.37	111.60	30.79	451.1	5.311	39.40	52002.36***
	[1.3].GARCH	92.86	146.46	55.76	536.9	3.730	17.34	11137.07***
[2]. Analytical Hierarchy Process	**[2.1]. SD**	14.95	114.87	90.96	923.9	3.408	18.97	12684.53***
	[2.2]. ARCH	92.31	111.66	31.30	460.2	5.391	40.58	55036.34***
	[2.3].GARCH	92.18	146.83	57.27	546.6	3.752	17.46	11282.77***
[3]. Data Envelopment Analysis	**[3.1].SD**	11.55	118.65	91.30	923.7	3.061	16.23	9398.38***
	[3.2]. ARCH	92.21	110.81	29.03	437.0	5.112	38.48	49493.88***
	[3.3].GARCH	96.24	151.10	56.32	551.1	3.624	17.09	10763.88***

Note: *** *at 1% Level of Significance (LOS)* | *Compiled and Computed by Author*

The various composite risk indexes have been compared with the performance of the India VIX graphically, exhibited in *Figures 1-9,* indicating that the Composite Risk Index have co-movement with the India VIX, and the fluctuations have also been analysed at the time of uncertainties. A higher level of fluctuation was seen during the 1st quarter of 2020, indicating that the turbulence period was regarded as highly uncertain and unpredictable, leading to greater chaos in the financial market due to the COVID-19 pandemic.

The mean range of the various types of Composite Risk Index is slightly nearer between 110.81 to 151.10, with a standard deviation range of 29.03 to 91.30; considering the context of the study, the present research is keenly interested in checking the mean difference statistically among the various CRI on the basis of different method of weight derivation and the different types of volatility variable inputs. The choice of the parametric or nonparametric statistical tool to test the significance of mean difference among the various CRI indices is based on the results of the normality test. The various CRI Indexes' skewness is greater than 0, and kurtosis is more than 3, indicating that the various CRI Indexes are not normally distributed; in addition to the above, the *Jarque Bera* (JB) Test also confirms the same. CRI and VIX are not normally distributed.

Figure 1: The graph of the composite index SD based on the Factor Analysis (PCA)

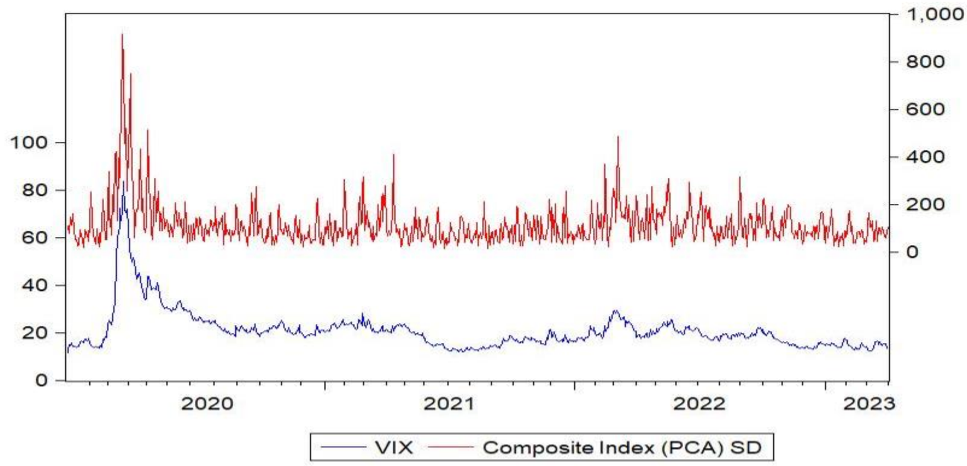


Figure 2: The graph of the composite index ARCH based on the Factor Analysis (PCA)

