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Hedging Effectiveness with CNX Bank Nifty and Nifty Futures: VECH (H,) Approach

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Abstract

CNX bank nifty trading performance represents the state of Indian banking sector and thereby evaluates the socio-economic objectives. Using bivariate IGARCH (1, 1) model for both CNX bank nifty and nifty futures this study found that there persist long-run relationship between the spot and futures prices and thus returns. Here, this study calculated the futures prices with the usual cost of carry model considering the call rate as the proxy for the financing rate. This study also found that the hedge ratios for both the index futures are negative and caused the market as imperfect one. In this situation, investment decision requires the optimal investment preferences and choices with resource generations and diversifications. The study confirms that there is a living run relationship between the spot and future prices and hence returns exist for both the index futures.

I. Introduction

INDIA IS A mixed economy. Of course, there is no term like this in the world economic literature. Probably it starts with South Asia that too from India. This economy has a typical nature where, both the socialist and capitalist economic thoughts exist. Accordingly, the role and the significance of public and private sector became an important thought at each level of object's economic activity. Therefore, object has to think on preferences and economic choices for investment decisions.

These economic activities heavily depend on both organized and unorganized sectors of the economy. Out of several, the service sector is gaining a lot of importance towards the development and growth of the economy. Particularly the 'Banking' sector has the crucial role in financial

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market to bring the economy at an optimum and equilibrium state of socioeconomic objectives. In Indian economy, globalization has made it relatively easy, particularly in post reforms period. Due to the pressure of global competition, it seems that the Indian banking system is moving towards an efficient and productive one at least in infrastructural facilities for easy transactions. However, the financial market still needs further association with this sector for the development of the economy.

As far as the efficiency and performance of banking system is concerned, probably the dynamic modern approach of $CAMEL^1$ (Mohan, 2006) is the best way to focus on socio-economic objectives. This approach integrates the measures of risks, agency costs, principal-agent relationships, and quality of bank services. Thereby the other efficiency and performance indicators like interest spread, operating cost, production cost, intermediation cost, employee cost, net interest margin, fund allocation, ownership effect etc. can be assessed through CAMEL approach.

In this financial market perspective, Scholtens and Dam (2007) have argued that banks, which are adopting the Equator Principle $(EP)^2$, signal the corporate social responsibility conduct that improves the reputation and reduces the risks. On operating profit, they have observed that the EP banks are associated with lower returns. Costs also absorb these returns at the implementation of this principle. Here decomposition of the financial risk has also significant differences in bank size and leverage. These findings convey that adopting EP is not a window dressing but exhibits the real costs. For larger banks, the adaptation of EP shows the reduction of risks but without observation in financial data. Adapting EP as an event, they found that shareholder is not reacting negatively for signing up, as this will not significantly affect his value. Of course, this may be the reason that there is no direct trade off between corporate social responsibility and stock returns.

Using Black-Scholes (*B-S*) option pricing model, Laeven (2002) has estimated the cost of deposit insurance, as a proxy for the bank risk measurement. Laeven found that the cost of deposit insurance is high with the higher loan growth of the bank i.e. when the amount of net loan outstanding is added to the *B-S* model specification to control bank-specific size effects, the higher cost of deposit insurance becomes statistically significant. In this mechanism, the author found that the banking system is less risky with high GDP per capita income and low inflation. So the proxy of 'the cost of deposit insurance' may be used as early warning of banking crises.

Barik and Supriya (2007a) have observed that due to asymmetric information flow in Indian nifty futures market, the subjective and objective motives are not realizing. Thereby, there is a mismatch between the supply and demand sides of the trading causing the futile and inequilibrium trades. In nifty futures market, Barik and Supriya (2007b) have observed that the market activities like speculation, hedging, and arbitrage are dominating the market causing monopoly character of it. This hinders the socio-economic

objectives. Of course, one may argue that by the course of time the market will become competitive one. Therefore, all of the above findings are motivating to measure risk, agency cost, principal-agent relationship, and quality of financial services. Particularly, Indian bank derivatives market would be an appropriate area of research as this is directly linked with the banking sector.

1.1 CNX Bank Nifty and Nifty

The post liberalization period is experiencing a dramatic change for this banking sector. It seems, 'bank' became next to 'money' with all of its functions. Therefore, the active integration and participation of the financial market has been increasing with the banking sector. In securities market, reforms introduced the inclusion of the enactment of Securitization Act to set up loan recoveries, establishment of asset reconstruction companies, initiatives on improving recoveries from Non-Performing Assets (NPAs) etc. To achieve a good benchmark of the Indian banking sector, India Index Service and Product Limited (IISL) has developed the CNX bank Index. This provides investors and market intermediaries with a benchmark that captures the capital market performance of the Indian banks. This index consists of twelve scrips from the banking sector, which is traded on the National Stock Exchange of India Ltd (NSE). These scrips are Bank of Baroda, Bank of India, Canara Bank, Corporation Bank, HDFC Bank Ltd., ICICI Bank Ltd., Kotak Mahindra Bank Ltd., Oriental Bank of Commerce, Punjab National Bank, State Bank of India, Union Bank of India and UTI Bank Ltd. This CNX bank Index represents around 79% of the total market capitalization of the banking sector as on March 31, 2005³. Like bank nifty, the CNX nifty has the greater role towards the active market participation and resource generation. Therefore, a number of underlying developments have been taking place during this liberalization period with the objective of risk reduction and thereby efficient banking system maximizing socioeconomic objectives.

II. The Study: Objective & Methodology

2.1 Objectives

Considering foregone discussions, objectives of the study are to measure and assess the risk involved in bank Index futures trading. This can be achieved through measuring the 'hedging ratio' with different effective hedging models. This is because, the 'hedging' has the significant role to stabilize the market, realizing the market efficiency and enabling the minimization of risk and thus maximizing profit/utility.

