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Time-Varying Hedge Ratios: An Application to the Indian Stock Futures Market

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Abstract

Using different unconditional and conditional versions of the bivariate BEKK-GARCH model of Engle and Kroner, we calculate time-varying hedge ratios for Indian stock futures market involving a cross-section of seven firms across a spectrum of industries. These models are solved not only with the usual square root exponent but also analysed with an unrestricted version where the exponent is set to one. Our results show time-varying hedge ratios with the exponent set to one improve over hedge ratios obtained from the square root exponent setup as well as over static hedge ratios calculated from the error correction types of models. Time-varying optimal hedge ratio calculation in this new framework makes perfect sense in terms of portfolio allocation decision involving individual stock futures.

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1. Introduction

Time-varying optimal hedge ratios are well established financial instruments of risk management. Calculating optimal hedge ratios and analyzing their reliability assume significant importance especially in cases where futures and cash price movements are not highly correlated, thus generating considerable basis risks. Although there has been a considerable literature comparing the performance between time-varying hedge ratios and static hedge ratios in commodity and index futures markets, there is little exploration of these estimators in stock futures markets. The aim of this paper is to explore both these estimators (and extensions of) and to evaluate these estimators using a subset of new and exciting stock futures contracts now traded in India's National Stock Exchange (NSE), for almost four years. In addition, this study also illustrates a way to improve time-varying optimal hedge ratios in non-commodity futures market transactions. The improvement in the time-varying hedge ratio calculation is achieved when we place unity restrictions on parameter matrices in a BEKK type bivariate GARCH framework (based on Engle and Kroner (1995)) after allowing for lead-lag relationships between futures and cash returns. One main advantage of putting this restriction is to allow for mean reversion in volatility, i.e., we do not restrict the GARCH parameter estimates to be strictly positive. A second advantage is in terms of computational simplicity. We show how to derive dynamic hedge ratios using this alternative restriction. We expect that this approach will provide quite flexible volatility estimates with the potential to impose greater weights on most recent shocks, similar to any asymmetric GARCH process.

We use daily closing cash and futures return data from January 2002 to September 2005 for seven[1] Indian firms to establish our findings, which includes big manufacturing firms (Associated Cement Company (*ACC)*, Grasim Industries (*GRASIM*), and Tata Tea Companies Limited (*TATATEA*)), energy utilities firms (Bharat Heavy Electricals Limited (*BHEL*), and Tata Power and Utilities Company Limited (*TATAPOW*)) as well as telecommunication and information technology enabled services firms (Mahanagar Telephone Nigam Limited (*MTNL*) and Satyam Computers Limited (*SATYAM*)). In doing so, we deviate from existing literature (see Moschini and Myers (2002) for instance) which primarily analyzes optimal hedge ratios in commodity markets and not in other financial markets. We also provide contrasting examples where the variance ratios of the stock futures and spot returns are similar so that static models should provide good hedge ratio estimates.

It is well known in the finance literature that optimal hedge ratios need to be determined for risk management, and more so in cases where futures and cash price movements are not highly correlated, generating considerable basis risks. The current literature employs either autoregressive conditional heteroskedasticity (ARCH) framework of Engle (1982) or generalized ARCH (GARCH) approach of Bollerslev (1986) to estimate hedge ratios in commodities markets as underlying cash and futures prices show time-varying, persistent volatility. Among past studies, Baillie and Myers (1991) and Myers (1991) use bivariate GARCH models of cash and futures prices for six agricultural commodities, beef, coffee, corn, cotton, gold and soybeans to calculate optimal hedge ratios in commodity futures. Cecchetti, Cumby and Figlewski (1988) employ a bivariate ARCH model to generate optimal hedge

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[1] We have started with a sample of nineteen different firms across a broad spectrum of industries. However, in this paper, we present our findings involving seven firms only, as other firms' data are either characterized by structural breaks due to price splitting within the sample period or not providing enough conditional volatility to pursue the analysis involving time-varying hedge ratios.

ratios involving T-bond futures. Bera, Garcia and Roh (1997) use diagonal vech representation of bivariate GARCH model to estimate time-varying hedge ratios for corn and soybeans. Recently, Moschini and Myers (2002), using weekly corn prices, show that a new parameterization of bivariate GARCH processes establishes statistical superiority of time-varying hedge ratios over constant hedges. To derive optimal hedge ratios, all the above studies make simplifying but restrictive assumptions on the conditional covariance matrix to ensure non-negative variances of returns and generate tractable solutions. But the improvement in generating time-varying optimal hedges over constant hedge ratios appears to be minimal even after imposing these restrictions.[2] Other studies of financial futures such as Yeh and Gannon (1998) consider the Australian Share Price Index Futures (SPI) and Lee, Gannon and Yeh (2002) analyse the U.S Standard and Poor's 500 (S&P), the Nikkei 225 (Nikkei) Index Futures and the SPI Futures data. In all of these cases the static models provide a Beta of around 0.7 (substantial excess volatility in the futures relative to the cash index) and the conditional correlations GARCH model dominates in terms of variance reduction. The hedge ratios in Lee, Gannon and Yeh (2002) report substantial variation around the average of 0.7 for the S&P as well as the SPI and for the Nikkei, the variation ranged from 0.3 to 2.0. In another study, Au-Yeung and Gannon (2005) show that the square root BEKK-GARCH model provides substantial variation relative to more restrictive GARCH and static models. Furthermore, they also report statistically significant structural breaks in either or both of their cash or/and futures data, which corresponds to the timing of regulatory interventions. In all of these studies involving financial futures, the spot and futures are cointegrated in variance but there is substantial variation in the basis which

[2] See Bera, Garcia and Roh (1997) for more discussion about potential gain in optimal hedge ratios after placing simplifying restrictions on conditional covariance matrix.

allowed these time-varying hedge ratio estimators to dominate. If the spot and futures are not cointegrated in variance then these GARCH type estimators do provide substantial variation in hedge ratio estimates and dominate static models in terms of variance reduction.

The above discussion clearly shows that most of the earlier works in deriving hedge ratios have been done on either agricultural commodities or stock index futures markets. This focus on commodities comes from the fact that commodities are primarily consumables which varies significantly because of uncertainty regarding their production as well as seasonal effects. Also, commodities are generally not substitutable unlike other financial instruments. Similar observations can also be made for stock index futures. Like the commodity futures that impounds storage, time value and commodity specific risks in the futures contract, index futures also maintain basis risk because the cost of rebalancing the underlying portfolio is rather large. This means the resulting rebalancing in the futures contract generates excess risk. On the other hand, other financial instruments like shares are held for investment and can be substitutable with each other (unless the investor wants to build an exposure specific to a company). Therefore in our study we concentrate on individual stock futures. For the investors dealing in particular stock(s), the individual stock futures market is most specific and appropriate to hedge their exposure. As a result, calculating optimal time varying hedge ratios becomes important from both the financial as well as policy perspectives.

Looking at the way to improve the performance of time-varying optimal hedge ratio, we apply a far more general restriction on the conditional covariance matrix that allows for mean reversion in volatility and calculate time-varying optimal hedge ratios for seven Indian firms' individual stock futures data. For comparison purposes, we generate optimal hedge ratios from the generic BEKK of Engle and Kroner (1995) after imposing square root restriction on parameter matrices (as is the norm in the existing literature). Our analysis shows considerable improvement in calculating time-varying optimal hedge ratios from the general framework over the bivariate GARCH process of Engle and Kroner (1995). We also employ both of these estimators in a nested set of models to test the volatility lead/lag effect between the spot and futures markets, extending the approach of Au-Yeung and Gannon (2005). The final models are then compared with the classic static hedge ratio estimators in terms of minimizing the risk in the spot position.

The paper is organized as follows. In the next section, we highlight the methodology to calculate time-varying optimal hedge ratios after imposing a unity constraint on parameter matrices of a bivariate GARCH model. Standard stationarity and cointegrating relationships in returns are also explored in this section. Section three provides the data detail and reports preliminary analysis involving descriptive statistics from the data in our sample. Section four contains results and comparative discussions from the empirical analysis. Section five concludes after exploring directions in further research. All the results in tabular form are presented in appendix A. Appendix B has all the figures from the analysis.

2. Empirical Methodology and Estimation of Time-Varying Hedge Ratios

The standard ADF and PP unit root test results are reported in the table 4 of appendix A at the end of the paper. As it is usual in studies of cash and futures markets, we also find that the price series are generally non-stationary, the returns are very significant and stationary and the basis is also very significant and stationary. However, the level of significance for the basis is not of the same order as for the cash and futures returns. This may reflect the lack of speculative activity in the cash and futures for these series so that there is a low level of realized volatility.

After addressing the issues of stationarity in returns series, we model interactions in futures and cash returns with the following time-varying bivariate BEKK-GARCH procedures and impose general but non-restrictive assumption of unity constraint on parameter matrices to calculate time-varying optimal hedge ratios.