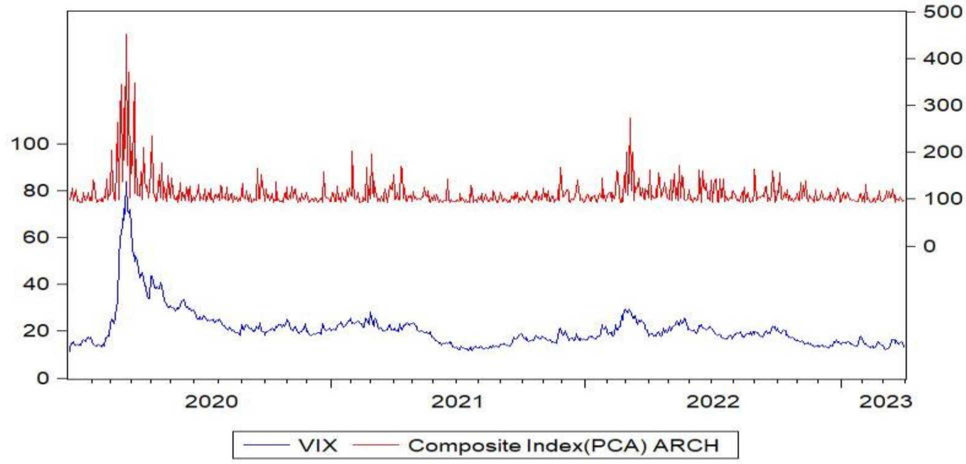


Figure 3: The graph of the composite index GARCH based on the Factor Analysis (PCA)

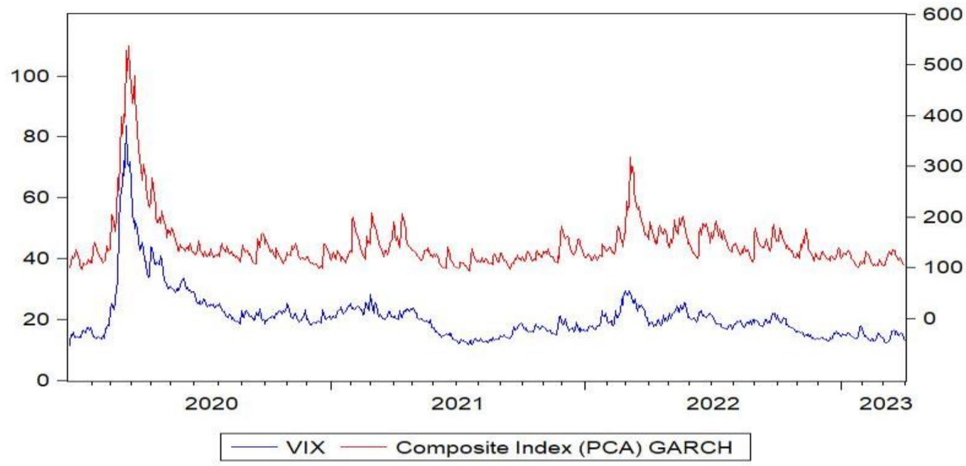


Figure 4: The graph of the composite index SD based on the Analytic Hierarchy Process

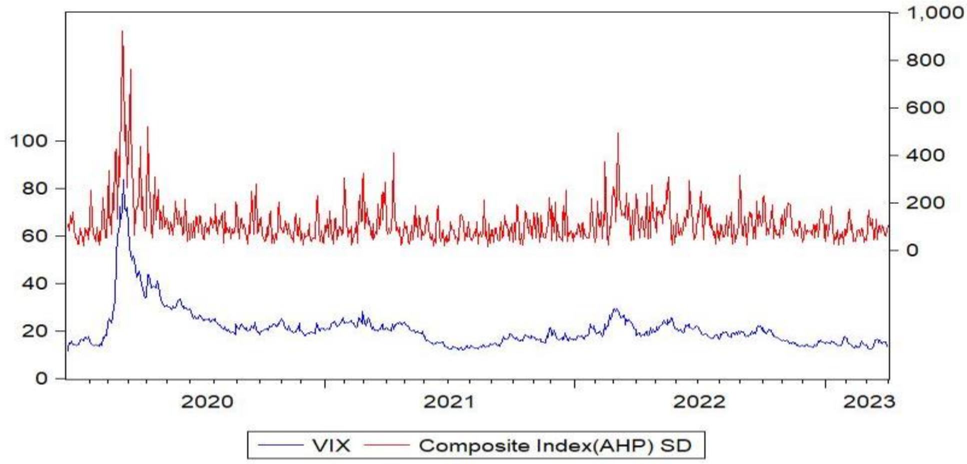


Figure 5: The graph of the composite index ARCH based on the Analytic Hierarchy Process