2.2 Methodology

Understanding the original work of Bollerslev (1986 and 1987), Bollerslev, Chou and Kroner, (1992), two stage *IGARCH* models of Barik and Supriya (2005, 2007a and 2007b), *GARCH* model of Park and Switzer (1995) i.e., the constant correlation bivariate *GARCH* model and multivariate *GARCH* model of Bollerslev, Engle and Wooldridge, (1988), this study follows the bivariate *IGARCH* (1, 1) model. The study has considered both *CNX* bank nifty Index and *CNX* nifty Index at National Stock Exchange of

India Ltd. (*NSE*), where, the analysis on the linkage between the financial market and the banking sector is discussed. That is, some of the scrips are common in both the indexes. Even if they are not common in both the indexes, the inter linkages and interdependencies are focused as both of them are contributing for resource allocation and mobilization in the Indian financial market. Here, the hedging models are constructed using a two period investment decision based on the utility maximization model through the mean-variance returns. This ensures the economic analysis on the bank nifty and nifty futures. Therefore, using the spot price (*S*) and futures price (*F*) for both these indices, hedging portfolios are constructed and forecasted.

2.2.1 The Model

Now S_t = spot price, F_t = Futures price, B_t = holding of futures at time t'. The payoff at t+1 is $x_t = S_{t+1} - b_t F_{t+1}$. That is to produce one unit of the spot and going short in 'b,' unit of futures at time't'. Here the optimal hedge ratio is ' \hat{b}_{i} ', which is maximizing the investors utility/profit and minimizing the risk. The futures price is calculated by using usual cost of carry model where, the proxy for the rate of interest is the Mumbai inter-bank call rate. That is; futures price = closing price + [closing price \times (call rate – dividend yield)] \times ((T-t)/365). This is because, through the theoretical or calculated futures price, the financial market is linked with the derivatives market. Depending upon this call rate the investment decision on bank nifty futures is focused. Because, the relationship between the day-to-day rate of interest and investment decision in financial market and thereby in whole economy, is the crucial factor. Accordingly, the liquidity adjustment policy depends on this relationship along with the open market operations. Of course, one may argue that if the bank nifty futures contract is having 90-92 days contract period (about three months), where as the call rate is for one day or less than the futures contract period, then, how one will make the investment decision depending upon this financing rate (call rate).

The answer is as follows. In this study, the near month contract for both bank and nifty futures is considered with call rate as financing rate. Here assumption for an investor is that this call rate is constant for the contract period of three months from the particular day of investment. This is for those who have invested in this particular trading day. There may be a change in call rate due to the demand supply pressure in the call money market. But, the object has to make the decision with the call financing rate of today, ignoring the probable call rate change in tomorrow. This is because, object is in the urgent need of financial resources to invest. Therefore, these investors are ready to invest in derivatives market for a particular settlement date irrespective of the market mechanism for call rates. In this context, the economic demand-supply for call rate will not have any impact on futures investment decision. Here only the resource allocation is the matter of concern. So the call rate is considered as the financing rate for the period of three months consisting sixty days.

Again, investors will close their loan accounts in next lending trading day in the call market (within one day). Apart from the actual trading days (i.e., approximately twenty days per month or five days per week), rest of the trading days are not a matter of concern for the investors in relation to call rate. At least psychologically, this holds well with the investor. So, in total the cost of carry period is sixty days out of three months contract period i.e. the cost of carry period is ${}^tT - t' = 91 - 60 = 31$ days. Accordingly, the futures price or theoretical price is calculated. Therefore, the dynamics of 'spot price – futures price' is calculated. Using this calculation the optimal hedge ratio i.e. ' \hat{b}_i^* ' is defined through the bivariate *IGARCH* model.

In this case, the IGARCH4 model specifies mean equations as

$$s_{t} = \alpha_{0} + \alpha_{1}(S_{t-1} - \mathcal{F}_{t-1}) + \varepsilon_{St}$$

$$f_{t} = \beta_{0} + \beta_{1}(S_{t-1} - \mathcal{F}_{t-1}) + \varepsilon_{Ft}$$

$$\begin{bmatrix} \varepsilon_{s} \\ \varepsilon_{p} \end{bmatrix} | \psi_{t-1} \sim N(0, H_{t})$$
(1)

where, $s_t = \Delta S_t = S_{t-1}$ and $f_t = \Delta F_t = F_{t-1}$ are spot and futures returns. Both these returns depend on the dynamics of $(S_{t-1} - \gamma F_{t-1})$ which shows the dynamic changes of spot and futures prices. In this case, $(S_{t-1} - \gamma F_{t-1})$ is the error correction term. Here, $(\mathcal{E}_{St}, \mathcal{E}_{Ft}) \sim N$ (0, H) and ' ψ_{t-1} ' represents the information set.

The usual VECH (H.) model is

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} c_{SS} \\ c_{FF} \\ c_{SF} \end{bmatrix} = \begin{bmatrix} a_{SS} a_{SF} a_{S3} \\ a_{FS} a_{FF} a_{F3} \\ a_{3S} a_{3F} a_{33} \end{bmatrix} \begin{bmatrix} \mathcal{E}_{1,t-1}^2 \\ \mathcal{E}_{2,t-1}^2 \\ \mathcal{E}_{1,t-1} \mathcal{E}_{2,t-1} \end{bmatrix} + \begin{bmatrix} b_{SS} b_{SF} b_{S3} \\ b_{FS} b_{FF} b_{F3} \\ b_{3S} b_{3F} b_{33} \end{bmatrix} \begin{bmatrix} h_{1,t-1}^2 \\ h_{2,t-1}^2 \\ h_{1,t-1} h_{2,t-1} \end{bmatrix}.$$
(2)

For h_{ijt} , where, i=1, 2 and j=1, 2, the estimated vector matrices for H_t , C_t , A_t and B_t are

$$H = \begin{bmatrix} h_{SS} h_{SF} \\ h_{FS} h_{FF} \end{bmatrix} i.e., \begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix}, \quad C = \begin{bmatrix} c_{SS} \\ c_{FF} \\ c_{SF} \end{bmatrix}, \quad A = \begin{bmatrix} a_{SS} a_{SF} \\ a_{FS} a_{FF} \end{bmatrix} \quad and \quad B = \begin{bmatrix} b_{SS} b_{SF} \\ b_{FS} b_{FF} \end{bmatrix}$$