The daily continuous returns in the ongoing analysis are generated from the formula below:

Futures daily continuous return: $R_{1,t} = \ln(P_{1,t} / P_{1,t-1})$ (1)

Spot daily continuous return: $R_{2,t} = \ln(P_{2,t} / P_{2,t-1})$ (2)

Where, $R_{1,t}$ and $P_{1,t}$ represent the daily continuous return and daily price of futures at time t respectively, and $P_{1,t-1}$ is the daily price of futures at time $t-1$. Similarly, $R_{2,t}$ and $P_{2,t}$ represent the daily continuous return and daily closing price of the spot at time t, and $P_{2,t-1}$ is the daily closing price of the spot one period prior. Preliminary estimation allowing the returns to follow an autoregressive process of order one and restricting the first lag parameter to zero in the returns equation provide similar results for the GARCH parameter estimates. It is therefore not necessary to report results of the spot and futures returns as an autoregressive process. Equation (3) shows that the returns are modeled by its mean return level only. To capture the second-order time dependence of cash and futures returns, a bivariate BEKK GARCH (1,1) model proposed by Engle and Kroner (1995) is utilized. The model that governs the joint process is presented below.

$$R_t = \alpha + u_t$$

(3)

$$u_t \mid \Omega_{t-1} \sim N(0, H_t)$$

(4)

where, the return vector for futures and cash series is given by $R_t = [R_{1,t}, R_{2,t}]$, the vector of the constant is defined by $\alpha = [\alpha_1, \alpha_2]$, the residual vector $u_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]$ is bivariate and conditionally normally distributed, and the conditional covariance matrix is represented by H_t, where $\{H_t\} = h_{ij,t}\ for\ i, j = 1,2$. Ω_{t-1} is the information set representing an array of information available at time $t-1$. Given the above expression, the conditional covariance matrix can be stated as follows:

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + G_{11}' H_{t-1} G_{11}$$

(5)

where, the parameter matrices for the variance equation are defined as C_0, which is restricted to be lower triangular and two unrestricted matrices A_{11} and G_{11}. Therefore the second moment can be represented by:

$$H_t = C_0' C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}, \varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}, \varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$

(6)

As we have mentioned before, the majority of existing literature impose simplifying but restrictive constraints on the parameters of the conditional covariance matrix. These constraints ensure that the coefficients to be strictly positive. In most of these studies a square root constraint is imposed on the parameter matrices.

In this paper, we deviate from the above approach in the following two ways. First, we impose the square root constraint on the parameter matrices and second, we impose the unity constraint on the parameter matrices to leave the power parameter as one. In this latter case the interpretation of parameter estimates obtained will be different from the current literature. When the Beta GARCH parameters are allowed to be negative, the underlying interpretations change and point to mean reversion in volatility in the system. Also, with negative Betas, there are now greater weights allowed on more recent shocks leading to greater sensitivity to those shocks. When calculating hedge ratios with the parameter matrix exponents set to unity, the estimated covariance and variance terms still need to be positive as the square root of the ratio of the conditional variance between the spot and futures over the variance of the futures needs to be calculated. The parameter estimates in this case will be the square of those estimated from the former specifications so that the time-varying variance covariance matrix from this new specification will be the square of that obtained using the former model specification. Therefore, the estimated hedge ratio will be the square root of projected term from the covariance equation between the spot and futures divided by the projected term from the variance of the futures. This works well as long as none of the projected covariance or variance terms are negative.

The equation (6) for H_t can be further expanded by matrix multiplication and it takes the following form:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} \quad (7)$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{12}h_{11,t-1} + (g_{21}g_{12} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} \quad (8)$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + g_{12}^2 h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2 h_{22,t-1}$$

(9)

The application of the BEKK-GARCH specification in our analysis is advantageous from the interaction of conditional variances and covariance of the two return series; therefore it allows testing of the null hypothesis that there is no causality effect in either direction. In addition, although the current versions of the BEKK-GARCH model guarantees, by construction that the covariance matrices in the system are positive definite, we expect the same result although we are not strictly imposing this in the estimation procedure.

Thereafter, we test the lead-lag relationship between return volatilities of spot and futures as restricted versions of the above model with both square root and unity restrictions imposed in the following way.[3] First, either off diagonal terms of the matrix A_{11} and G_{11} is restricted to be zero so that the lagged squared residuals and lagged conditional variance of spot/futures do not enter the variance equation of futures/spot as an explanatory variable. To test any causality effect from spot to futures, a_{12} and g_{12} are set to zero. The variance and covariance equations will take the following form.

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1}$$

(10)

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{22}h_{12,t-1} + g_{21}g_{22}h_{22,t-1}$$

(11)

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + g_{22}^2 h_{22,t-1}$$

(12)

[3] This is an extension of the approach taken in Au-Yeung and Gannon (2005).

Conversely, a_{21} and g_{21} are set equal to zero when we test the causality effect from futures to spot. The log likelihood from these estimations is then compared against that of the unrestricted model by applying the likelihood ratio test in an artificial nested testing procedure. The likelihood ratio tests are reported in rows fifteen and sixteen of tables 7 and 8 in appendix A. The estimated outputs of unrestricted versions of the GARCH models are also presented in tables 7 and 8 in appendix A (see rows one to fourteen in each of these tables).

All the maximum likelihood estimations are optimized by the Berndt, Hall, Hall and Hausmann (BHHH) algorithm.[4] From equations (7) to (12), the conditional log likelihood function $L(\theta)$ for a sample of T observations has the following form:

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta) \quad (13)$$

$$l_t(\theta) = -\log 2\pi - 1/2 \log\left|H_t(\theta)\right| - 1/2 \varepsilon_t^{'}(\theta) H_t^{-1}(\theta) \varepsilon_t(\theta) \quad (14)$$

where, θ denotes the vector of all the unknown parameters. Numerical maximization of equation (13) and (14) yields the maximum likelihood estimates with asymptotic standard errors.

The likelihood ratio test is used for assessing the significance of the lead-lag relationship between the spot and futures return volatilities. This test is done by comparing the log likelihood of an unrestricted model and a restricted model:

$$D = -2LLR = -2\ln\left(\frac{L_0}{L_1}\right) = -2(\ln L_0 - \ln L_1) \quad (15)$$

[4] Marquardt maximum likelihood has also been applied, however, BHHH algorithm is found to have better performance.

where, LLR = Log Likelihood Ratio

L_0 = Value of the likelihood function of the restricted model

L_1 = Value of the likelihood function of the unrestricted model

The statistic D follows a χ-distribution with k degrees of freedom, where k is the number of restrictions in the restricted model. The null hypothesis and alternate hypothesis of two tests are:

$$H_0^* : a_{12} = g_{12} = 0 \text{ or } a_{21} = g_{21} = 0$$

H_1^*: *any off-diagonal term in the A and G matrix is not equal to zero*

Given the models of spot and futures prices developed below, the time-varying hedge ratio can be expressed as:

$$\hat{b}_t^* = \frac{\hat{h}_{sf,t}}{\hat{h}_{ff,t}}$$

(16)

which is defined similarly in Baillie and Myers (1991) and Park and Switzer (1995). These hedge ratios are reported (plotted) in appendix B.

3. Data and Descriptive Statistics

The seven firms' data for this study are downloaded from the National Stock Exchange (NSE) of India website[5]. We use a sample of seven most liquid stocks, which, the NSE has started trading from November 2001. The main sample for this study is the daily returns of these seven stock futures and the returns of their underlying stocks in the spot market. The stock futures series analyzed here uses data on the near month contracts as they carry the highest trading volume. We select January 2002 to September 2005 as our overall sample window, which gives us 944

[5] The web address is http://www.nse-india.com.

data points. To take care of any potential expiration effects in the sample, the stock futures contracts are rolled over to the next month contract on two days prior to their respective expiry date.

All the stock returns and their basis plots are reported in appendix B. Figures 1 and 2, in appendix B, show returns from individual stock futures and their respective cash prices. Figure 3 reports the basis series. From figure 1, apart from *SATYAM*, all the futures returns seem close to zero (relatively smoothed returns), though *BHEL* and *TATAPOW* show the highest levels of excess kurtosis in futures returns (see table 1 in appendix A for reference). Closing cash returns series from figure 2, appendix B, also behave similarly to the patterns we have identified from the futures return series (see table 2 in appendix A for reference). A quick look at the higher order moments from the descriptive statistics (tables 1 and 2 in appendix A) clearly point that the all returns series are leptokurtic, a regular feature of financial returns series. We also looked for trends and seasonal components in these returns series, but could not find any evidence of trend or seasonality. Note that normality is rejected for all the cash and futures returns series. All the basis series from figure 3 in appendix B, show convergence around zero except for *BHEL* and *GRASIM*. Unit root tests involving Augmented Dickey-Fuller and Phillips-Perron test statistics show enough evidence of possible cointegrating relationships between futures and cash returns, as all the futures and cash prices series are integrated of order one in (log) levels (see table 4 in appendix A for reference). Table 5 in the first appendix report results from tests for cointegration, and we find that futures and cash returns for all the seven firms' in our sample are cointegrated, thus sharing a long-term equilibrium relationship.

