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Dynamic Parametric and Nonparametric Hedging: Evidence from the Arab Gulf Equity Markets

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Abstract

This paper examines the optimal hedging strategies in the Arab Gulf equity markets using a parametric and a nonparametric dynamic approaches in modeling the conditional variances and covariances of equity returns. The parametric approach is based on a multivariate VAR-GARCH model of daily returns, with BEKK specification of Engle and Kroner (1995), and the nonparametric approach adopts a dynamic system based on Filtered Historical Simulation (FHS) of Barone-Adesi et al. (1999) and nonparametric regression. These approaches are then used to calculate optimal portfolio weights and optimal ratios of hedging long and short positions in the Gulf Cooperation Council major sectors, namely, Service, Financial and Industrial. The results show that the nonparametric approach provides higher hedging effectiveness and hence superior hedging strategies.

Keywords: Multivariate GARCH, Filtered Historical Simulation, Optimal Hedging
JEL Classification: G10, G15

1. Introduction

Market risk management imposes dealing with the key issue of controlling the variances and covariances of individual positions in an investment portfolio. The risk management success of such activity requires taking into account the time varying feature of conditional variances and covariances. Hence, investors' evaluation of the interacting dynamics among markets allow for adjustment and useful implementation of hedging strategies. In order to achieve this, hedgers are required to gauge their strategies with a metric that allows checking their performances. Many approaches have been developed to estimate an optimal hedge ratio that is also known as the minimum-variance hedge ratio. However, these approaches suffer from the existence of serial correlation and heteroscedasticity in asset price series (Herbst *et al.*, 1993).

The collective evidence shows that GARCH-based dynamic hedging strategies are empirically appropriate (see Kroner and Sultan, 1993). Ku *et al.* (2007) applied the dynamic conditional correlation (DCC) model of Engle (2002) with error correction terms to investigate the optimal hedge ratios of British and Japanese currency futures markets, and compared the DCC and OLS estimates. The empirical results show that the DCC model yields the best hedging performance. Chang *et al.* (2011)

examined the performance of four models (namely CCC, VARMA-GARCH, DCC and BEKK) for the crude oil spot and futures returns of two major international crude oil markets (BRENT and WTI). The calculated optimal hedging ratios from each multivariate conditional volatility model suggested time-varying hedge ratios, which recommended to short in crude oil futures, with a high portion of one dollar long in crude oil spot. The hedging effectiveness indicated that DCC (BEKK) was the best (worst) model for optimal hedge ratio calculation in terms of the variances of portfolio reduction. Furthermore, Hakim and McAleer (2009) analyzed whether multivariate GARCH models incorporating volatility spillovers and asymmetric effects of negative and positive shocks on the conditional variance provide different conditional correlation forecasts. They suggested that incorporating volatility spillovers and asymmetric effects of negative and positive shocks on the conditional variance does not affect the forecasts of conditional correlations.

The trend shows that multivariate GARCH models have not yet fully enjoyed the same popularity in practice as their univariate counterparts. There are certain impediments that inhibit practitioners to use these models. The lack of theoretical foundation and the computational burden that goes along the increasing number of parameters estimates in function of the number of assets and markets employed constitute a major inhibiting factor. The multivariate GARCH models proposed in the literature assume constant conditional correlations over time. Models such as the BEKK model of Engle and Kroner (1995), the Dynamic Conditional Correlation (DCC) model of Engle (2002) and Varying Conditional Correlation (VCC) model of Tse and Tsui (2002), accommodate for time varying conditional correlations. However, such models do not attach a vector autoregressive moving average component that enables examining the cross effects of both the conditional volatility and conditional correlation. This paper builds on the early work of Chan, Lim, & McAleer (2005) and Hammoudeh *et al.* (2009) in using VAR-GARCH models in a multivariate context.

Regardless of the popularity of the financial time series modeling, the main challenge remains in the a priori assumption of imposing a realistic distributional structure in the conditionally heteroskedastic error terms (see Hafner and Herwartz, 2006). In addition, the absence of i.i.d. characteristics renders the historical financial time series inappropriate as a toll of estimating the conditional variance-covariance matrix. Furthermore, there is evidence of time-varying skewness in equity returns, which if explored could better enable us to find alternative strategies for hedging uncovered positions in the equity markets. Such challenges could be met by using a dynamic model based on Filtered Historical Simulation (FHS) of Barone-Adesi *et al.* (1999) combined with nonparametric regression. Such technique has been used by Giannopoulos, Nekhili, and Koutmos (2010) to examine dependencies in covariance changes and to carry an impulse response analysis to investigate the dynamic responses to volatility shocks among major equity markets, namely, US, UK, Germany, and Japan.

Based on the alternative models discussed earlier, this paper examines the shock and volatility transmission among three sectors, namely Financial, Service and Industrial, for the Gulf Cooperation Council (GCC) countries that include Saudi Arabia, UAE, Qatar, Bahrain, Kuwait and Oman. It follows using the estimated results to compute the weights of the sectors in an optimal portfolio of each GCC country, and the optimal hedge ratios that minimize overall risk for holding the sectors in portfolios.