Therefore, the VECH (H_i) is

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} c_{SS} \\ c_{FF} \\ c_{SF} \end{bmatrix} + \begin{bmatrix} a_{SS} \mathcal{E}_{1,t-1}^2 \\ a_{FF} \mathcal{E}_{2,t-1}^2 \\ a_{FS} \mathcal{E}_{1,t-1} \mathcal{E}_{2,t-1} \end{bmatrix} + \begin{bmatrix} b_{SS} h_{1,t-1}^2 \\ b_{FF} h_{2,t-1}^2 \\ b_{FS} h_{1,t-1} h_{2,t-1} \end{bmatrix}$$
(3)

This study has considered for the time-varying variances and covariances. Therefore, the second moment is parameterized with a bivariate constant correlation IGARCH model. The following model parameterized the conditional variances of two variables as ARMA (1, 1)⁵. models in squared residuals. Here, the assumption is that, there is the constant correlation between the two residuals. Therefore the variance vector is

$$H = \begin{bmatrix} h_{SS,t} & h_{SF,t} \\ h_{FS,t} & h_{FF,t} \end{bmatrix} = \begin{bmatrix} h_{S,t} & 0 \\ 0 & h_{F,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} h_{S,t} & 0 \\ 0 & h_{F,t} \end{bmatrix}$$
(4)

Here, the conditional variance equations are;

$$h_{St}^{2} = c_{SS} + a_{SS} \varepsilon_{S,t-1}^{2} + b_{SS} h_{S,t-1}^{2}$$

$$h_{Ft}^{2} = c_{FF} + a_{FF} \varepsilon_{F,t-1}^{2} + b_{FF} h_{F,t-1}^{2}$$
(5)

where, *IGARCH* (1, 1) specifications for equation (5) are and $a_{FF} + b_{FF} \approx 1$. In this case, other properties for *VECH* (H_i) are withstanding.

As a result, the VECH (H) is

$$\begin{bmatrix} h_S^2 \\ h_F^2 \end{bmatrix} = \begin{bmatrix} c_{SS} \\ c_{FF} \end{bmatrix} + \begin{bmatrix} a_{SS} \varepsilon_{1,t-1}^2 \\ a_{FF} \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{SS} h_{1,t-1}^2 \\ b_{FF} h_{2,t-1}^2 \end{bmatrix}$$
(6)

With
$$h_{SF,t} = c_{SF} . \sqrt{h_{St}^2 h_{Ft}^2}$$

Now, equation (4) shows the structure of the bivariate conditional variance with constant correlation, ' ρ ' and equation (5) is the bivariate *IGARCH* (1, 1) model. The optimal hedge ratio is calculated with the variance estimates from equation (4) and equation (5). That is:

$$\hat{b}_{t}^{*} = \frac{\hat{h}_{SF,t}}{\hat{h}_{FF,t}} \tag{7}$$

In addition, with this bivariate IGARCH(1,1) estimation, the conventional OLS hedge ratio is defined with the restriction of " $\alpha_1 = \beta_1 = a_{ss} = b_{ss} = a_{FF} = B_{FF} = 0$ ". The conventional OLS hedge ratio that accounts for the cointegration between spot and futures prices where the long-run relationship between them exists with the restriction of ' $a_{ss} = b_{ss} = a_{FF} = B_{FF} = 0$ '.

Now after estimating the above optimal hedge ratios, the constructed payoff time series i.e., $\sigma^2(S_{t+1} - b_t \cdot F_{t+1})^6$ for both bank nifty and nifty portfolios are forecasted with Theil test statistics. Using Theil test statistics, this study has observed 'hedging effectiveness' models for both the portfolios with all the estimated optimal hedging ratios. Thereby the efficient hedging method is also defined. In addition, there is the analysis on risk-return trade off for both CNX bank nifty and CNX nifty futures returns.

III. Data, Discussion and Empirical Findings

The present study used the daily data for S & P CNX nifty and CNX bank nifty Index futures contract from June 13, 2005 to October 08, 2007 consisting 606 observations with the total of 4242 observations. Daily spot prices (returns) data for both bank nifty and nifty index futures are collected from the NSE³. Daily futures prices (returns) data are calculated with the above cost of carry model for both the index futures. The call rate data are collected from the RBI⁷. The dividend yields for both the index futures are collected from the NSE³. The public sector bank dividend yields data are included in this study. This is because; most of the scrips in bank nifty index are from the scheduled commercial banks of PSUs. Therefore, these dividend yields are the proxy yields for the bank nifty futures. The dynamic return series are also calculated for both the index futures.

This study has considered the econometric model specification where all of the variables like spot returns, dynamic futures returns, and error correction terms are modeled without any logarithmic transformation. This is because; the logarithm of futures return series and the lags of spot and futures returns are having both negative and positive units. The logarithmic transformation on these variables or data produces missing values in estimation and thereby poor result. Therefore, without any logarithmic transformation, this study is modeled at the same units of measurement for all the above variables. The Granger, Geweke-Meese-Dent (*GMD*) variation and Sim causality tests show that both the nifty futures and bank nifty futures return Granger, *GMD* and Sim cause the nifty spot and bank nifty spot returns with appropriate statistical significance level⁸.

Now, the issue on long-run relationship between spot and futures returns is focused. It is estimated that the spot and futures returns of both bank nifty and nifty index futures are perfectly contemporaneously correlated where; the cross-autocorrelation does not exist. Through the Engle-Granger-2-step procedure, the coefficients of equation (8) and equation (9) are estimated. These equations represent equilibrium correction or error correction models for bank nifty and nifty index futures respectively.