4. Results and Discussion

The results from estimated unrestricted versions of bivariate BEKKs of Engle and Kroner (1995) are reported in appendix A. Table 7 reports the parameters estimates involving square root constraint on parameter matrices and table 8 shows the estimated values from unity constraint on parameter matrices. First two rows in these tables report conditional means and rows three to thirteen show conditional covariance parameters from log-likelihood estimation. Rows fifteen and sixteen in both of these tables show likelihood ratio test statistics for lead-lag relationships between future and spot returns (denoted by LR-Test1) and vice-versa (denoted by LR-Test2). Model evaluation statistics involving third and fourth order moments (skewness and kurtosis) as well as tenth-order serial correlations[6] from standardised residuals are reported in rows sixteen to twenty-three in each of these tables. To summarize the results based on conditional means, conditional variances, residual diagnostics checks and optimal hedge ratios, we find that the bivariate GARCH model with unity constraint on parameter matrices outperform the bivariate GARCH model with square root constraint on parameter matrices.

Looking at table 7 results involving conditional covariance between futures and cash prices (parameters $\hat{A}_{22}$ and $\hat{G}_{22}$), we find strong evidence of interactions between futures and cash returns, as all parameter coefficients are positive and significant, except for *MTNL*. Therefore, as is emphasized in Baillie and Myers (1991) also, it is quite imperative to look for time-dependent conditional covariance (as well as time-varying hedge ratios) and not constant covariance. The sum of the parameter coefficients, $\hat{A}_{11}$ and $\hat{G}_{11}$ add up to one for three out of seven firms, for the other four firms, *ACC*, *GRASIM*, *MTNL* and *TATATEA*, it adds up to more than one.

[6] We have also checked with first, fifth, fifteenth and twentieth orders of serial correlations from standardised residuals. However, the results do not improve much as compared to the tenth-order serial correlation test statistics. Therefore, we are presenting the results with tenth-order serial correlation in the appendix tables. Other results are available upon request from the authors.

However, this is not unusual for these multivariate estimators and does not constitute a violation of the stationarity condition as required for univariate GARCH processes. The stationarity condition for the class of multivariate GARCH estimators has been derived for particular restricted versions.

The lead-lag relationships between futures and cash returns, analyzed with the artificial nesting of the likelihood-ratios, show unambiguous evidence of no lead-lag relationships between these two sets of returns data, except for *TATAPOW* series with the square root constraint. This is the only case where the restricted model is not dominated by the unrestricted model. It follows that an unrestricted GARCH estimator is preferred over the restricted causality versions and over pairs of univariate GARCH hedge ratio estimators. These nested tests provide quite different results than those reported in Au-Yeung and Gannon (2005) which finds a significant one way volatility transmission from the Hong Kong index futures to the cash index.

Specification tests indicate moderately excess kurtosis for all the residuals with one interesting fact that excess kurtosis from the cash returns series is higher in those four cases, where the conditional second-moment properties of the data would be considered non-stationary in variance for univariate GARCH (1,1) processes. Similarly, evidence of serial correlation in the standardized residuals can be detected for the same sets of firms. Overall, it seems that the modified bivariate BEKK of Engle and Kroner (1995) produces consistent results in terms of model estimations and residual diagnostics. The optimal hedge ratios estimates calculated from this framework are displayed in figure 4 in appendix B. It is interesting to note that *TATAPOW* series, which does support the evidence of a lead-lag relationship between the cash and futures returns show considerable volatility in the hedge ratio, whereas, all other hedge ratios seem to follow a smoothed pattern around one (perfect hedge).

Also note that for those four series (*ACC*, *GRASIM*, *MTNL* and *TATATEA*); the optimal hedge ratio follows an almost smoothed pattern around one, thus calling for a perfect hedge.

Results from bivariate GARCH models with unity constraint on parameter matrices (see table 8 in appendix A for reference) show improvements in conditional covariance over the results from bivariate GARCH models with square root constraint (see table 7 in appendix 1 for reference), as now all the $\hat{A}_{22}$ and $\hat{G}_{22}$ parameter estimates are positive and significant. As in the case of square root constraint on parameter matrices, we also find that there is mixed evidence involving parameter matrices $\hat{A}_{11}$ and $\hat{G}_{11}$, with the sum of these coefficients add up to more than unity for four out of seven cases. Likelihood ratio tests unambiguously reject lead-lag relationships between futures and cash returns for all the seven firms. Diagnostic tests from the standardized residuals show evidence of moderate leptokurtosis from both the returns' series. Box-Pierce test statistics show serial correlations in residuals for four firms, *ACC*, *GRASIM*, *MTNL* and *TATATEA*, as was the case in earlier scenario. Comparing the hedge ratios (see figure 5 in appendix B for reference) with the hedge ratios from earlier framework, we find that, except for *ACC* and *TATAPOW* series, all the other firms' hedge ratios show less volatility and appear to be much more well behaved. This behavior can also be confirmed if we cross-check the fourth order moments (kurtosis) from these two different frameworks. Bivariate GARCH models with unity constraint on parameter matrices show some improvement over the bivariate GARCH framework with square root constraint on parameter matrices as for four firms (from futures equation), the evidence of leptokurtosis from unity constraint model is less than that of the square root constraint model. Overall, it seems that the bivariate GARCH model with unity constraint on parameter matrices fare well compared with the bivariate GARCH model with square root constraint on parameter matrices, as conditional covariances, conditional means, residual diagnostics and hedge ratios from the unity constraint framework, and all show considerable improvements over the other alternative scenario.

When we consider the variance ratios reported in table 6 our earlier speculation of the performance of the static hedge ratios when the spot and cash variance ratios are close to one is confirmed. In 5 of the 7 cases the residual variance ratios calculated from the residual variance of the competing model relative to the variance of the spot return is smaller for the static model compared to our BEKK-GARCH estimators. However, the variance ratios of the static model barely out perform the restricted model with Beta set to one. This confirms our previous conjecture. What is encouraging is the dominance of either of the BEKK-GARCH models over the static models in two of the cases. These cases correspond to series (the TATA conglomerations) where there appears to be either occasional excess volatility in the cash of futures series. It is also interesting to note that the BEKK-GARCH model with unity constraint dominates the other version with the square root constraint, in terms of variance minimization, in six out of the seven cases. We expect that when we extend the analysis to the remaining Indian stock futures and cash stock prices the results may be more in line with some of the earlier reported results from cash index and futures price processes. We also suspect that these time varying models will provide strong results for data in these and similar markets sampled on an intra-day basis.

5. Conclusion

In this paper we have not delved into an extensive review of the relevant literature but instead focused on those important papers that have provided some initial evidence on the behavior of various commodities and index futures volatility behavior. We have extended this to consider the volatility of stock futures i.e., those traded on an emerging and of high interest market (Indian stock futures market). We identify the peculiar features of this dataset with those studied previously and find results that are sensible.

However, we do extend the BEKK-GARCH model and find that it does perform very well relative to the static models, given the data. The relaxation of the square root restriction in this multivariate framework does lead to more efficient estimation. The probability of obtaining hedge ratios with this latter model that must be set to zero (because we need to take the square root of the derived squared covariance to the squared variance of the futures) is low for this dataset. This may not be the case for other commodity and financial futures data.

One motivating factor for future research lies in further consideration of stock futures series where the volatility is more extreme. Another is the investigation of these models to allow structural breaks in either or both cash and futures equations and undertaking nested testing along similar lines as undertaken here for asymmetric effects. Sign effects can also be easily implemented within this framework as are higher order multivariate GARCH (M-GARCH) effects.

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Appendix A

Table 1: Descriptive Statistics for Futures Returns Series

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
Mean	0.001	0.002	0.002	0.001	0.001	0.001	0.002
Median	0.001	0.001	-0.001	0.000	0.001	0.001	0.001

Maximum	0.071	0.141	0.110	0.141	0.102	0.134	0.123
Minimum	-0.115	-0.281	-0.076	-0.142	-0.163	-0.244	-0.138
Std. Dev.	0.020	0.024	0.018	0.026	0.028	0.025	0.020
Skewness	-0.138	-1.379	0.108	0.211	-0.018	-1.086	-0.006
Kurtosis	5.090	27.163	5.497	7.029	5.418	15.194	8.248
Jarque-Bera	174.680	23240.070	246.941	644.922	229.956	6028.288	1082.051
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	943	943	943	943	943	943	943

Notes: "Std. Dev." denotes standard deviation. "Jarque-Bera" represents Jarque-Bera test statistic for normality and "Prob." denotes the corresponding p-value for testing normality. "Obs." stands for the number of sample observations.

Table 2: Descriptive Statistics for Cash Returns Series

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
Mean	0.001	0.002	0.002	0.001	0.001	0.001	0.001
Median	0.001	0.001	0.001	-0.000	-0.001	0.001	0.001
Maximum	0.077	0.131	0.115	0.150	0.096	0.113	0.119
Minimum	-0.091	-0.234	-0.074	-0.139	-0.168	-0.227	-0.135
Std. Dev.	0.020	0.024	0.019	0.027	0.028	0.024	0.020
Skewness	0.038	-0.731	0.320	0.195	-0.009	-1.070	0.078
Kurtosis	4.619	15.565	5.841	6.395	5.186	13.501	7.732
Jarque-Bera	103.243	6287.515	333.456	459.091	187.733	4512.868	880.615
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	943	943	943	943	943	943	943

Notes: "Std. Dev." denotes standard deviation. "Jarque-Bera" represents Jarque-Bera test statistic for normality and "Prob." denotes the corresponding p-value for testing normality. "Obs." stands for the number of sample observations.

