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A Vector Error Correction Model (VECM) Approach to Investigate the Linear Behaviour of Stocks, Bonds and Hedge Funds

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ABSTRACT:
One of the major concerns in todays' world of economic finance, especially investments in asset classes like stocks and bonds, is whether the returns on these asset classes are linear or non-linear. To test the linearity behaviour, this paper employs the Granger causality test (Granger, 1969) in the Vector Error Correction Model (VECM) scheme between stock, bond and hedge fund returns. The findings from the empirical evidence reveal that in bivariate and multivariate mode there is bidirectional short-run linear causality between stocks, bonds and hedge funds. In addition, the result also highlights that there exists a bidirectional long-run linear causality among stocks bonds and hedge funds while there is a unidirectional long-run linear causality between stocks and hedge funds. The outcome of this study is extremely useful to the institutional asset portfolio managers and also to the individual investors as it helps them in understanding the capital market structure better.

Keywords: **Cointegration, Granger Causality, Linearity, Unit Root Test, Vector Error Correction Model**

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INTRODUCTION

One of the major concerns in todays' world of economic finance, especially investments in asset classes like stocks and bonds, is whether the returns on these asset classes are linear or non-linear. As it is well known that future is uncertain and hence in finance, there is no theory which can guide for the prior expectations of asset returns. Numerous researches have been conducted to examine the behaviour of asset classes returns. Though, in theory of finance, the assumption of linearity has been adopted by various researchers [18][19][20][22][23] in their respective models, but that assumption is not essential. Further, it is important to understand that in empirical finance, when the time series returns are considered, then the linearity condition becomes an essential measure and hence accounts properly. In addition, the linearity condition becomes more important, especially in the case of hedge funds, where the returns are non-normal in nature. Also, the dynamic nature of hedge fund strategies like the use of derivatives, short-selling and leverages [6] make it different from the behaviour of stocks and bonds returns. As a consequence, for better portfolio management, the need for testing the linearity between hedge funds, stocks and bonds is warranted.

In empirical finance, many asset pricing models like CAPM (Capital Asset Pricing Model) [49][50] and portfolio theories like [22][23] modern portfolio theory is based on linearity assumption and thus, to run these models the asset class returns should be linear. In addition, if the conditional mean is not linear then it requires some more complex settings to run these empirical finance models in a non-linear structure.

Despite the fact that the hedge fund returns are non-normal, several studies have examined the features of hedge fund returns and how they behave in a portfolio mix with stocks and bonds [7][24][29][39]. In addition, these studies have shown the non-normal behaviour of hedge fund returns and highlighted that hedge fund returns are serially correlated. Further many studies have shown that the hedge fund return distributions are not linear [6][9][47]. Nevertheless, the phenomenal growth of hedge fund industry inspires the researchers to scrutinize this alternative investment class in the literature.

This paper conducts the test for linear conditional mean in two set of modes. First, in the bivariate mode, this study observes the linear behaviour of stocks, bonds and hedge funds returns together taking one asset class as dependent variable and one asset class as independent variable. Second, in the multivariate mode, the linear behaviour of stocks, bonds and hedge funds returns are observed taking one asset class as dependent variable and other two asset classes as independent variable.

To test the linearity behaviour, this study employs the Granger causality test [10] in the VECM scheme between stock, bond and hedge fund returns. The Granger causality test helps in determining whether the movement in one asset class returns causes the movement of other asset class returns. In other terms it helps in examine whether one return series could be predict by the past information of other return series.

By employing VECM approach, the findings from the empirical evidence reveal that in bivariate and multivariate mode there is bidirectional short-run linear causality between stocks, bonds and hedge funds. In addition, the result also highlights that there exists a bidirectional long-run linear causality among stocks and bonds & bonds and hedge funds while there is a unidirectional long-run linear causality between stocks and hedge funds.

The rest of the paper is outlined as follows. Section one provides a brief overview of the associated work. Section two documents the model applied for testing linearity. Section three describes the data employed. Section four examines the results while the final Section bids concluding remarks.