The bank nifty equilibrium correction or error correction model is:

$$S_{bt} = \lambda_{bo} + \lambda_{b1} F_{bt} + u_{bt}$$

$$\Delta S_{bt} = \zeta_{b0} + \delta_{b1} u_{bt-1} + \zeta_{b2} S_{bt-1} + \zeta_{b3} F_{bt-1} + v_{bt}$$
(8)

The nifty equilibrium correction or error correction model is;

$$S_{nt} = \lambda_{no} + \lambda_{n1} F_{nt} + u_{nt}$$

$$\Delta S_{nt} = \zeta_{n0} + \delta_{n1} u_{nt-1} + \zeta_{n2} S_{nt-1} + \zeta_{n3} F_{nt-1} + v_{nt}$$
(9)

Here, the equilibrium correction terms like $\delta_{b1}u_{bt-1}$ for bank nifty and

 $\delta_{nl}u_{nl}$ for nifty index futures, are included as independent variables for Engel-Granger second step estimation, where the cointegrating vectors are $(1-\lambda_{b0}-\lambda_{b1})$ and $(1-\lambda_{n0}-\lambda_{n1})$. From Table I and Table III, one can observe that the estimated slope coefficients in the cointegrating regressions are close to unity and this is what is predicted in theory. Again, DF test statistics on residuals with constants are 24.53 and 24.51, which are greater than the DF critical value 1.13 at 5% level (Pindyck and Rubinfeld 1998, p.509). DF test statistics on residuals without constant are -24.6589 and -24.7638, which are more negative than the Engle-Granger critical value -4.48 at 5% level (Brooks 2002, p.676). Therefore, all the variables in equation (8) and equation (9) are stationary in nature where, the null of a unit root in the regression residual corresponding to the no cointegration case is rejected. Thus, the result is that the bank nifty and nifty spot prices and futures prices are cointegrated. This proves that the spot and futures prices are cointegrated in error correction model by accepting the alternative hypothesis of unit root. Hence, the theory i.e., long-run relationship between spot and futures prices holds good. In addition, here after we can easily move for the Engle-Granger-2-step test procedure.

Table I
Cointegration Test for Bank Nifty

Coefficient	With Constant	Without Constant
the of their constitution for	Estimated value	Estimated value
â	09.6124***	TE SHIRE TO THE BEAUTIFUL TO
Â.	-00.0133*	-00.0134*
DF test on residuals	Test statistics	Test statistics
	-24.5253	-24.6589

Note: * Significant at 0% level. *** Significant at 10% level.

Table II
Estimated Error Correction Model for Bank Nifty

Coefficient	With constant Estimated value	t-ratio	Without constant Estimated value	t-ratio
$\hat{\zeta}_{\omega}$	-6.9700	-0.2953	<u> </u>	_
ζ̂ы	-0.0840**	-2.0352	0.0828**	-2.0197
ξ̂ _{b2}	0.0019	0.4068	0.0008	0.4429
ζ_{b3}	-0.0034****	-0.9467	-0.0034****	-0.9519

Note: ** Significant at 5% level. **** Significant at 25% level.

From Table II and Table IV, we can observe that the estimated coefficients i.e. ' $\hat{\delta}_{bl}$ ' and ' $\hat{\delta}_{nl}$ ' of the error correction terms are negative and significant at appropriate statistical significance level. This indicates that to get equilibrium return, the spot return will fall at the front of the positive difference between the spot and futures prices. The spot return will rise at the front of the negative difference between the spot and futures prices.

Table III Cointegration Test for Nifty

Coefficient	With Constant Estimated value	Without Constant Estimated value
$\hat{\lambda}_{n0}$	06.3021*	The second
$\hat{\lambda}_{n1}$	-00.0068**	-00.0069**
DF test on residuals	Test statistics	Test statistics
\hat{u}_{nt}	-24.5111	-24.7638

Note: ** Significant at 0% level. **** Significant at 5% level.

> Table IV Estimated Error Correction Model for Nifty

Coefficient	With constant Estimated value	t-ratio	Without constant Estimated value	t-ratio
Ŝ _{n0}	0.9287	0.0839	-	_
$\hat{\zeta}_{n1}$	-0.0316****	-0.7680	-0.0318****	-0.7759
$\hat{\xi}_{n2}$	0.0009	0.2657	0.0012****	0.9988
ζ_{n3}	-0.0018****	-0.7290	-0.0017****	-0.7240

Note: **** Significant at 25% level.

The signs of estimated coefficients like ' $\hat{\zeta}_{b3}$ ' and ' $\hat{\zeta}_{n3}$ ' suggest that the futures price does lag the spot price. However, this is a short-run phenomenon in the context of liquidity adjustment process. Within a short time period, this will be adjusted with either efficient call money market mechanism or appropriate liquidity adjustment mechanism through the central bank. Here we cannot exclude the term i.e., $spot \times (call\ rate - dividend\ yield) \times ((T-t)/365)$ in index futures return, which is more accurate than the cost of carry model i.e., ($spot\ price - dividend\ yield$). With lower significance level, the estimated coefficients like ' $\hat{\zeta}_{b2}$ ' and ' $\hat{\zeta}_{n2}$ ', show that there are positive autocorrelations for both bank nifty and nifty spot prices¹⁰. Therefore, from all of these results, the long-run relationship between spot and futures prices and hence returns, for both bank nifty and nifty index futures is confirmed.

Now, the parameters in equation (1), equation (3), and equation (6) are estimated for both the futures index returns. Parameters of these models are

estimated with bivariate model, cointegrated *OLS* bivariate model and conventional *OLS* bivariate model, which are presented in Table V, Table VI and Table VII respectively. Each bivariate model consists with *IGARCH* (1, 1) and constant correlation *IGARCH* (1, 1) model for the both bank nifty and nifty index futures returns. Here the conditional covariance matrices of bank nifty and nifty returns are allowed to vary over time. In this case, it is assumed that all agents or objects used to update their estimates of these conditional returns at each time-period depending upon the information of last trading day returns⁵.