Table 3: Descriptive Statistics for Basis Series

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
Mean	-0.377	0.418	-0.974	-0.380	-0.538	-0.486	-0.850
Median	-0.700	-0.550	-1.500	-0.450	-0.600	-0.700	-1.000
Maximum	9.300	24.250	22.250	4.700	13.750	42.000	16.250
Minimum	-5.150	-8.700	-19.300	-8.100	-5.650	-11.600	-9.650
Std. Dev.	2.019	3.782	5.415	0.993	1.795	2.612	2.637
Skewness	2.001	1.728	0.962	1.555	1.299	5.486	1.845
Kurtosis	8.778	7.741	5.455	13.028	9.978	80.571	11.117
Jarque-Bera	1942.722	1354.308	382.633	4336.360	2181.193	2414.790	3127.227
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	944	944	944	944	944	944	944

Notes: "Std. Dev." denotes standard deviation. "Jarque-Bera" represents Jarque-Bera test statistic for normality and "Prob." denotes the corresponding p-value for testing normality. "Obs." stands for the number of sample observations.

Table 4: Unit Root Tests for Returns and Basis Series

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
ADF-FuPL	1.342	1.665	-0.3261	-2.763	-0.299	-0.223	2.942
PP-FuPL	1.278	1.479	-0.398	-2.921	0.190	-0.305	2.716
ADF-FuRD	-24.357	-25.391	-23.621	-24.023	-23.770	-24.070	-13.456
PP-FuRD	-30.589	-29.114	-28.229	-27.574	-32.296	-29.805	-27.720
ADF-CaPL	1.481	1.585	-0.343	-2.793	-0.363	-0.182	2.213
PP-CaPL	1.522	1.462	-0.432	-2.935	0.199	-0.276	2.754

ADF-CaRD	-24.251	-25.251	-23.562	-24.057	-24.030	-23.920	-13.275
PP-CaRD	-31.176	-29.218	-27.953	-27.951	-32.357	-28.052	-27.871
ADF-BaL	-4.607	-4.340	-9.453	-8.975	-8.116	-8.917	-6.237
PP-BaL	-10.904	-15.658	-13.394	-11.018	-12.021	-20.702	-10.697

Notes: "ADF-PL" denotes the value of Augmented Dickey-Fuller test statistic for price series in log-levels. "ADF-RD" stands for Augmented Dickey-Fuller test statistic for returns series (or price series in log-difference). Similarly, "PP-PL" and "PP-RD" represent Phillips-Perron test statistics for prices in log-levels and in return series, respectively. "Fu" stands for futures, "Ca" stands for cash and "Ba" represents basis price series in the entire above notation.

Table 5: Cointegration Test between Futures and Cash Return Series

$$\Delta\hat{e}_t = \delta + \gamma\hat{e}_{t-1} + v_t \,;\; \hat{e}_t = Fu_t - \hat{\beta}_1 - \hat{\beta}_2 Ca_t$$

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
$\hat{\delta}$	0.001	-0.003	-0.003	0.001	-0.001	0.001	0.001
	(0.039)	(0.085)	(0.121)	(0.020)	(0.038)	(0.074)	(0.051)
$\hat{\gamma}$	-0.214	-0.375	-0.272	-0.227	-0.246	-0.501	-0.198
	(0.020)	(0.025)	(0.022)	(0.021)	(0.021)	(0.028)	(0.019)
τ_{test}	-10.614	-14.733	-12.167	-10.976	-11.483	-17.740	-10.181
$\tau_{critical}$	-3.900	-3.900	-3.900	-3.900	-3.900	-3.900	-3.900

Notes: Numbers in parentheses are standard errors; τ_{test} is the t (tau) test statistic for the estimated slope coefficient. $\tau_{critical}$ shows the Davidson-MacKinnon (1993) critical value at 99% level of significance to test the null hypothesis that the least squares residuals are nonstationary. In the above table, we reject all the null hypotheses that least squares residuals are nonstationary, and conclude that futures and cash returns series are cointegrated.

Table 6: Comparison of Variance Ratios from Different Models

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
Ols_diffbeta	0.043	0.040	0.047	0.036	0.016	0.114	0.051
Ols_beta1	0.045	0.041	0.048	0.037	0.017	0.127	0.052
Sqrt_paras	0.050	0.044	0.060	0.137	1.053	0.080	0.049
Unity_paras	0.335	0.043	0.055	0.041	0.017	0.078	0.048

Notes: "Ols_diffbeta" denotes the ratio of variances from OLS regression of spot returns on futures and spot returns. "Ols_beta1" stands for the ratio of variances from OLS regression of spot returns on futures when the beta coefficient is restricted to one and spot returns. "Sqrt_paras" specifies the ratio of variances from bivariate GARCH models with square root constraint on parameter matrices and spot returns. "Unity_paras" refers to the ratio of variances from bivariate GARCH models with unity constraint on parameter matrices and spot returns.

Table 7: Estimation of bivariate GARCH Models with Square Root Constraint on Parameter Matrices

$$R_t = \alpha + u_t \,,\; R_t = \left[R_{1,t}, R_{2,t}\right]' \,,\; u_t \mid \Omega_{t-1} \sim N\left(0, H_t\right)$$

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + G_{11}' H_{t-1} G_{11}$$

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
$\hat{\alpha}_1$	0.144	0.245	0.162	0.167	0.152	0.194	0.221
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.063)	(0.000)
$\hat{\alpha}_2$	0.137	0.252	0.127	-0.062	0.189	0.201	0.208
	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)	(0.061)	(0.032)
$\hat{C}_{011}$	0.343	0.395	0.208	0.967	0.274	0.506	0.610
	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.041)	(0.049)

$\hat{C}_{021}$	0.146 (0.000)	0.093 (0.095)	0.010 (0.006)	-0.268 (0.000)	-0.288 (0.000)	0.186 (0.007)	0.443 (0.077)
$\hat{C}_{022}$	0.356 (0.000)	0.405 (0.025)	0.365 (0.009)	0.817 (0.001)	-0.131 (0.001)	0.479 (0.037)	0.664 (0.091)
$\hat{A}_{11}$	0.055 (0.000)	0.354 (0.039)	0.152 (0.002)	0.581 (0.000)	0.149 (0.000)	0.433 (0.032)	0.091 (0.067)
$\hat{A}_{12}$	-0.324 (0.000)	0.412 (0.016)	0.158 (0.002)	0.636 (0.001)	0.117 (0.001)	-0.233 (0.033)	-0.113 (0.086)
$\hat{A}_{21}$	0.250 (0.000)	0.104 (0.040)	0.253 (0.003)	-0.136 (0.000)	0.204 (0.000)	-0.104 (0.035)	0.414 (0.063)
$\hat{A}_{22}$	0.611 (0.000)	0.009 (0.025)	0.274 (0.001)	-0.233 (0.000)	0.215 (0.001)	0.556 (0.038)	0.586 (0.083)
$\hat{G}_{11}$	1.146 (0.000)	0.679 (0.036)	1.040 (0.002)	0.513 (0.001)	0.818 (0.001)	0.880 (0.027)	0.937 (0.037)
$\hat{G}_{12}$	0.243 (0.000)	-0.250 (0.078)	0.084 (0.000)	-0.560 (0.001)	-0.448 (0.000)	0.116 (0.024)	0.417 (0.209)
$\hat{G}_{21}$	-0.205 (0.000)	0.130 (0.030)	-0.180 (0.002)	0.255 (0.000)	0.076 (0.001)	0.038 (0.025)	-0.173 (0.046)
$\hat{G}_{22}$	0.696 (0.000)	1.082 (0.069)	0.778 (0.001)	1.351 (0.000)	1.369 (0.000)	0.800 (0.023)	0.366 (0.203)
Log-L	-2733.584	-2726.748	-2675.222	-3490.872	-4020.872	-2683.115	-3022.363
LR-Test1	940.286	342.308	609.726	1396.636	3086.112	22.614	1151.626
LR-Test2	940.796	342.578	609.778	1401.950	3064.282	3.149	1126.142
S_{Fu}	0.003	0.135	0.154	0.250	0.115	-0.610	0.131
K_{Fu}	4.263	4.914	5.765	5.495	5.381	5.736	5.963
$Q_{Fu}(10)$	12.162	12.089	16.915	22.348	6.998	14.346	17.920
$Q^2_{Fu}(10)$	4.996	7.609	9.631	14.031	8.711	15.022	9.466
S_{Ca}	0.159	0.214	0.364	0.303	0.094	-0.400	0.198
K_{Ca}	4.466	4.889	5.959	5.601	4.756	4.712	6.249
$Q_{Ca}(10)$	11.521	10.625	20.884	19.769	9.491	23.745	23.922
$Q^2_{Ca}(10)$	3.408	5.396	7.251	16.843	16.964	14.726	9.703

Notes: Numbers in parentheses are standard errors; LR-Test1 denotes likelihood ratio test involving first restriction: $a_{12} = g_{12} = 0$ and LR-Test2 denotes likelihood ratio test involving second restriction: $a_{21} = g_{21} = 0$; S represents skewness of standardised residuals and K represents kurtosis of standardised residuals with subscripts "Fu" and "Ca" denoting the moments coming from futures and cash equation respectively; $Q(10)$ and $Q^2(10)$ show the Box-Pierce statistics for tenth-order serial correlations in the residuals and squared normalized residuals respectively, with the subscripts "Fu" and "Ca" denoting the moments coming from futures and cash equation, respectively.