I. RELATED WORK

It may be noticed that, in the theory of finance, there exists no such condition for asset returns to be linear or non-linear. Despite this, the presence of non-linearity in the return series has been explained by many researchers [25][46]. The theoretical foundation has come from the notion of market equilibrium with market resistances and transaction costs. Several studies have assumed that in the presence of market resistances and transaction costs, the asset prices partially deviate which in turn misprice the asset value from the market equilibrium [26][32]. These mispricing cause arbitrageurs to enter into the market and tune the asset prices move back to the equilibrium but that modification is non-linear. However that theoretical concept is more effective in narrow settings where the daily return series are examined as compared to monthly return series because the effect of price movement is less supportive in the latter case as the sample frequency is small.

Further, the studies [8][14][15][16] have paid attention to examine the non-linearity pattern without presuming that transaction costs actually affect the asset price. In addition, they argued in two perspectives; first, that investor behaviour itself possesses thoughtful biases which may not be consistent with von Neumann-Morgenstern (VNM) Maximize Expected Utility Theorem [27] and thus cause the non-linear movement of asset prices. Second, they argue that the non-linearity in asset prices could also be explained by the restrictions of arbitrage theory propounded by Shleifer and Vishny[5]. The study by Shleifer and Vishny[5]assume that during risky market situations, the arbitrage forces may not be effective because of capital limitations, thereby, causing in non-linear movements of asset prices. Further, in empirical finance, researchers have suggested that prior to running the non-linear model, it is better to test for the presence of non-linearity in the data [11].

Although, the above literature provides the rationale that the non-linearity persists in narrow setting, however, there is a little direction provided by these rationales, especially in the context of portfolio construction, to observe the linearity of monthly asset returns. As a consequence, this study focuses on the observation of linearity of asset classes in the low frequency setting of monthly returns. Also, it is of utmost important to decide which model to run either linear or non-linear. From the theory of finance, to avoid the model misspecification in portfolio construction, it seems rational to examine the linear dependence of asset classes returns.

In Social Science, especially in econometrics, Granger [51] developed the linear Granger causality test to identify the causal relationship between two or more time series returns. More specifically, Granger causality test examine whether one return series lag terms significantly describe the other return series in a vector autoregressive regression (VAR) model [44][52]. However, this test is not well suited for identifying non-linear causal relationships. Though, many researchers have evaded this limitation by developing a non-linear Granger causality test [12][17]. Further, Engle and Granger [38]developed the concept of cointegration which becomes a more robust tool for modeling and testing time series returns. In addition Engle and Granger [38] illustrates that the co-integrating variables can be embodied by VECM to identify the short run and long run causality among the variables. So to run VECM the variables should pass the Johansen cointegration test developed by Johansen and Juselius [45]. The beauty of the linear Granger causality test lies in the fact that it can be applied in both bivariate and multivariate settings. Thus, this study employs the linear Granger causality test in the VECM scheme to know the short run and long run causality between the asset classes returns.

All the above cited research contributions represent few of the numerous tests of linearity established in the strand of (non)linearity literature. Still one can find many more that have not been cited above and the exhaustive review of all the literature is far behind the scope of this study. Finally, the review of literature enlightens us that the non-linearity concept is not properly defined and has been identified in numerous forms by applying various tests.

However, the aforementioned linearity tests have been employed by numerous researchers in different empirical perspectives namely in bivariate and multivariate modes. The study of bivariate and multivariate mode is important because in the portfolio construction process, the mean-variance investors have to presume the linearity condition when involving two or more asset classes. It may be noteworthy that many researches done in this context were based on testing the linear causal relationship by applying the VECM between market index returns and macroeconomic variables [1][2][4][30][31][33][34][35][36][37]. Apart from the above cited studies, there are several studies that have been analyzed the returns of asset classes together by applying VECM to observe the long term and short term relation and volatility.Campbell and Aminer[28] applied a log linear framework integrated with VAR and revealed that the movement in stock and bond prices is due to the news in the respective sector like stock prices move due to news about the future dividends and yields while the bond prices movement is caused due to news about the inflation rate changes. Gregoriou and Rouah[21] analyzed different hedge fund strategies and various equity markets (S&P 500, MSCI World, NASDAQ, Russell 2000) and revealed that only two hedge fund strategies were having cointegration with different stock market indices. Füss and Herrmann [42] investigated the long-term and short-term interdependence between the developed equity market and hedge fund strategies. In addition, [41] applied multivariate cointegration analysis to test for the existence of cointegration among conventional (S&P 500 and large cap stocks and bonds) and alternative (NASDAQ, commodities, emerging markets) portfolio and hedge funds. In addition, they have also analyzed the benefit of diversification by including hedge funds with these traditional and alternative portfolios. Further, Füss and Kaiser [40] extended the Füss and Herrmann [42] study and analyzed the long-term and short-term relationships between the conventional asset classes for the emerging market regions