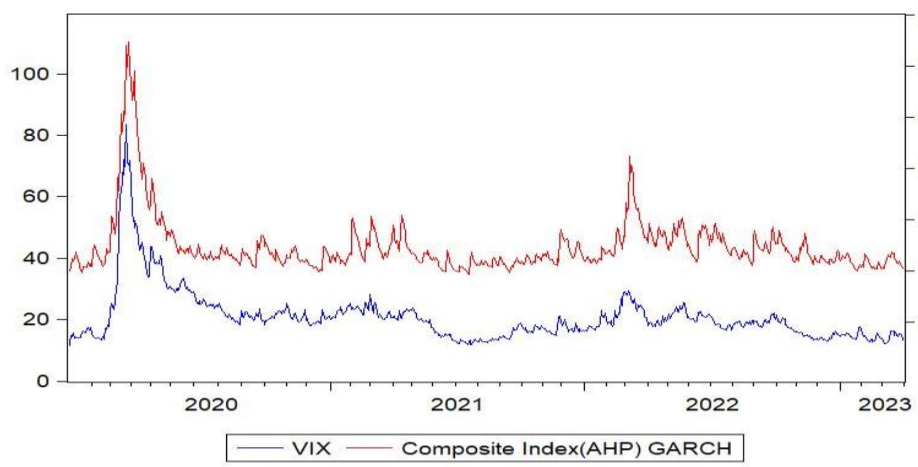


Figure 6: The graph of the composite index GARCH based on the Analytic Hierarchy Process

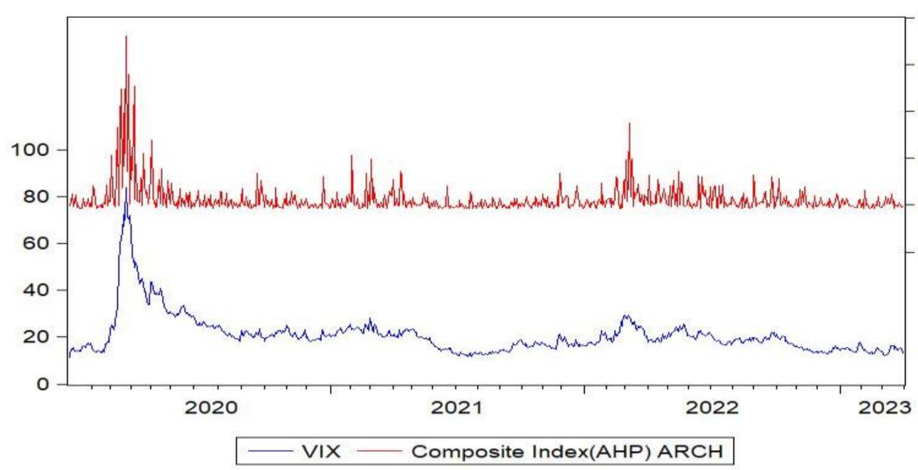


Figure 7: The graph of the composite index SD based on the Data Envelopment Analysis

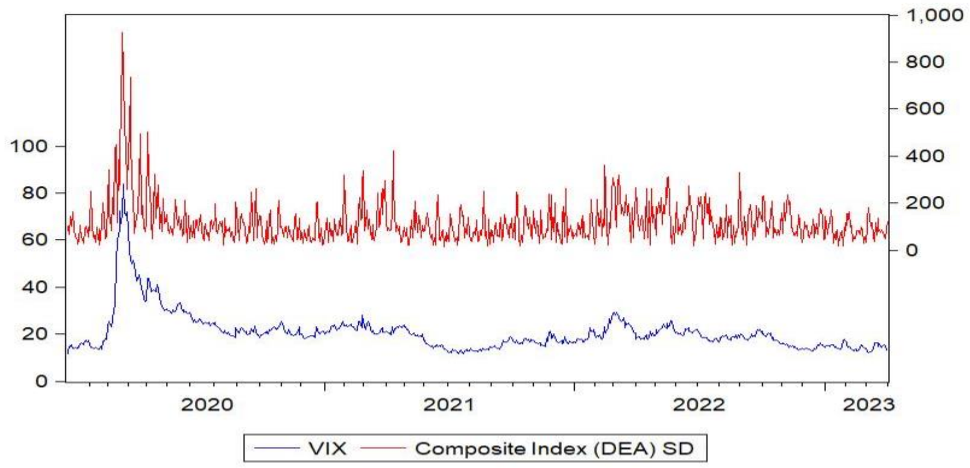


Figure 8: The graph of the composite index ARCH based on the Data Envelopment Analysis