Table 8: Estimation of bivariate GARCH Models with Unity Constraint on Parameter Matrices

$$R_t = \alpha + u_t,\ R_t = [R_{1,t}, R_{2,t}]',\ u_t \mid \Omega_{t-1} \sim N(0, H_t)$$
$$H_t = C_0'C_0 + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + G_{11}'H_{t-1}G_{11}$$

	ACC	*BHEL*	*GRASIM*	*MTNL*	*SATYAM*	*TATAPOW*	*TATATEA*
$\hat{\alpha}_1$	0.185 (0.000)	0.049 (0.000)	0.080 (0.028)	0.033 (0.000)	0.142 (0.000)	0.191 (0.056)	0.158 (0.060)
$\hat{\alpha}_2$	0.128 (0.052)	0.020 (0.001)	0.061 (0.029)	-0.065 (0.000)	0.178 (0.025)	0.195 (0.854)	0.144 (0.062)
$\hat{C}_{011}$	0.252 (0.324)	0.389 (0.000)	0.222 (0.036)	0.213 (0.000)	0.257 (0.002)	0.567 (0.047)	0.530 (0.081)
$\hat{C}_{021}$	-0.134 (5.341)	0.397 (0.057)	-0.156 (0.019)	0.466 (0.000)	0.182 (0.142)	0.182 (0.008)	-0.373 (0.033)
$\hat{C}_{022}$	0.939 (0.778)	0.655 (0.104)	0.041 (0.033)	0.279 (0.001)	0.286 (0.036)	0.598 (0.038)	0.646 (0.107)

$\hat{A}_{11}$	0.122 (0.102)	0.020 (0.001)	0.334 (0.053)	-0.207 (0.001)	0.082 (0.006)	0.434 (0.036)	0.723 (0.151)
$\hat{A}_{12}$	0.005 (0.109)	-0.159 (0.034)	0.166 (0.046)	0.009 (0.000)	0.032 (0.023)	-0.214 (0.038)	0.201 (0.149)
$\hat{A}_{21}$	0.099 (0.098)	0.165 (0.000)	0.055 (0.051)	0.352 (0.001)	0.021 (0.007)	-0.100 (0.040)	-0.398 (0.150)
$\hat{A}_{22}$	0.195 (0.110)	0.370 (0.038)	0.233 (0.045)	0.235 (0.001)	0.066 (0.023)	0.545 (0.044)	0.122 (0.149)
$\hat{G}_{11}$	0.958 (0.108)	0.684 (0.015)	0.809 (0.028)	0.446 (0.000)	0.878 (0.027)	0.859 (0.029)	0.894 (0.201)
$\hat{G}_{12}$	0.019 (0.066)	0.700 (0.070)	-0.006 (0.033)	-0.052 (0.001)	-0.063 (0.102)	0.086 (0.027)	0.742 (0.218)
$\hat{G}_{21}$	-0.181 (0.096)	0.266 (0.017)	0.112 (0.027)	0.501 (0.001)	-0.029 (0.030)	0.052 (0.031)	0.009 (0.205)
$\hat{G}_{22}$	0.779 (0.090)	0.244 (0.077)	0.928 (0.032)	0.908 (0.001)	0.911 (0.109)	0.815 (0.031)	0.143 (0.222)
Log-L	-3758.781	-2642.024	-2406.334	-3479.952	-7388.717	-2685.579	-2450.568
LR-Test1	844.526	74.282	330.004	1079.938	9821.802	341.782	10.514
LR-Test2	2991.010	156.424	68.93	1377.788	2048.738	329.008	171.142
S_{Fu}	-0.164	-0.371	0.396	0.197	0.012	-0.629	0.133
K_{Fu}	4.416	7.788	5.933	5.303	4.759	5.857	5.059
$Q_{Fu}(10)$	18.548	15.124	22.251	25.847	8.183	14.296	25.334
$Q^2_{Fu}(10)$	78.387	59.569	10.380	26.393	15.734	14.370	7.138
S_{Ca}	-0.016	-0.089	0.715	0.219	0.001	-0.410	0.197
K_{Ca}	4.170	6.121	7.815	5.393	4.584	4.728	5.626
$Q_{Ca}(10)$	15.119	13.049	23.986	25.041	10.717	24.058	30.590
$Q^2_{Ca}(10)$	68.298	40.263	5.585	40.785	27.141	16.145	2.317

Notes: Numbers in parentheses are standard errors; LR-Test1 denotes likelihood ratio test involving first restriction: $a_{12} = g_{12} = 0$ and LR-Test2 denotes likelihood ratio test involving second restriction: $a_{21} = g_{21} = 0$; S represents skewness of standardised residuals and K represents kurtosis of standardised residuals with subscripts “Fu” and “Ca” denoting the moments coming from futures and cash equation respectively; $Q(10)$ and $Q^2(10)$ show the Box-Pierce statistics for tenth-order serial correlations in the residuals and squared normalized residuals respectively, with the subscripts “Fu” and “Ca” denoting the moments coming from futures and cash equation, respectively.

Appendix B

Figure 1: Futures Returns Series

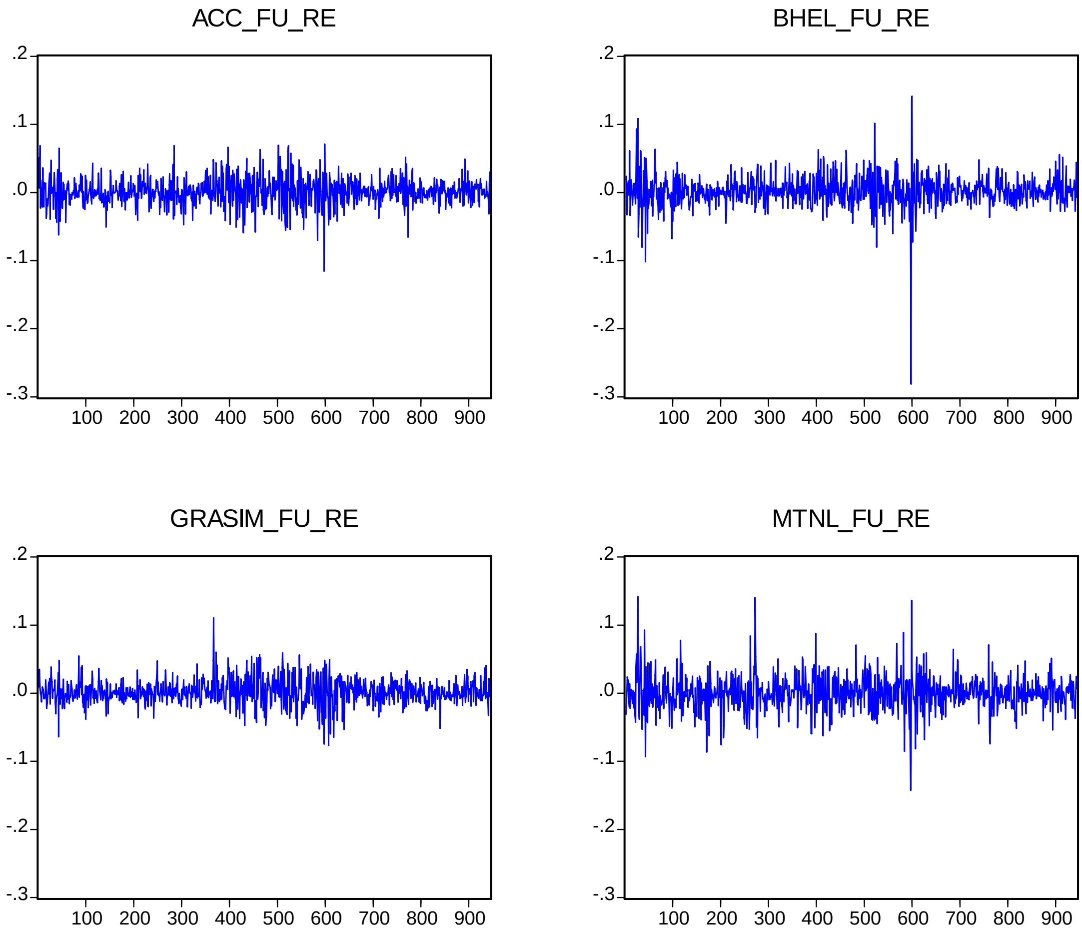


Figure 1: Futures Returns Series (continued)