(Asia, Eastern Europe and Latin America) and hedge fund and found that the advantage of diversification arises by including hedge funds to the emerging market equity-bond portfolio. In other strand, [3] integrates the VECM and General Auto Regressive Conditional Heteroscedasticity (GARCH) model and revealed the long run linkage between stocks and bond market returns. In different study Chen [43] analyzed the stock market (in low volatility state) and bond market (in high volatility state) and found non-negative correlation between the two asset classes. Also, Masmoudi[48] applied linear Granger causality and VAR model to investigate the linkage between traditional financial assets of Canada, France and Germany and global macro hedge fund strategy. In his finding, Masmoudi[48] revealed the short-term and long-term dependence between traditional financial assets and global macro hedge fund strategy.

The study of the above cited literature suggests some of the problems that need to be addressed. First, extensive research has been conducted on the subject in various international markets but Indian market has been still in the nascent stage relative to the mammoth growth of the bourses have witnessed. This study makes an attempt to fulfill this gap by examining the data from the Indian capital market to identify the linearity behaviour of three most important asset classes in the world viz, stocks, bonds and hedge funds. Secondly, none of the above cited study focused on examining the linearity of hedge fund returns with stocks and bonds from a viewpoint of mean-variance investor. This study investigates the bivariate and multivariate tests in a way which is reliable to a mean-variance investor for making portfolio selection decisions. We now continue to detail the methodological stipulations of this study.

II. METHODS AND MODELS EMPLOYED

The study employs the linear Granger [10] causality test in the VECM theme, to examine the short-run and long-run linearity relationship among the variables in bivariate and multivariate mode. To provide accuracy in the estimate of the relationship, it is thus necessary to prior determine the presence of unit root and cointegration between the time series. This helps in implementing VECM scheme which presumes that all variables are endogenous.

II.1 Augmented Dickey-Fuller (1981) Stationary Test

The study applies Augmented Dickey-Fuller (henceforth ADF) test developed by Dickey and Fuller [13] to examine the unit root in each series with the following hypothesis:

H_0: $\theta = 0$i.e., the time series is non-stationary and need to be differenced (has a unit root)

H_a: $\theta < 0$ i.e., the time series is stationary (has no unit root)

The ADF test is expressed by the following ordinary least square (OLS) relationship:

$$\Delta y_t = \alpha_0 + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \qquad (1)$$

where, t is a deterministic trend, α and β are the constants, p is the lag order selected based on Schwarz Bayesian Criterion (SBC). If the calculated value, in absolute term, is more than the t-statistic value (or the p-value less than 5%), this rejects the null hypothesis (θ=0) and conclude that the time series is stationary.

If the null hypothesis rejected at level (without differencing), then the order of the stationary series is designated as I(0) whereas if the null hypothesis rejected at first difference then the order of the stationary series is designated as I(1). Similarly, for second difference the order of the stationary series is designated as I(2).

II.2 **Johansen-Juselius (1990) Cointegration Test**

If the time series are non-stationary at level and when the variables are integrated of same order, the Johansen test of cointegration developed by Johansen and Juselius [45] can be applied to obtain the number of co-integrating vector(s). Johansen-Juselius [45] multivariate cointegration model can be expressed as:

$$\Delta y_t = \alpha_0 + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

where, $\Pi$and $\Gamma_i$are the coefficient matrices, Δ is the symbol of difference operator and p is the lag order selected based on Schwarz Bayesian Criterion (SBC). Johansen-Juselius [45] techniques use two likelihood ratio test statistics to obtain the number of co-integrating vector(s) namely, the Trace test and the Maximum Eigenvalue test which can be computed respectively as:

$$T(r) = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i) (3)$$

$$\lambda_{max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1}) \qquad (4)$$

where, $\hat{\lambda}_i$is the expected eigenvalue of the characteristic roots ad T is the sample size. The null hypothesis of the Trace test (equation 3) investigates the number of r co-integratingvectors against the alternative of n co-integrating vectors. The null hypothesis of the Maximum Eigenvalue test (equation 4) investigates the number of r co-integrating vectors against the alternative of r+1 co-integrating vectors. So, if the variables are found to be co-integrated after applying Johansen-Juselius test then it can be concluded that their exists long-run equilibrium relationship between the variables. Further, that long-run equilibrium relationship can be examined by applying VECM scheme.

II.2 **Vector Error Correction Model (VECM)**

It can be understood that cointegration indicates the presence of causality among two time series but it does not detect the direction of the causal relationship. According to Engle and Granger [38], the presence of cointegration among the variables shows unidirectional or bi-directional Granger causality among those variables. Further, they demonstrate that the cointegration variables can be specified by an Error Correction Mechanism (henceforth ECM) that can be estimated by applying standard methods and diagnostic tests. The VECM regression equation can be expressed as follows:

$$\Delta y_t = \alpha_1 + p_1 ecm1_{t-1} + \sum_{i=0}^{n} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta x_{t-i} + \sum_{i=0}^{n} \gamma_i \Delta z_{t-i} + \varepsilon_{1t} \qquad (5)$$

$$\Delta x_t = \alpha_2 + p_2 ecm2_{t-1} + \sum_{i=0}^{n} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta x_{t-i} + \sum_{i=0}^{n} \gamma_i \Delta z_{t-i} + \varepsilon_{2t} \qquad (6)$$

where, β_i, $\delta_i$and $\gamma_i$are the short-run coefficients, Δ is the symbol of difference operator, p is the lag order, $ecm1_{t-1}$and $ecm2_{t-1}$are the Error Correction Term (henceforth ECT) and ε_{1t}&ε_{2t} are the residuals. Further, the $ecm1_{t-1}$ is the lagged value of the residuals derived from the co-integrating regression of y on x (equation 5) whereas the $ecm2_{t-1}$ is the lagged value of the residuals derived from the co-integrating regression of x on y (equation 6).

Now, unidirectional causality between y to x (i.e., y Granger cause x) will happen in the equation 5 if, the set of estimated coefficients ($\delta_i$and γ_i) on the lagged values of 'y' is jointly significant (short-run causality) and the ECT coefficient p_1 is negative and statistically significant (long-run causality). Similarly, unidirectional causality between x to y (i.e., x Granger cause y) will happen in the equation 6 if, the set of estimated coefficients ($\beta_i$and γ_i) on the lagged values of 'x' is jointly significant (short-run causality) and the ECT coefficient p_2 is negative and statistically significant (long-run causality). Hence, if both the variables Granger cause one other, then it can be concluded that there is a two-way feedback relationship between y and x. Thus, the VECM representation allows us to discriminate amongst the long-run and short-run dynamic relationships.

III.SOURCES OF DATA

To account for the data for stocks, bonds and hedge funds this study considered the major indices which are designed to measure the performance of the Indian capital universe as the proxies for all the three asset classes, i.e., the study employs the S&P BSE Sensex and CNX Nifty Equity Index as the proxy for stocks, the NSE G-SEC and ICICI I-Bex India Bond Index as the proxy for bonds and the Eureka Hedge India Hedge Fund Index as the proxy for hedge fund returns. Data have been sampled from January 2002 to December 2016 consisting of 180 observations of all the indices mentioned above [24].

To minimise the impact of systematic risk, the study employed monthly index returns for each investment rather than employing the returns of individual bonds, stocks or hedge funds. Also, the study involves the estimation of multi-asset portfolios; hence, it employs periodic monthly excess (original return – risk free rate) returns. The choice of taking risk-free rate is of utmost importance.

The study uses the average of worst three annualized yield of one year maturity T-bills from 2002 to 2016. The National Stock Exchange T-bill index is used for the proxy for risk-free rate of return and it was observed that the worst three yields arose in the year 2010, 2004 and 2003 respectively and the average is found to be 5.04% annually (.42% monthly) [24].