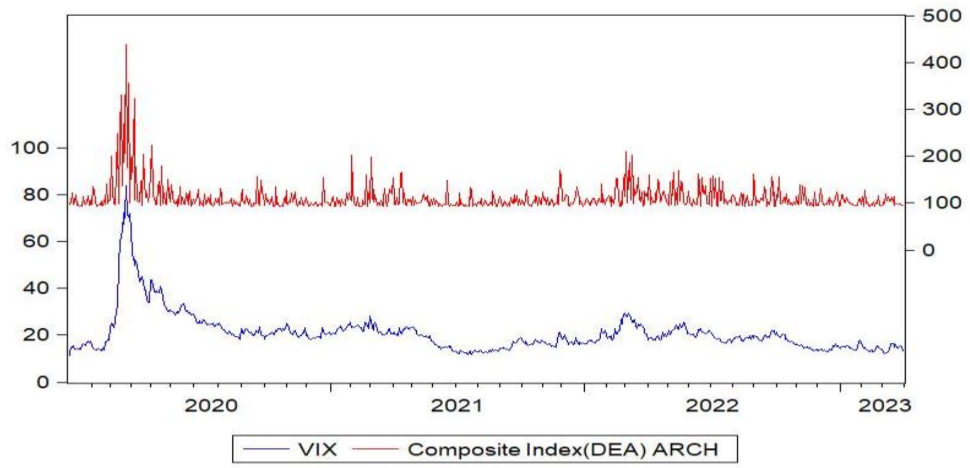
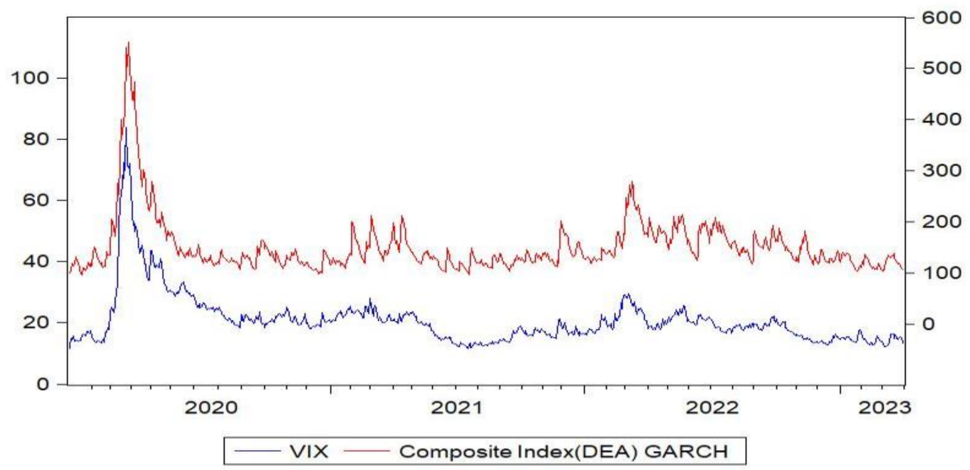


Figure 9: The graph of the composite index GARCH based on the Data Envelopment Analysis



Therefore, the present study uses the Kruskal Wallis (KW) nonparametric test to check whether there is significant statistical mean difference among the various Composite Risk Indexes on the basis of different types of variable inputs (i.e., *SD, ARCH, GARCH*) and the method deriving the weight (i.e., *PCA, AHP, DEA*) of the respective index. If a significant difference exists among the various types of variable inputs or the method deriving the weight, an appropriate pair-wise comparation test is used to understand the homogeneity among the pairs. The results of the inter and intra comparation of the different types of variable inputs (i.e., *SD, ARCH, GARCH*) and the method deriving the weight (i.e., *PCA, AHP, DEA*) of the respective CRI series are reported in *Table 3.*