Table V Bivariate Model

A. CNX Bank Nifty

IGARCH (1, 1)
$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} 45.92^* \\ -194.44^* \end{bmatrix} + \begin{bmatrix} 9.7127e - 03^* \\ 0.04^* \end{bmatrix} \begin{bmatrix} S_{t-1} - \gamma F_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} 19678.73^* \\ 24685.85^* \\ -6251.51^* \end{bmatrix} + \begin{bmatrix} 0.61^* \varepsilon_{1,t-1}^2 \\ 1.22^* \varepsilon_{2,t-1}^2 \\ 0.27^* \varepsilon_{1,t-1} \varepsilon_{2,t-1} \end{bmatrix} + \begin{bmatrix} -0.60^* h_{1,t-1}^2 \\ 0.61^* h_{2,t-1}^2 \\ 0.13^* h_{1,t-1} h_{2,t-1} \end{bmatrix}$$

Constant correlation IGARCH (1,1)

$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} -16.30 \\ -146.22^{**} \end{bmatrix} + \begin{bmatrix} 0.01^{**} \\ 0.02^{**} \end{bmatrix} [S_{t-1} - \mathcal{F}_{t-1}] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h^2 \end{bmatrix} \begin{bmatrix} 2060.14^* \end{bmatrix} \begin{bmatrix} 0.48^* c^2 \end{bmatrix} \begin{bmatrix} 0.52^* h^2 \end{bmatrix}$$

$$\begin{bmatrix} h_{st}^2 \\ h_{ft}^2 \end{bmatrix} = \begin{bmatrix} 3069.14^* \\ 24438.06^* \end{bmatrix} + \begin{bmatrix} 0.48^* \, \mathcal{E}_{1,t-1}^2 \\ 0.65^* \, \mathcal{E}_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} 0.52^* h_{1,t-1}^2 \\ 0.35^* \, h_{2,t-1}^2 \end{bmatrix}$$

B. CNX Nifty

IGARCH (1,1)

$$\begin{bmatrix} s_{t} \\ f_{t} \end{bmatrix} = \begin{bmatrix} 0.52^{*} \\ -347.30^{*} \end{bmatrix} + \begin{bmatrix} -0.05^{*} \\ -0.04^{*} \end{bmatrix} \begin{bmatrix} S_{t-1} - \mathcal{F}_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} 2840.25^{*} \\ 13371.51^{*} \\ -2379.99^{*} \end{bmatrix} + \begin{bmatrix} 1.00^{*} \varepsilon_{1,t-1}^{2} \\ 0.82^{*} \varepsilon_{2,t-1}^{2} \\ 0.04^{*} \varepsilon_{1,t-1} \varepsilon_{2,t-1} \end{bmatrix} + \begin{bmatrix} -1.1238e - 03^{*} h_{1,t-1}^{2} \\ 0.17^{*} h_{2,t-1}^{2} \\ 0.96^{*} h_{1,t-1} h_{2,t-1} \end{bmatrix}$$

Constant correlation IGARCH (1,1)

$$\begin{bmatrix} s_{t} \\ f_{t} \end{bmatrix} = \begin{bmatrix} 8.15 \\ -109.07^{*} \end{bmatrix} + \begin{bmatrix} -0.00008 \\ 0.03^{*} \end{bmatrix} [S_{t-1} - \gamma F_{t-1}] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$
$$\begin{bmatrix} h_{st}^{2} \\ h_{tt}^{2} \end{bmatrix} = \begin{bmatrix} 216.96^{*} \\ 8401.31^{*} \end{bmatrix} + \begin{bmatrix} 0.30^{*} \varepsilon_{1,t=1}^{2} \\ 0.61^{*} \varepsilon_{2,t=1}^{2} \end{bmatrix} + \begin{bmatrix} 0.70^{*} h_{1,t=1}^{2} \\ 0.39^{*} h_{2,t=1}^{2} \end{bmatrix}$$

Note: * Significant at 0% leve

** Significant at 25% leve

Table VI Cointegrated OLS Bivariate Model

A. CNX Bank Nifty

IGARCH (1, 1)

$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} -3.35^* \\ -249.98^* \end{bmatrix} + \begin{bmatrix} -0.006^* \\ 0.05^* \end{bmatrix} \left[S_{t-1} - \mathcal{F}_{t-1} \right] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} 11668.88^* \\ 62392.81^* \\ -4119.01^* \end{bmatrix} + \begin{bmatrix} 1.00^* \mathcal{E}_{1,t-1}^2 \\ 1.00^* \mathcal{E}_{2,t-1}^2 \\ 0.34^* \mathcal{E}_{1,t-1} \mathcal{E}_{2,t-1} \end{bmatrix} + \begin{bmatrix} -0.00085^* h_{1,t-1}^2 \\ -0.00087^* h_{2,t-1}^2 \\ 0.66^* h_{1,t-1} h_{2,t-1} \end{bmatrix}$$

Constant correlation cointegrated OLS bivariate IGARCH (1, 1) model

$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} -12.58 \\ -148.19^{**} \end{bmatrix} + \begin{bmatrix} 0.004 \\ 0.03^{**} \end{bmatrix} [S_{t-1} - \gamma F_{t-1}] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{st}^2 \\ h_{ft}^2 \end{bmatrix} = \begin{bmatrix} 3216.64^* \\ 23836.42^* \end{bmatrix} + \begin{bmatrix} 0.49^* \varepsilon_{1,t-1}^2 \\ 0.63^* \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} 0.51^* h_{1,t-1}^2 \\ 0.37^* h_{2,t-1}^2 \end{bmatrix}$$

B. CNX Nifty

IGARCH (1, 1)

$$\begin{bmatrix} s_{t} \\ f_{t} \end{bmatrix} = \begin{bmatrix} 10.92^{*} \\ -167.54^{*} \end{bmatrix} + \begin{bmatrix} -3.8053e - 04^{*} \\ 0.05^{*} \end{bmatrix} [S_{t-1} - \gamma F_{t-1}] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} 2549.20^* \\ 23228.25^* \\ -1452.67^* \end{bmatrix} + \begin{bmatrix} 1.00^* \varepsilon_{1,t-1}^2 \\ 1.00^* \varepsilon_{2,t-1}^2 \\ 0.68^* \varepsilon_{1,t-1} \varepsilon_{2,t-1} \end{bmatrix} + \begin{bmatrix} -1.5752e - 04^* h_{1,t-1}^2 \\ -7.0919e - 05^* h_{2,t-1}^2 \\ 0.32^* h_{1,t-1} h_{2,t-1} \end{bmatrix}$$