IV. EMPIRICAL RESULTS AND FINDINGS

IV.1 Analysis of Summary Statistics

Table 1 summarizes the statistical summary of all the indices used in the study, which reflects the significant features of financial market like mean, standard deviation (second moments), negative skewness (third moments), excess kurtosis (fourth moments), the classical performance measure Sharpe ratio and the jarque-bera (JB) normality test statistics value.

Table 1: Summary Statistics

This table represents the descriptive statistical summary of the excess monthly index returns of the three asset classes used in this study. Sampled data contains 180 observations from January 2000 to December 2014. * shows the data is statistically significant at the 1% confidence level.

Sector	Stock Index		Bond Index		Hedge Fund Index
	S&P BSE SENSEX	CNX NIFTY Equity Index	NSE G-SEC India Bond Index	ICICI I-Bex India Bond Index	Eureka Hedge India Hedge Fund Index
Variable					
Mean	0.78	0.80	0.15	0.40	0.47
Standard Deviation	7.08	7.19	1.84	1.94	5.84
Skewness	-0.18	-0.26	0.74	1.40	0.19
Excess Kurtosis	1.31	1.59	7.60	8.97	1.29
Median	0.79	1.04	0.10	0.36	1.28
Maximum	27.84	27.65	10.40	12.36	23.81
Minimum	-24.31	-26.83	-6.71	-5.50	-16.73
Jarque- Bera Statistic	12.57	19.15	422.00	623.68	13.59
Jarque- Bera p-value	0.0019*	0.0001*	0.0000*	0.0000*	0.0011*
Sharpe Ratio	0.110	0.111	0.083	0.207	0.080

It can be evident from Table 1 that all the six indices have rejected the normality test on the basis of JB test statistic p-value. Also, it is evident (see Table 1) that investor's desire of higher returns in the market come at the cost of high second moments and negative third moments in the return distribution. In addition, it can be observed that the hedge funds have a lesser monthly mean return than stocks monthly mean returns over the sample period studied.

Also all the six indices exhibit positive excess kurtosis which indicates that most of the data values in the return series were concerted around the mean with thicker tails. Further, the Sharpe ratio was high for the bond index (ICICI I-Bex) showing the importance of fixed income securities which provides security against the negative market movement.

IV.2 **Analysis of Bivariate and Multivariate Linear Granger Causality test in the VECM scheme**

As discussed in Section II that before implementing the bivariate and multivariate linear Granger Causality test in the VECM scheme, it is important to analyze the result of unit root and cointegration test.

IV.2.1 **Analysis of Augmented Dickey-Fuller (1981) Stationary Test**

The result of the ADF test is shown in Table 2.

Table 2: Augmented Dickey Fuller Test

Variables	Level	First Difference	Order of Integration
S&P BSE Sensex	-2.467344^ [-3.141565]	-13.00429* [-4.011352]	I (1)
CNX Nifty	-2.586361^ [-3.141565]	-13.49781* [-4.010440]	I (1)
ICICI I-Bex	-1.147031^ [-3.141565]	-11.72572* [-4.010440]	I (1)
NSE G-Sec	-2.186166^ [-3.141565]	-12.78920* [-4.010440]	I (1)
EH India Hedge Fund Index	-2.174038^ [-3.141649]	-11.06305* [-4.010440]	I (1)

* denotes significance at 1% and ^ denotes non-significance at 10%, respectively

It is evident (see Table 2) that the null hypothesis of time series being stationary cannot be rejected at their level with trend and intercept, since the ADF test statistic values are insignificant at 10% level. However, when the first differences with trend and intercept are taken then all the time series become stationary at 1% level. Hence, all the variables are stationary in first difference with no unit root and have same order of integration I (1).

IV.2.2 **Analysis of Johansen-Juselius (1990) Cointegration Test**

As the ADF test shows that the data is stationary in first difference and the variables are integrated of same order, the Johansen-Juselius cointegration test is applied to determine the long-run equilibrium relationship among the variables.

The result of Johansen test for all possible three asset classes combinations is shown in Table 3 to Table 6 along with the trace statistics value. It is interesting to note that (see Tables 3 – 6) the trace statistics rejects the three null hypotheses (none, at most 1 and at most 2 cointegration among the variables) and indicates 3 co-integrating equations at 5% level of significance.