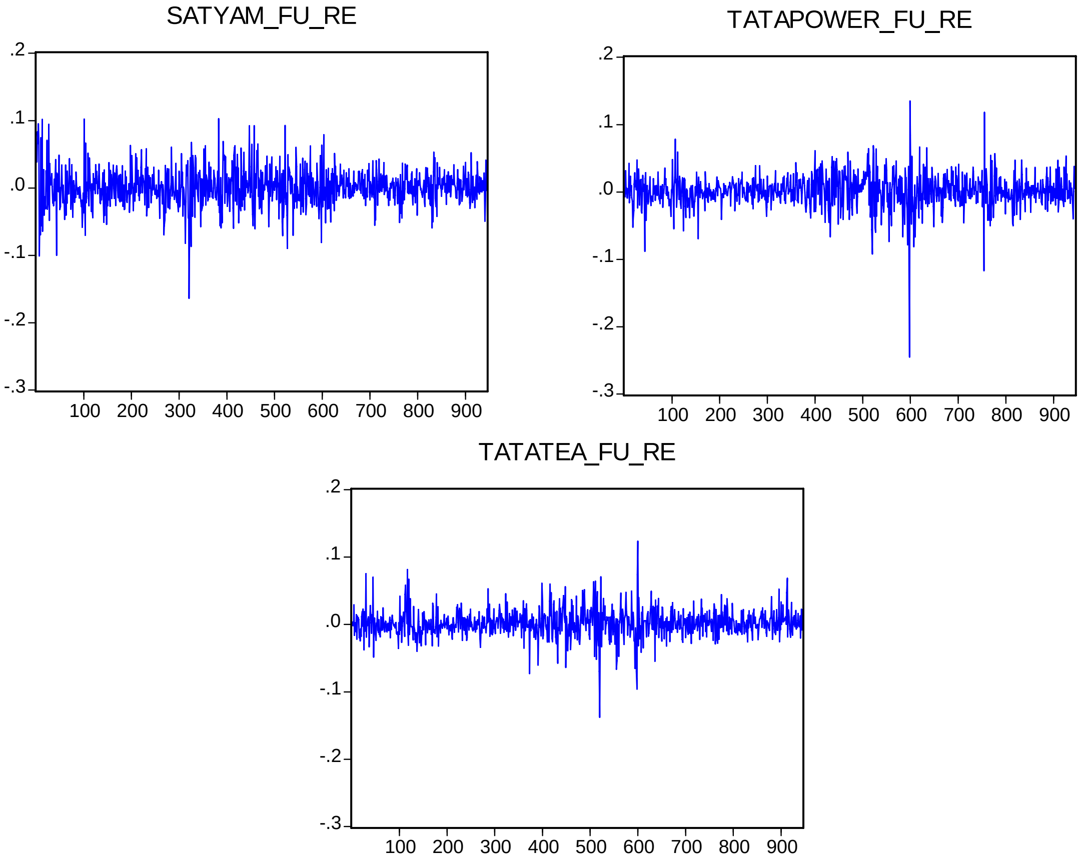


Figure 2: Cash Returns Series

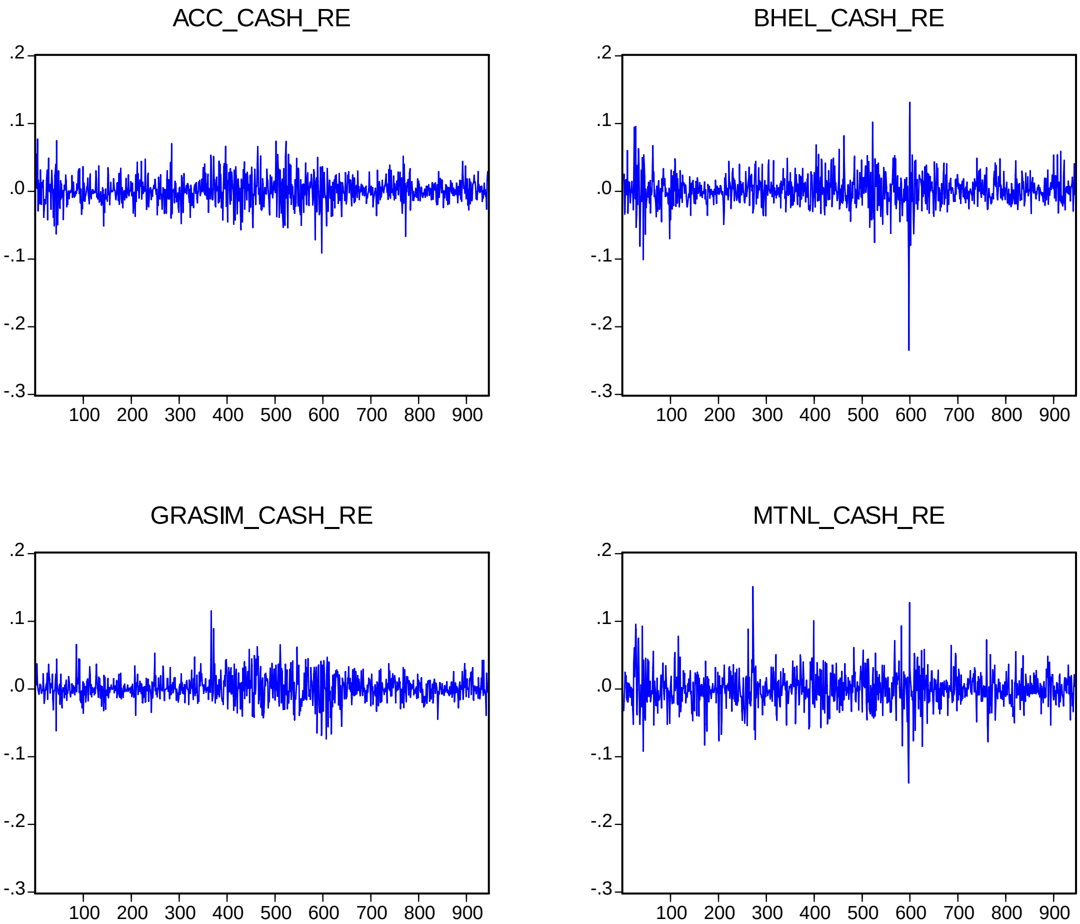


Figure 2: Cash Returns Series (continued)