The results of Table 3 reveal that there is a significant mean rank difference among the various composite risk indexes constructed based on the type of volatility series as input and the method of weight assigned. On the basis of weight assigned through *Principal Component Analysis* (PCA), there is a significant mean rank difference among the different types of volatility series used as input for constructing the composite risk index. Since the significant mean rank is statistically proven, the pair wise comparation test was conducted to understand the homogeneity between the pairs. The results of the pair-wise comparation exhibit that even though the CRI constructed on the basic various types of volatility series as input is statistically different, the SD and ARCH volatility series-based CRI have an equality and heterogeneity with GARCH-based CRI.

Table 3: Results of the inter and intra comparation of various Composite Risk Indexes

Inter and Intra Comparation of Mean Significant Difference		Types of volatility as input variable			Test Stat [Sig]
		[1] SD	[2] ARCH	[3] GARCH	
Method of Assigning the Weights	[1] PCA	114.40^{a} [0.644**]	111.60^{a} [0.609**]	146.46^{bI} [0.859**]	513.60**
	[2] AHP	114.86^{a} [0.646**]	111.66^{a} [0.611**]	146.83^{bI} [0.862**]	506.15**
	[3] DEA	118.65^{a} [0.607**]	110.81^{a} [0.595**]	151.19^{bII} [0.842**]	544.31**
Test Stat. [Sig]		1.671^{NS}	1.862^{NS}	13.810**	

Note: 1. Numerical subscript indicates the cluster formation based on type of volatility & alphabet subscript indicates the cluster formation based on method of weight derivation; 2. values stated in [ ] are bi-variate correlation of respective index with India VIX; 3. **at 5% Level of Significance (LOS) | Computed and Compiled by Author

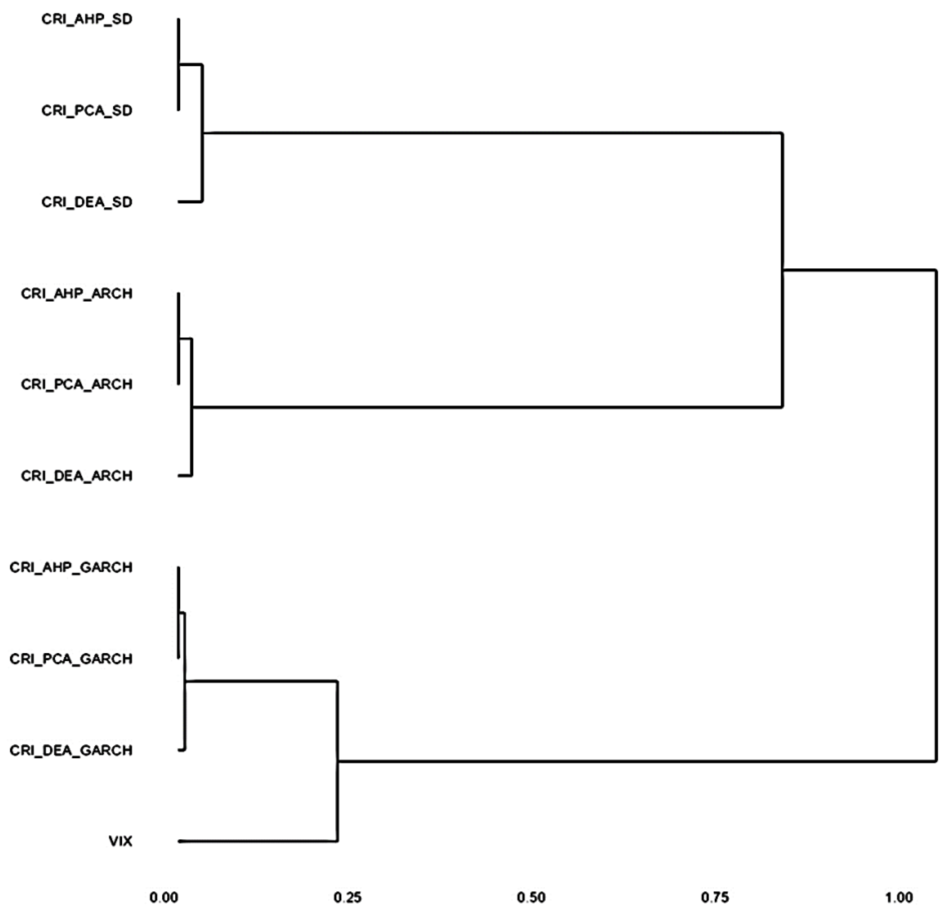
Meanwhile, the CRI weight derived by the analytical hierarchy p*rocess* (AHP) was evaluated for a pair-wise comparison test to infer the uniformity between the pairs. The results specified that there is a significant mean rank difference in the construction of composite risk among the numerous types of volatility series. The SD and ARCH volatility series-based CRI have an equivalence and form a group and vary with the GARCH-based CRI.