Finally, from the cointegration test, it can be concluded that there are three co-integrating vectors between the stocks, bonds and hedge funds and thus, VECM is now applied to examine the short-run and/or long-run equilibrium relationships among these three variables.

Table 3: Johansen Cointegration Test: Series A: Hedge Fund CNXNIFTY ICICI I-Bex
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.425486	193.0357	29.79707	0.0001
At most 1 *	0.272917	94.38249	15.49471	0.0000
At most 2 *	0.190650	37.65131	3.841466	0.0000

Table 4: Johansen Cointegration Test: Series B: Hedge Fund CNX NIFTY NSE G-Sec
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.425019	194.4466	29.79707	0.0001
At most 1 *	0.280068	95.93818	15.49471	0.0000
At most 2 *	0.189724	37.44762	3.841466	0.0000

Table 5: Johansen Cointegration Test: Series C: Hedge Fund S&P BSE ICICI I-Bex
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.414222	189.6659	29.79707	0.0001
At most 1 *	0.274109	94.46909	15.49471	0.0000
At most 2 *	0.189715	37.44576	3.841466	0.0000

Table 6: Johansen Cointegration Test: Series D: Hedge Fund S&P BSE NSE G-Sec
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.415722	191.5787	29.79707	0.0001
At most 1 *	0.279272	95.92537	15.49471	0.0000
At most 2 *	0.190560	37.63143	3.841466	0.0000

Trace test indicates 3 co-integrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

IV.2.3 **Analysis of Bivariate and Multivariate results of VECM**

The existence of cointegration vectors between variables recommends a short-term and long-term equilibrium relationship between the variables under consideration. Table 7 and Table 8 represent the results of chi-square test statistic p-values for VECM in bivariate and multivariate mode with lag order 1[1].

[1]The lag order of one is selected by applying the lowest value of Schwarz Bayesian Criterion (SBC).

In addition, Table 7 and Table 8 show three different terms for each possible combination. The first term represents the ECT coefficient value while the second term is the chi-square test statistic p-value of the ECT which determines the long-run relationship between the variables. The third and final term is the adjusted Wald test coefficient p-value which determines the short-run relationship between the variables.

Table 7: Bivariate Results of Vector Error Correction Model (VECM)

This table reports the χ^2Statistic p-values for VECM in a bivariate mode with lag order one. Three terms are calculated for each possible combination. The first term represents the ECT coefficient value while the second term is the chi-square test statistic p-value of the ECT which determines the long-run relationship between the variables. The third and final term is the Wald test coefficient p-value which determines the short-run relationship between the variables, respectively. * and ** denotes significant at 1% and 5%, respectively.

Dependent Variable		Independent Variable			
Panel A: Stock vs. Bond and Stock vs. Hedge Fund					
Bond and Hedge Fund Index		**ICICI I-BEX**	**NSE G-SEC**	**Eureka Hedge India Hedge Fund Index**	
S&P BSE SENSEX	**ECT**	-0.603028	-0.634647	-1.332745	
	p-value	0.0000*	0.0000*	0.0000*	
	Wald Coefficient	0.0001*	0.0004*	0.0010*	
CNX NIFTY	**ECT**	-0.677887	-0.709047	-1.454783	
	p-value	0.0000*	0.0000*	0.0000*	
	Wald Coefficient	0.0001*	0.0006*	0.0005*	
Panel B: Bond vs. Stock and Bond vs. Hedge Fund					
Stock and Hedge Fund Index		**S&P BSE SENSEX**	**CNX NIFTY**	**Eureka Hedge India Hedge Fund Index**	
ICICI I-BEX	**ECT**	-0.504755	-0.445510	-0.655080	
	p-value	0.0000*	0.0000*	0.0000*	
	Wald Coefficient	0.0000*	0.0000*	0.0000*	
NSE G-SEC	**ECT**	-0.522420	-0.460074	-0.665808	
	p-value	0.0000*	0.0000*	0.0000*	
	Wald Coefficient	0.0000*	0.0000*	0.0001*	
Panel C: Hedge Fund vs. Stock and Hedge Fund vs. Bond					
Stock and Bond Index		**S&P BSE SENSEX**	**CNX NIFTY**	**ICICI I-BEX**	**NSE G-SEC**
Eureka Hedge India Hedge Fund Index	**ECT**	0.280743	0.347139	-0.316572	-0.348052
	p-value	0.0264**	0.0022*	0.0000*	0.0000*
	Wald Coefficient	0.0108**	0.0238**	0.0022*	0.0032**