Constant correlation cointegrated OLS bivariate IGARCH (1, 1) model

$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} 8.15 \\ -109.07^* \end{bmatrix} + \begin{bmatrix} -0.00008^* \\ 0.03^* \end{bmatrix} \left[S_{t-1} - \gamma F_{t-1} \right] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{st}^2 \\ h_{ft}^2 \end{bmatrix} = \begin{bmatrix} 216.95^* \\ 8401.32^* \end{bmatrix} + \begin{bmatrix} 0.30^* \varepsilon_{1,t=1}^2 \\ 0.61^* \varepsilon_{2,t=1}^2 \end{bmatrix} + \begin{bmatrix} 0.70^* h_{1,t=1}^2 \\ 0.39^* h_{2,t=1}^2 \end{bmatrix}$$

Note: * Significant at 0% level

** significant at 5% level

Table VII Conventional OLS Bivariate Model

A.CNX Bank Nifty

IGARCH (1, 1)

$$\begin{bmatrix} s_{t} \\ f_{t} \end{bmatrix} = \begin{bmatrix} -14.35^{*} \\ -317.82^{*} \end{bmatrix} + \begin{bmatrix} 3.1709e - 03^{*} \\ 0.05^{*} \end{bmatrix} [S_{t-1} - \gamma F_{t-1}] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} 16328.54^* \\ 16020.15^* \\ -13447.46^* \end{bmatrix} + \begin{bmatrix} 0.06^* \varepsilon_{1,t-1}^2 \\ 0.33^* \varepsilon_{2,t-1}^2 \\ 0.03^* \varepsilon_{1,t-1} \varepsilon_{2,t-1} \end{bmatrix} + \begin{bmatrix} 0.04^* h_{1,t-1}^2 \\ 0.83^* h_{2,t-1}^2 \\ 0.02^* h_{1,t-1} h_{2,t-1} \end{bmatrix}$$

Constant correlation conventional OLS IGARCH (1,1)

$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} -25.66 \\ -7.39 \end{bmatrix} + \begin{bmatrix} 0.007^{**} \\ 0.001 \end{bmatrix} [S_{t-1} - \gamma F_{t-1}] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{st}^2 \\ h_{ft}^2 \end{bmatrix} = \begin{bmatrix} 2994.44^* \\ 24160.71^* \end{bmatrix} + \begin{bmatrix} 0.48^* \varepsilon_{1,t-1}^2 \\ 0.62^* \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} 0.52^* h_{1,t-1}^2 \\ 0.38^* h_{2,t-1}^2 \end{bmatrix}$$

B. CNX Nifty

IGARCH (1, 1)

$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} -19.20^* \\ 73.64^* \end{bmatrix} + \begin{bmatrix} -7.2735e - 03^* \\ 0.02^* \end{bmatrix} [S_{t-1} - \mathcal{F}_{t-1}] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{SS} \\ h_{FF} \\ h_{SF} \end{bmatrix} = \begin{bmatrix} 3077.79^* \\ 11186.57^* \\ -1513.05^* \end{bmatrix} + \begin{bmatrix} 1.02^* \varepsilon_{1,t-1}^2 \\ 0.52^* \varepsilon_{2,t-1}^2 \\ 1.08^* \varepsilon_{1,t-1} \varepsilon_{2,t-1} \end{bmatrix} + \begin{bmatrix} -0.03^* h_{1,t-1}^2 \\ 0.48^* h_{2,t-1}^2 \\ -0.10^* h_{1,t-1} h_{2,t-1} \end{bmatrix}$$

Constant correlation conventional OLS GARCH (1, 1)

$$\begin{bmatrix} s_t \\ f_t \end{bmatrix} = \begin{bmatrix} 11.74^* \\ -104.78^* \end{bmatrix} + \begin{bmatrix} -0.0009 \\ 0.03^* \end{bmatrix} \left[S_{t-1} - \gamma F_{t-1} \right] + \begin{bmatrix} \varepsilon_{St} \\ \varepsilon_{Ft} \end{bmatrix}$$

$$\begin{bmatrix} h_{st}^2 \\ h_{ft}^2 \end{bmatrix} = \begin{bmatrix} 234.00^* \\ 8353.66^* \end{bmatrix} + \begin{bmatrix} 0.32^* \varepsilon_{1,t=1}^2 \\ 0.61^* \varepsilon_{2,t=1}^2 \end{bmatrix} + \begin{bmatrix} 0.68^* h_{1,t=1}^2 \\ 0.39^* h_{2,t=1}^2 \end{bmatrix}$$

Note: * Significant at 0% level,

** Significant at 5% level.

In Table V, Table VI and Table VII, one can observe that most of the maximum likelihood estimated parameters are significant at 0% level. The estimated coefficients like ' $\hat{\alpha}_1$ ' and ' $\hat{\beta}_1$ ' in all *IGARCH* (1, 1) and constant

correlation *IGARCH* (1, 1) models are positive, reasonable, and highly significant for bank nifty conditional mean returns. This implies that the bank nifty error correction term significantly determines bank nifty spot and dynamic futures returns at appropriate units.

Except bivariate IGARCH(1,1) model, the estimated coefficients like ' $\hat{\alpha}_1$ ' and ' $\hat{\beta}_1$ ' in all IGARCH(1,1) and constant correlation IGARCH(1,1) models are positive, reasonable, and highly significant for nifty conditional mean returns. This implies that the nifty error correction term significantly determines nifty spot and dynamic futures returns at appropriate units. However, the estimated coefficient ' $\hat{\alpha}_1$ ' for constant correlation IGARCH(1,1) is negative along with negative value at the bivariate IGARCH(1,1) model. This is of course due to the short-run micro and macroeconomic fundamental instabilities, which can be corrected with appropriate economic policies (see 'The Model' section 2.2.1, para 2 and para 3).