At the same time, the CRI weight derived by *Data Envelopment Analysis* (DEA) examined the comparison test amongst the pairs of various volatility series to evaluate the homogeneity. The outcome outlined a significant difference in the mean rank of various DEA-based volatility series. The GARCH-based CRI was heterogenous in nature to the SD and ARCH-based CRI, which were homogenous in nature.

However, as per the method of assigning the weights, on the basis of the SD and ARCH volatility series, there is no significant mean rank difference between them. Whereas in the case of the GARCH volatility series, there is a statistically significant difference in mean rank among the various methods of assigning the weights. Therefore, a pair-wise comparation test was conducted to understand the homogeneity between the sets. The results of the pair-wise comparation exhibit, all the methods of weight derivation-based CRI are diverse.

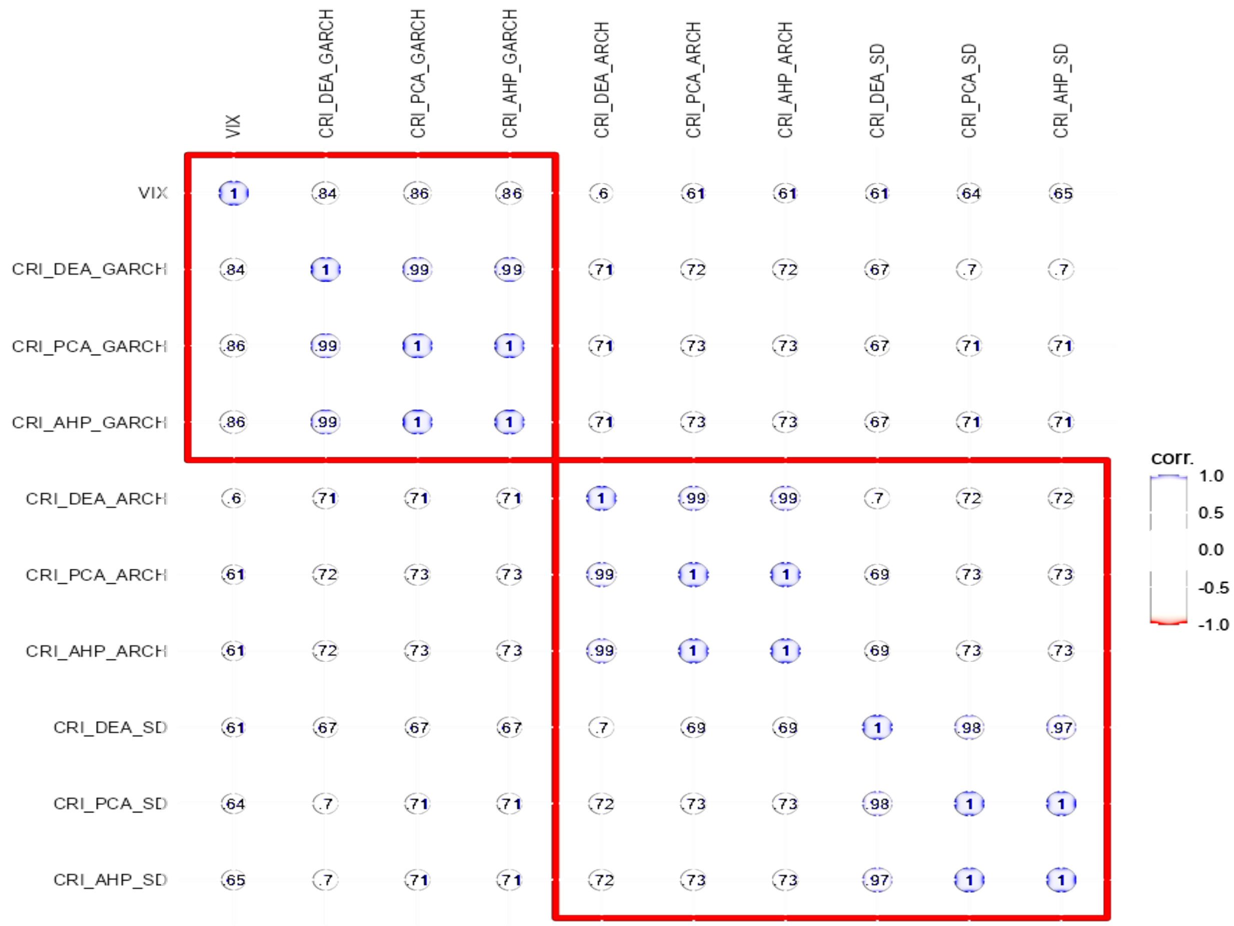
In addition to the above statistical test, the dendrogram shows substantial visual evidence of groups among the composite risk indexes based on different types of variable inputs (i.e., *SD, ARCH, GARCH*) and the method deriving the weight (i.e., *PCA, AHP, DEA*). F*igure 10* exhibits the cluster formation of the various types of composite risk indexes; the diagram form is bifurcated into two broad clusters. The *first cluster* consists of India VIX and the GARCH-based Composite Risk Indexes under the different methods deriving the weight (i.e., *PCA, AHP, DEA*). The remaining SD & ARCH-based Composite Risk Indexes under the different methods deriving the weight (i.e., *PCA, AHP, DEA*) are forming the *second cluster*. It confirms the results of the significant difference in the mean score test. Further, to substantiate the evidence of clustering based on the correlation structure of the different types of composite risk index among India VIX is shown in *Figure 11.*