It is evident from Panel A and Panel B (see Table 7) that in bivariate mode with stocks (dependent variable) and bonds (independent variable) & bonds (dependent variable) and stocks (independent variable), respectively; the ECT coefficients value are negative and statistically significant at 1%

level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Panel Aof Table 7 reports all the significant p-value at 1% level. This concludes the rejection of null hypothesis of ‘no-cointegration’ and confirms the existence of bidirectional short-run and long-run equilibrium relationship between stocks and bonds.

Further, it is evident from Panel A (see Table 7) that in bivariate mode with stocks as dependent variable and hedge funds as independent variable; the ECT coefficients value are negative and statistically significant at 1% level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Panel A of Table 7 reports all the significant p-value at 1% level. This concludes the rejection of null hypothesis of ‘no-cointegration’ and confirms the existence of unidirectional short-run and long-run equilibrium relationship between stocks and hedge funds. Also, it can be noticed from Panel C of Table 7 with hedge funds as dependent variable and stocks as independent variable, the ECT coefficients value are positive and statistically significant at 5% level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Panel C of Table 7 reports all the significant p-value at 5% level. This concludes the non-existence of long-run and presence of short-run equilibrium relationship between hedge funds and stocks.

Further, it is evident from Panel B and Panel C (see Table 7) that in bivariate mode with bonds (dependent variable) and hedge funds (independent variable) & hedge funds (dependent variable) and bonds (independent variable), respectively; the ECT coefficients value are negative and statistically significant at 1% level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Table 7 reports all the significant p-value at 1% level. This concludes the rejection of null hypothesis of ‘no-cointegration’ and confirms the existence of bidirectional short-run and long-run equilibrium relationship between bonds and hedge funds.

The inferences that can be drawn from the VECM bivariate test suggest that there exists a bidirectional short-run linear causality among the three asset classes. In addition, there exists a bidirectional long-run linear causality among stocks and bonds & bonds and hedge funds while there is a unidirectional long-run linear causality between stocks and hedge funds.

Next, Table 8 represents the VECM result in multi-variate mode. It is evident from Panel A of Table 8 that in multi-variate mode with stock as dependent variable and bonds / hedge funds as independent variable; the ECT coefficients value are negative and statistically significant at 1% level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Panel A of Table 8 reports all the significant p-value at 1% level. This concludes the rejection of null hypothesis of ‘no-cointegration’ and confirms the existence of linear short-run and long-run equilibrium relationship between stocks and bonds / hedge funds in multi-variate mode.

Further, it is evident from Panel B (see Table 8) that in multi-variate mode with bonds as dependent variable and stocks / hedge funds as independent variable; the ECT coefficients values are negative and statistically significant at 1% level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Panel B of Table 8 reports all the significant p-value at 1% level. This concludes the rejection of null hypothesis of ‘no-cointegration’ and confirms the existence of linear short-run and long-run equilibrium relationship between bonds and stocks / hedge funds in multi-variate mode.

Further, it is evident from Panel C of Table 8 that in multi-variate mode with hedge funds as dependent variable and stocks / bonds as independent variable; the ECT coefficients value are positive (BSE & NIFTY / NSE G-Sec) & negative (BSE & NIFTY / ICICI I-Bex) and statistically significant at 1% level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Panel C of Table 8 reports all the significant p-value at 5% level. This concludes the presence of short-run equilibrium relationship between hedge funds and stocks /bonds.

Table 8: Multi-variate Results of Vector Error Correction Model (VECM)

This table reports the χ^2Statistic p-values for VECM in a multi-variate mode with lag order one. Three terms are calculated for each possible combination. The first term represents the ECT coefficient value while the second term is the chi-square test statistic p-value of the ECT which determines the long-run relationship between the variables. The third and final term is the Wald test coefficient p-value which determines the short-run relationship between the variables, respectively. * and ** denotes significant at 1% and 5%, respectively.