The estimated constant coefficients like ' $\hat{\alpha}_0$ ' and ' $\hat{\beta}_0$ ' vary across the spot and futures returns. Almost all the estimated constant coefficient ' $\hat{\beta}_0$ ' in all *IGARCH* (1, 1) and constant correlation *IGARCH* (1, 1) models are largely negative, reasonable, and highly significant for both the bank nifty and nifty conditional mean returns. This implies that the reduced profit will be taxed on the long-run bank nifty and nifty futures returns. This hope makes investor to hold derivatives product even at undesired rate of returns¹¹.

From Table V, Table VI and Table VII it is observed that all the conditional variance and covariance matrix-elements are significant. This implies that the conditional covariance matrices are not constant where these returns are varying over time. Therefore, the risk premium for bank nifty and nifty is influenced and represented by their conditional covariance matrices.

Now using the estimated elements of variance and covariance matrices, the optimal hedge ratios for bank nifty and nifty are calculated (Table VIII and Table IX). It is calculated that all the optimal hedge ratios are negative for both *IGARCH* (1, 1) and constant correlation *IGARCH* (1, 1) models. From Table VIII, it is also observed that the hedge ratio i.e., -0.07 for cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) model is less negative than other hedge ratios. Therefore, for bank nifty futures the optimal cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) hedge ratio is efficient than other optimal hedge ratios. Again, it is observed that the hedge ratio i.e., -0.03 for bivariate *IGARCH* (1, 1) model is less negative than other hedge ratios. Therefore, for bank nifty futures the optimal bivariate *IGARCH* (1, 1) hedge ratio is efficient than other optimal hedge ratios.

Table VIII
Optimal Hedge Ratio with Different Hedging Models (Bank Nifty)

		Optimal hedge ratios for bank nifty	
S.N	N. Hedging Models	Constant Correlation IGARCH (1, 1)	IGARCH (1, 1)
1.	Bivariate Model	-0.25320	-0.0257
2.	Co-integrated OLS		
	Bivariate Model	-0.06601	-0.0566
3.	Conventional OLS		
	Bivariate Model	-0.83930	-0.0604

Table IX
Optimal Hedge Ratio with Different Hedging Models (Nifty)

Op	Optimal Hedge Ratios for Bank Nifty			
S.N	N. Hedging Models	Constant Correlation IGARCH (1, 1)	IGARCH (1, 1)	
1. 2.	Bivariate Model Co-integrated OLS	-0.1779	-0.0193	
3.	Bivariate Model Conventional OLS	-0.0625	-0.0193	
	Bivariate Model	-0.1352	-0.0205	

From Table IX, it is observed that the hedge ratio i.e., -0.06 for cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) model is less negative than other hedge ratios. Therefore, for nifty futures the optimal cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) hedge ratio is efficient than other hedge ratios. Again, it is observed that the hedge ratios i.e., -0.019 for both bivariate *IGARCH* (1, 1) and cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) model are less negative than the hedge ratio i.e., -0.021 of conventional *OLS* bivariate *IGARCH* (1, 1). Therefore, for nifty futures the optimal bivariate *IGARCH* (1, 1) and cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) hedge ratios are efficient than the conventional *OLS* hedge ratio.

Therefore, reasonably and empirically these results suggest that the cointegrated OLS constant correlation bivariate IGARCH (1,1) heading model for both bank nifty and nifty futures are acceptable. Again, bivariate IGARCH (1,1) hedging model for bank nifty, cointegrated OLS constant correlation bivariate IGARCH (1,1) and bivariate IGARCH (1,1) hedging model for nifty are acceptable. However, all the optimal hedge ratios are negative for both bank nifty and nifty futures. This indicates that the Indian futures market is not achieving the desired level of market efficiency causing market imperfection.

Now, it has been calculated that the coefficient correlation ' ρ_{12bn} ' for bank nifty in cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) model is -0.15. Here, bank nifty coefficient correlation ' ρ_{12bn} ' in bivariate *IGARCH* (1, 1) model is -0.15. The coefficient correlation ' ρ_{12bn} ' for nifty in cointegrated *OLS* constant correlation bivariate *IGARCH* (1, 1) model is -0.12. Here, nifty coefficient correlation ' ρ_{12bn} ' in bivariate *IGARCH* (1, 1) model

is -0.12. Again, these are restricted as constants. All of these results show that the index futures returns are not perfectly synchronized. Therefore, the variances of the portfolios are volatile in nature, where the returns are not positively correlated. In this case, the risk-return trade-off may not be expected at the appropriate level.

Table X
Theil Statistics for the Constructed Bank Nifty and Nifty Portfolios

Hedging Models	Steps	Bank Nifty	Nifty
Bivariate IGARCH	1	0.68230	0.68521
	2	0.56953	0.56155
THE PERSON NAMED IN COLUMN TWO IS NOT THE OWNER.	3	0.43059	0.50211
	4	0.36668	0.48328
	5	0.33172	0.56071
Constant correlation cointegrated	1	2.07388	0.71782
OLS bivariate IGARCH	2	0.84311	0.92736
gangpan marraganan 16 as an Bashavir milayai harangs bas a	3	0.70323	1.07814
	4	0.59101	1.30721
charge an animalist, arrestors when y	5	0.50613	1.58165
Cointegrated OLS bivariate IGARCH	1	villa en <u>p</u> alpubi	0.67973
ed in the ment of the holding rep	2	Sald Pro Salter	0.55459
	3	-	0.42606
	4	_	0.35850
	5	_	0.31413

To minimize the risk involved with the above hedging portfolios, the payoff time series i.e., $\sigma^2(S_{t+1} - \hat{b}_t^* F_{t+1})$ for both bank nifty and nifty futures returns are constructed and forecasted. Table X shows that forecasted Theil values are less than one at most of the forecasted steps for both bank nifty and nifty futures except the one-step of constant correlation cointegrated OLS bivariate IGARCH hedging model for bank nifty and three, four, and five-step of the same hedging model for nifty. Here, object is ready to pay more for a risky investment than its expected value. Therefore, the objective probabilities for profit can be determined, which are equal to the subjective probabilities. Therefore, forecast indicates that the investors are risk lover in Indian futures market. This implies that the above bivariate IGARCH and constant correlation cointegrated OLS bivariate IGARCH models are appropriate and efficient hedging models for bank nifty and nifty futures respectively. Cointegrated bivariate IGARCH (1, 1) for nifty is also an efficient hedging model where all forecasted Theil values are less than one¹². Here objects are risk lover with high profit motives. From all of these results, it is concluded that objects are prepared to pay where the utility of the cash given up in purchasing the index futures is just equal to the expected utility that the index futures provides. Therefore, the rupee values of the index futures are equal to the rupee values of its expected utility (see Houthakker and Williamson, 1996). From this, one can be sure that the above models are efficient hedging models through which 'hedging effectiveness' can be measured at the Indian futures market.