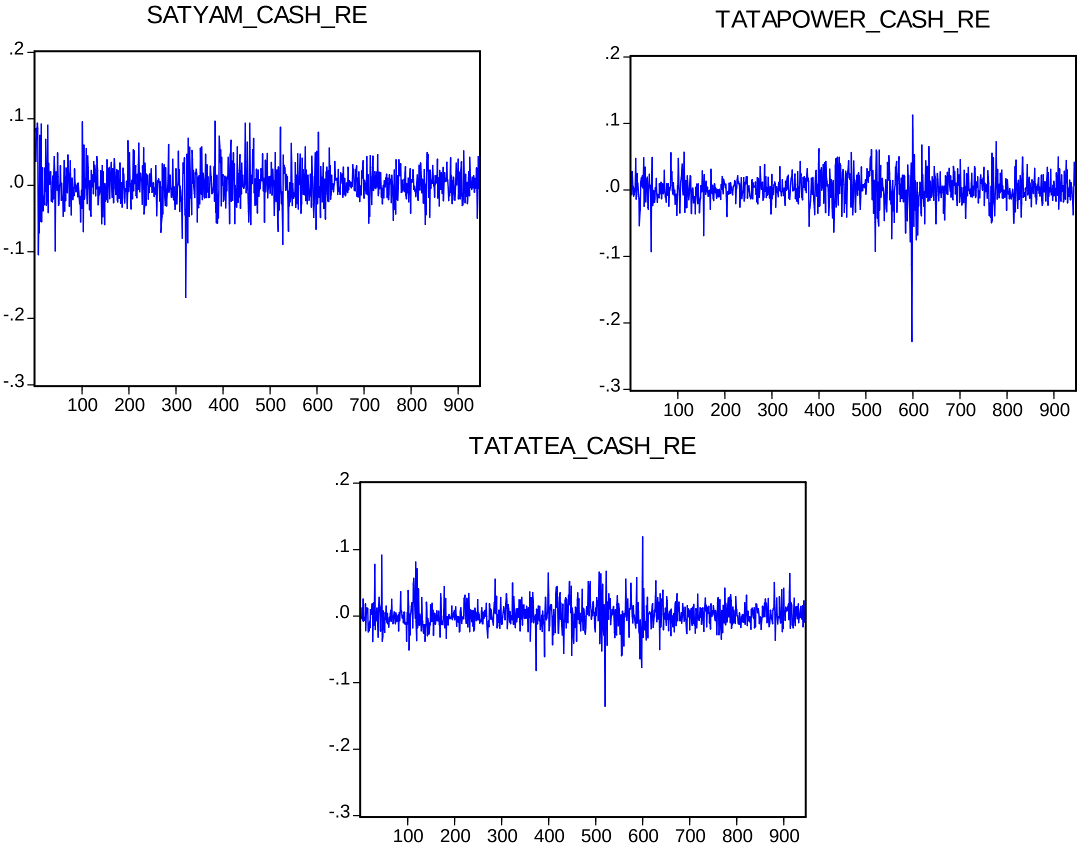


Figure 3: Basis Series

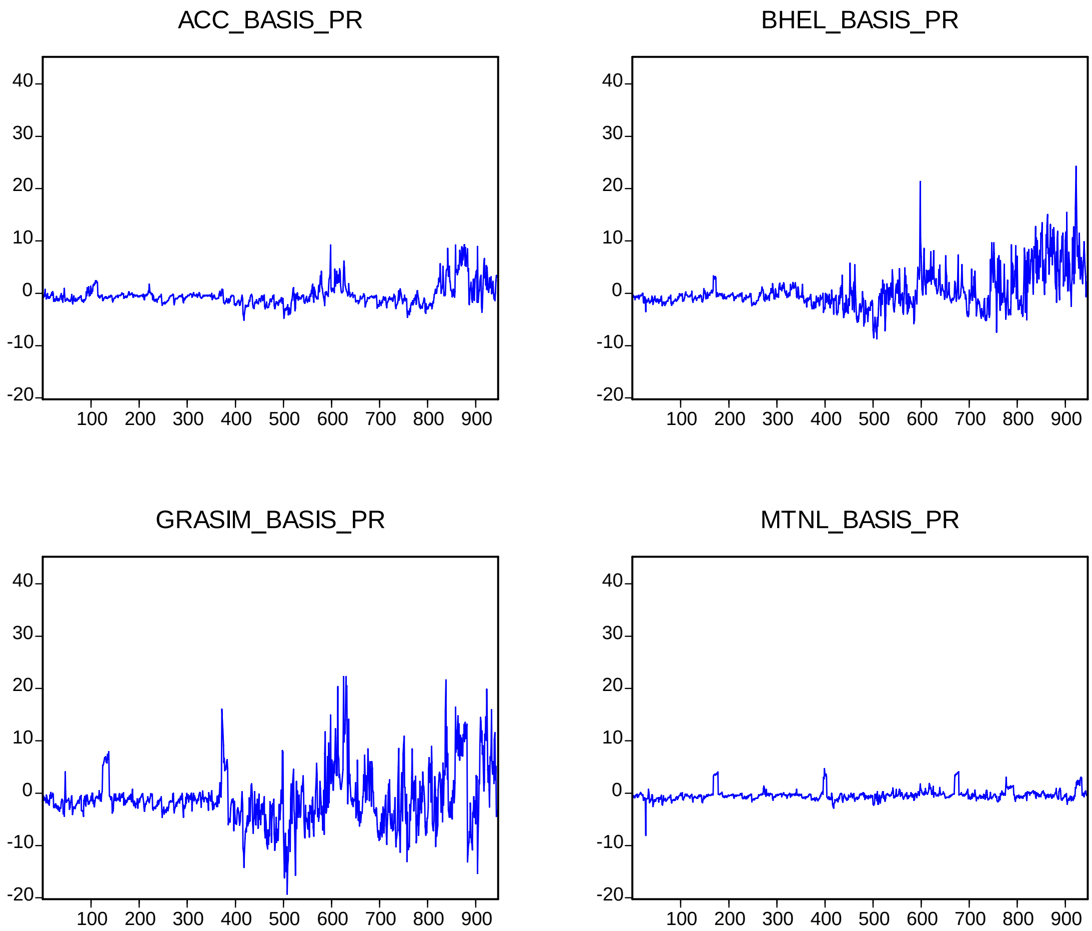


Figure 3: Basis Series (continued)

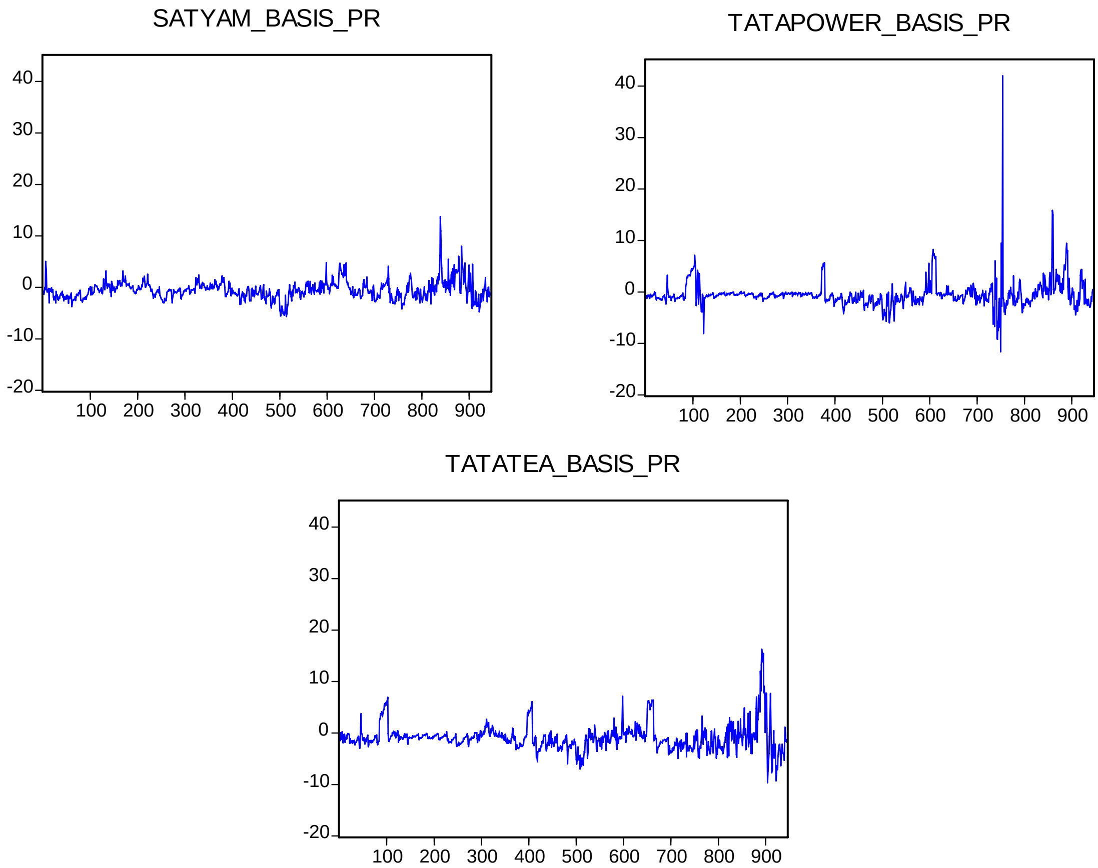


Figure 4: Hedge Ratios from bivariate GARCH Models with Square Root Constraint

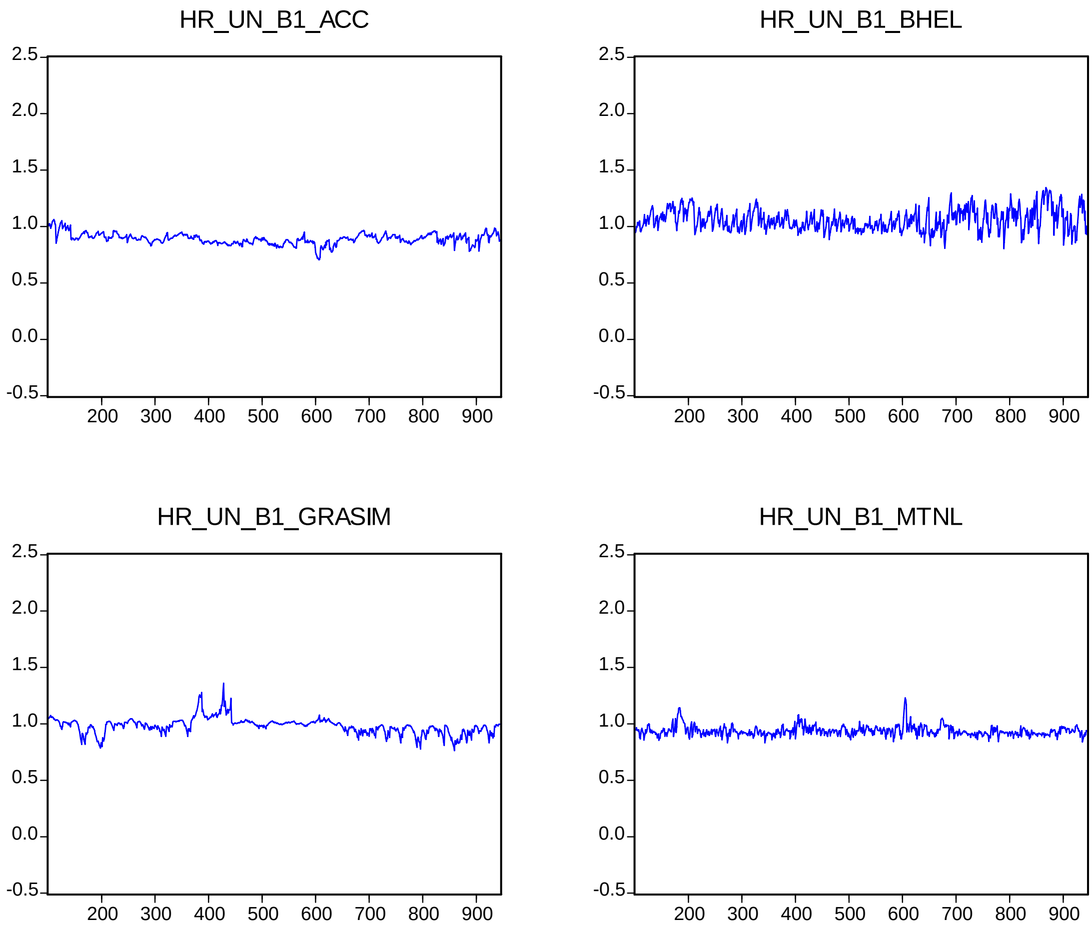


Figure 4: Hedge Ratios from bivariate GARCH Models with Square Root Constraint (continued)