Dependent Variable		Independent Variable			
Panel A: Stock vs. Bond and Hedge Fund					
Bond and Hedge Fund Index →		**ICICI I-BEX / Hedge Fund**	**NSE G-SEC / Hedge Fund**		
S&P BSE SENSEX	**ECT**	-1.083668	-1.106729		
	p-value	0.0000*	0.0000*		
	Wald Coefficient	0.0006*	0.0018*		
CNX NIFTY	**ECT**	-1.203154	-1.226372		
	p-value	0.0000*	0.0000*		
	Wald Coefficient	0.0006*	0.0021*		
Panel B: Bond vs. Stock and Hedge Fund					
Stock and Hedge Fund Index →		**S&P BSE / Hedge Fund**	**CNX NIFTY / Hedge Fund**		
ICICI I-BEX	**ECT**	-0.374816	-0.304889		
	p-value	0.0000*	0.0000*		
	Wald Coefficient	0.0000*	0.0000*		
NSE G-SEC	**ECT**	-0.388980	-0.311481		
	p-value	0.0000*	0.0000*		
	Wald Coefficient	0.0002*	0.0002*		
Panel C: Hedge Fund vs. Stock and Bond					
Stock and Bond Index →		**S&P BSE / ICICI I-BEX**	**CNX NIFTY / ICICI I-BEX**	**S&P BSE / NSE G-SEC**	**CNX NIFTY / NSE G-SEC**

Eureka Hedge India Hedge Fund Index	**ECT**	-0.046294	-0.086624	0.276092	0.305636
	p-value	0.0057*	0.0047*	0.0002*	0.0000*
	Wald Coefficient	0.0313**	0.0294**	0.0407*	0.0162**

Further, it is evident from Panel B (see Table 8) that in multi-variate mode with bonds as dependent variable and stocks / hedge funds as independent variable; the ECT coefficients values are negative and statistically significant at 1% level. In addition, when the estimated coefficients are diagnosed by applying Wald test statistic, Panel B of Table 8 reports all the significant p-value at 1% level. This concludes the rejection of null hypothesis of 'no-cointegration' and confirms the existence of linear short-run and long-run equilibrium relationship between bonds and stocks / hedge funds in multi-variate mode.

CONCLUSION

In empirical finance, the condition of linearity in the asset class returns is essentially needed. In addition, in portfolio selection context for the co-variance matrix to be valid, the assumption of linearity in the mean must hold. It is noteworthy that if assets class returns are not linear then the judgments made with the various portfolio selection models can lead to model misspecification. Hence, this study was an attempt to demonstrate the linear behaviour of three important asset classes in the world i.e, stocks, bonds and hedge funds by applying linear Granger causality test in the VECM theme to examine the short-run and long-run linearity relationship in bivariate and multivariate mode. Altogether, the study observed the long-run and short-run linear causality among stocks, bonds and hedge funds by applying unit root / stationary test, Johansen cointegration test and VECM approach.

The empirical findings of Augmented Dickey-Fuller unit root test showed that all the three variables are stationary in first difference with no unit root and have same order of integration I(1). In addition, the Johansen cointegration test revealed that there are three co-integrated vectors between the three asset classes returns employed. Further, the findings of the VECM scheme in bivariate and multivariate mode showed the bidirectional short-run linear causality among stocks, bonds and hedge funds. In addition, the result also highlighted that there exists a bidirectional long-run linear causality among stocks and bonds & bonds and hedge funds while there is a unidirectional long-run linear causality between stocks and hedge funds.

The finding that stocks, bonds and hedge funds are linear conditional mean offers further understanding to the performance of these vital asset classes. First, for mean-variance investors for deciding investment in portfolio, the indication of existence of linearity in the asset classes is a good sign. Second, the empirical evidence of short-run and long-run linear causality among stocks, bonds and hedge funds based on the VECM approach provides meaningful and motivating insights to institutional and individual portfolio fund managers. Last, the result of all the testing framework advocate that the markets are inefficient, and that the prices of one asset class (say hedge funds) can be estimated via the price figures of the other assets class (stocks and bonds).

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