Figure10: The dendrogram Cluster formation of the India VIX with the various Composite Risk Index



The cluster formation based on the correlation structure also confirms that various types of composite risk indexes have a strong, significant relationship with each other even though India VIX shows a significantly strong relationship with all the GARCH based Composite Risk Indexes under the different methods deriving the weight (i.e., *PCA, AHP, DEA*) compared to their counterpart composite risk index. Table 3 confirms the cluster formation based on the correlation structure quantitatively.

Figure11: The heatmap Cluster Classification of the India VIX with the various Composite Risk Index



5. CONCLUSION

The study intended to create a composite index to represent the aggregated volatility of the Indian Financial Submarket (*Commodity, Equity and Forex*) and its segments (*spot & futures*). Therefore the composite risk index is constructed based on two broad senses, based on the type of input variable [i.e. *Standard Deviation (SD), Auto-Regressive Conditional Heteroskedasticity (ARCH) and Generalized Auto Regressive Conditional Heteroskedasticity(GARCH)]* was used to create volatility series along with different methods for the derivation of the weights [*i.e. Factor Analysis based on Principal Component Analysis(PCA), Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA)*] Total nine [09] types of Composite risk index has been generated. The COVID-19 pandemic period indeed had a high level of turmoil during the 1st phase of the year. The GARCH-based

Composite Risk Index based on the different methods made evident that a higher level of correlation exists inter alia to explain the same phenomena of market volatility. The GARCH-based composite risk index constructed as per the different methods of weight PCA and AHP shows the same level of volatility compared to the composite risk index based on DEA, exhibiting better volatility results to policymakers as well as to retail financial market stakeholders.

The study attempts to portray the fluctuations in the Indian financial market accurately by assessing the volatility of the segments in the submarkets and intends to offer significant insights.

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The detailed data series regarding the sub-indices are available at the google drive link

https://docs.google.com/spreadsheets/d/1AcW2eiGcNglxOnj2yCUrjil2ApP2pYYt/edit#gid=1780602378