IV. Conclusion

From this study, it is clear that there is the long-run relationship between the spot and futures prices and hence returns exist for both the index futures. The optimal hedge ratios are negative for all the hedging models suggesting that the Indian futures market is inefficient and imperfect one. Accordingly, there is the need of appropriate policy measures in financial market for efficient market functioning and resource generations and diversifications. Therefore, the object (investor) will have the chance to make the optimal investment decision through optimal preferences and choices on it. Thereby the role of public and private sectors irrespective of their structure like organized or unorganized will be maximized (Panchamukhi). In effect, the socio-economic objectives in the society will be maximized.

V. Future Research Direction

As the need of emerging research on the area of financial economics and based on this study, the future research will be to measure the 'hedging effectiveness', to measure the 'speculation' and 'speculation effectiveness' etceteras for both the bank nifty and nifty index futures. In future, research can be conducted on other Indian derivatives instruments and their underlying effect. For this, the above appropriate hedging models can be used and followed.

Notes

- 1 C = Capital Adequacy, A = Asset Quality, M = Management, E = Earnings, L = Liquidity. Mohan, 2006 discussed about Berger and Humphrey, 1992 and Frexias and Rochet, 1997.
- 2 In adopting these equator principles (EP) the banks "...seek to ensure that the projects we finance are developed in a manner that is socially responsible and reflect sound environmental practices." (Scholtens and Dam, 2007, p. 1307)
- 3 National Stock Exchange of India.
- 4 See the footnote (5).
- The partial autocorrelation graphs for bank nifty and nifty spot returns show that, they are significant at zero, second, third, fourth, fifth, sixth etc., lag length. Here, the Schwarz Information Criteria and Akaike Information Criteria are optimum at ARMA (5, 0) model and ARMA (5, 3) model for bank nifty spot return. Both the information criteria are optimum at ARMA (4, 3) model and ARMA (4, 3) model for nifty spot return.

The dynamic futures returns for both bank nifty and nifty indices have been defined and calculated using the cost of carry model. The partial autocorrelation graphs for both the returns show that they are significant at zero, fourth, eighth, ninth, eleventh, etc., lag length. Here, the Schwarz Information Criteria and Akaike Information Criteria are optimum at *ARMA* (5, 5) model for bank nifty dynamic futures return. Both the information criteria are optimum at *ARMA* (5, 3) for nifty dynamic futures return.

The partial autocorrelation graphs for both the residuals in the regressions of spot and futures show that they are significant at zero, second, sixth, seventh, eighth, tenth etc., lag length. Here, the Schwarz Information Criteria and Akaike Information Criteria are optimum at ARMA (5, 1) and ARMA (5, 5) for both the residuals of the regressions of bank nifty spot return on its dynamic futures return and nifty spot return on its dynamic futures return.

The above results show that one lag length is not statistically significant for this particular study. Again, the optimal ARMA (p, q) is not at ARMA (1, 1) process. With strict empirical sense, we may have more than one lag length and ARMA (1, 1) model but results may not be contemporaneous. This particular study has considered the theoretical argument on one lag length and optimal ARMA (1, 1) process. Observation is that derivatives returns heavily depend on its near past or future trading-day's return. Say, opening price for today heavily depends on closing price of yesterday, not the day before yesterday or other closing and opening prices. Again, these returns do not depend on other cross returns to assure the contemporaneous trading. In this context, Bollerslev, Engle, and Wooldridge (1988) have stated that' A natural simplification is to assume that each covariance depends only on its own past values and surprises. Throughout this paper we have therefore, taken p = q = 1 and ... (p.120)'. With this logic, let me restrict and assume for the optimal one lag length and ARMA (1, 1) process. Hence, IGARCH model is IGARCH (1, 1) where the optimal ARMA (1, 1) model is considered for residuals and conditional variances. Thus VECH (H_i) follows the optimal p = q = 1 (see footnotes 10 and 12). In addition, this is tested that all of the time series variables are stationary.

It is empirically tested that the constructed payoff for bank nifty portfolio is optimal at ARMA (6, 4) model and for nifty portfolio is optimal at ARMA (4, 3) model. For

further information see the footnote (12).

7 Reserve Bank of India.

8 Empirical results are available from the author upon request.

9 Here both with and without constant case is discussed. Without constant equilibrium correction or error correction, model case is tested with Engle-Granger critical value and it is assumed that theory wise, with constant case is not that much different without constant case. Hence, assumption is that the statistical tests for both with and without constant equilibrium correction or error correction models are same.

10 Even with estimated significant lag length i.e., apart from one lag length, the empirical

test shows similar and equivalent results.

11 In this case, one can assume that the appropriate policy measure on 'securities transaction tax' and the market diversification through 'the introduction of new derivatives instruments' will be an incentive to hold the bank nifty and nifty futures.

12 Here using bivariate IGARCH (1, 1) estimates and using footnote (6), Theil values are determined where both the theoretical and empirical optimal orders are used. This is because; in case of the optimal hedge ratio model for nifty i.e., cointegrated bivariate IGARCH (1, 1) model, empirically derived optimal ARMA (4, 3) does not fit as several estimations on it show poor result or no-convergence. Therefore, in this case theoretical justification for p = q = 1 holds good for portfolio forecasting. This observation is an added advantage for the consideration of theoretical justifications that is p = q = 1 (see footnote 5).

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