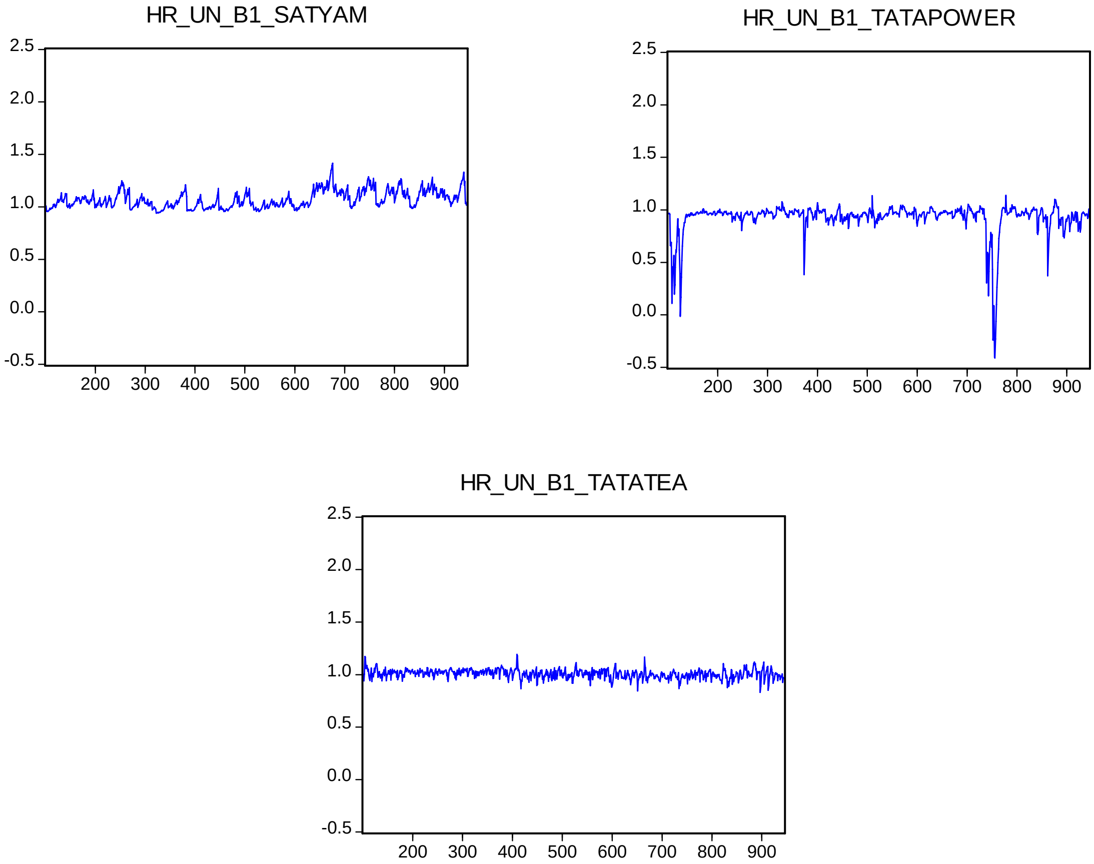


Figure 5: Hedge Ratios from bivariate GARCH Models with Unity Constraint

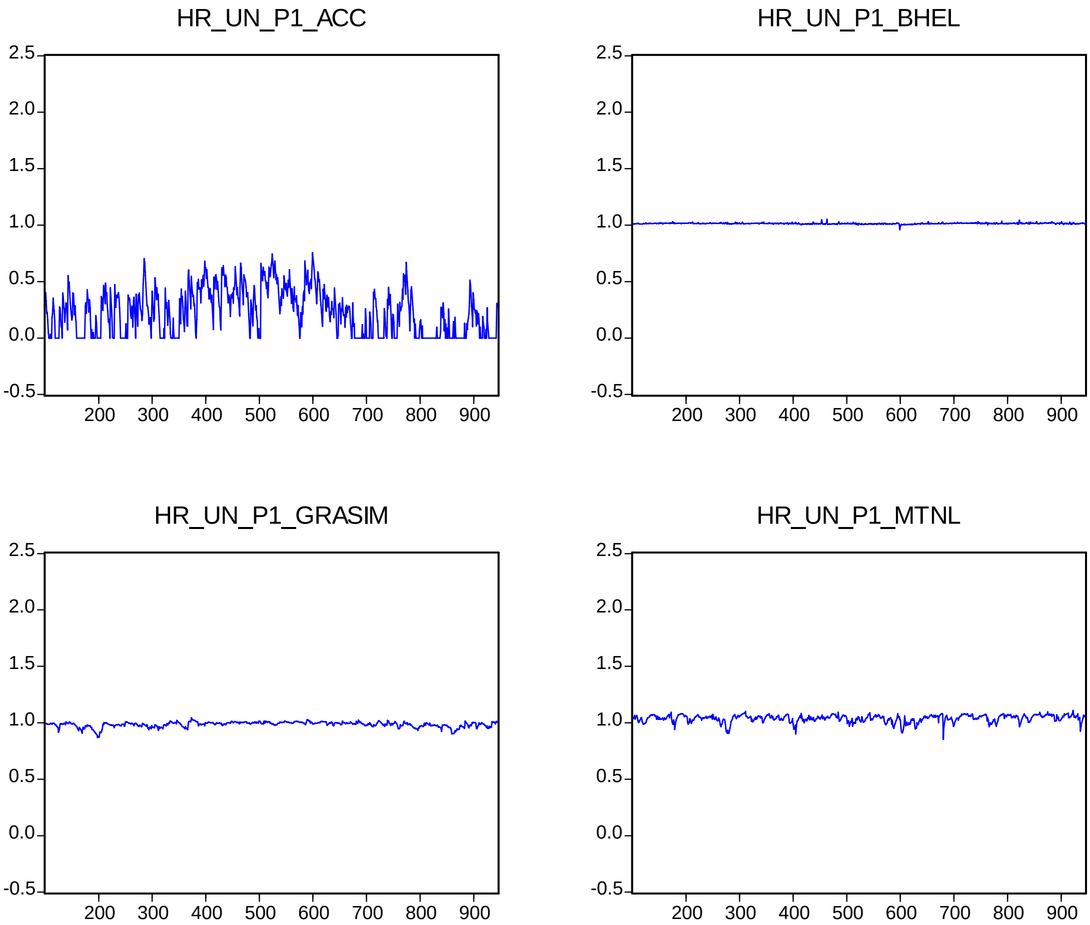
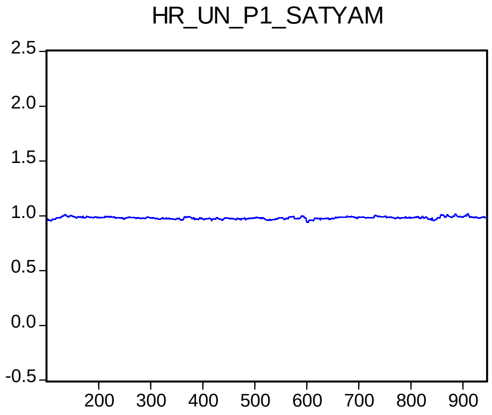


Figure 5: Hedge Ratios from bivariate GARCH Models with Unity Constraint (continued)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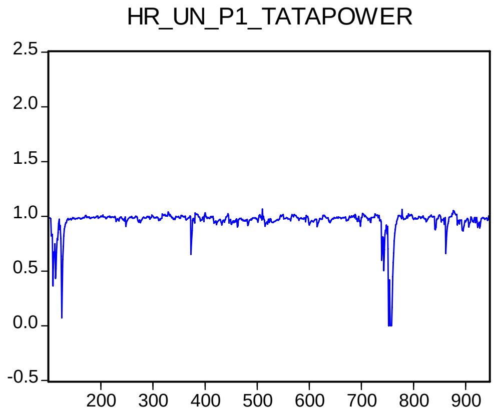
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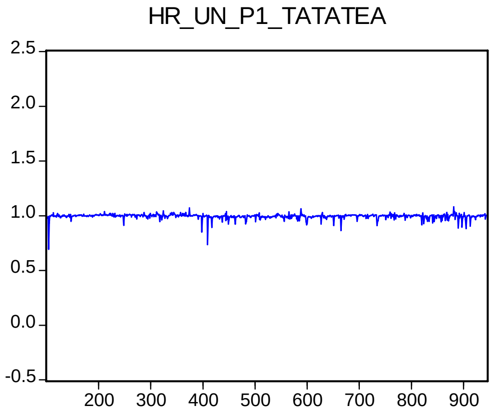
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0.0
-0.5
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