2. Methodology

2.1. Nonparametric Approach

During the last two decades, the main approach used to model volatility of financial assets is based on the empirical fact that the first differences of many asset prices are uncorrelated and their squares display serial correlation. This approach models the time-varying variances of the returns in Engle's (1982) class of autoregressive conditional heteroscedastic (ARCH) and Bollerslev's (1986) generalized ARCH (GARCH) models. One of the simplest models of this class, and as with most of daily time series, the AR-GARCH or asymmetric AR-GARCH. A typical AR-GARCH(1,1) system is represented by

$$R_t = \varphi + \mu R_{t-1} + \varepsilon_t$$
$$\varepsilon_t = H_t^{1/2} z_t \tag{1}$$

and where R_t is a Nx1 vector of return between time $t-1$ and t, H_t is the conditional variance of returns at time t, and z_t are i.i.d innovations, with N being the number of variables.

$$Corr_{t-1}(\varepsilon_t) = \sum_t = D_t^{-1/2} \mathrm{H}_t D_t^{-1/2} \text{ with } D_t = diag(h_{11,t},...,h_{NN,t}).$$

The model ensures that any historical patterns are removed and puts in evidence the volatility persistence and transmission among different markets. In the above system, the conditional distribution of the random terms is assumed to be normal. However, this normality assumption is rejected by many scholars like Fama and French (1993) or Longin and Solnik (2001), to list a few. Moreover, the functional forms of conditional covariance matrix and conditional correlation matrix are linear, and hence excluding any possible nonlinearity. These two restrictions may lead to inconsistency and inefficiency of estimations. Nevertheless, the existence of nonparametric techniques has helped in amending these restrictions. In this paper, the Filtered Historical Simulation (FHS) is adopted and it is combined with one of the nonparametric regression. The specification of $h_{i,t}$, i = 1, …, N, follows a univariate GARCH(1,1) processes.

$$h_{ii,t} = \omega + \alpha_{ii,t}\varepsilon_{t-1} + \beta h_{ii,t-1} \tag{2}$$

The Filtered Historical Simulation (FHS) follows the following steps: first the standardized residuals are obtained for each index, namely $z_{i,t} = \hat{\varepsilon} / \hat{h}_{i,t}^{1/2}$, then conditional variance is generated by

$$h^*_{i,t+j} = \hat{\omega}_i + \hat{\beta}_i h_{i,t+j-1} + \hat{\alpha}_i\left(\mu_{i,t+j-1} + \hat{\gamma}_i\right)^2, \text{ j=1,2,..,N} \tag{3}$$

to form the innovations $\mu_{i,t+j} = z_{i,t+j}\sqrt{h^*_{i,t+j}}$; second the conditional mean is obtained by using the innovations $u_{i,t+j}$ in the following model:

$$R^*_{i,t+j} = \hat{\varphi} + \hat{\mu}_i R^*_{i,t+j} + u_{i,t+j} \quad , \text{ j=1, 2,.., N} \tag{4}$$

For each index i, the above steps are repeated recursively to obtain different simulated pathways, with S is the number of times the draw from the standardized residuals is made and N is the sample size, as follows:

$$\hat{h}^{1/2}_{1,t-1} \rightarrow \begin{array}{llllll} \mathrm{z}_{1,\mathrm{t}} \rightarrow \sqrt{\mathrm{h}^*_{1,\mathrm{t+1}}} & \rightarrow R^*_{1,t+1} \ldots & \mathrm{z}_{1,\mathrm{t+N}} & \rightarrow \sqrt{\mathrm{h}^*_{1,\mathrm{t+N}}} & \rightarrow R^*_{1,t+N} \\ \mathrm{z}_{2,\mathrm{t}} \rightarrow \sqrt{\mathrm{h}^*_{2,\mathrm{t+1}}} & \rightarrow R^*_{2,t+1} \ldots & \mathrm{z}_{2,\mathrm{t+N}} & \rightarrow \sqrt{\mathrm{h}^*_{2,\mathrm{t+N}}} & \rightarrow R^*_{2,t+N} \\ \ldots & \ldots & & \ldots & \\ \mathrm{z}_{\mathrm{S},\mathrm{t}} \rightarrow \sqrt{\mathrm{h}^*_{\mathrm{S},\mathrm{t+1}}} & \rightarrow R^*_{S,t+1} \ldots & \mathrm{z}_{\mathrm{S},\mathrm{t+N}} & \rightarrow \sqrt{\mathrm{h}^*_{\mathrm{S},\mathrm{t+N}}} & \rightarrow R^*_{S,t+N} \end{array}$$

The FHS technique imposes the conditional covariances of the standardized residuals z to be constant. Therefore, and to take into account the dynamic changes in the conditional covariances of the underlying variables, a nonparametric technique is used as in Long and Ullah (2005). The nonparametric estimation of the conditional covariance matrix H_t is performed by using the Nadaraya-Watson (NW) estimator as follows:

$$H_t = \frac{\sum_{\tau=1}^{N} z_t z_t' K_\lambda(s_\tau - s_t)}{\sum_{\tau=1}^{N} K_\lambda(s_\tau - s_t)} \tag{5}$$

where s_t is a conditioning variable, $K_\lambda(.) = K(./\lambda)/\lambda$, K(.) is a kernel function, and λ is the bandwidth parameter. The Gaussian kernel is used with a bandwidth λ = b x 1.06 $\hat{S}_s N^{-1/(k+4)}$ and b is based on minimizing the MSE(H_t), k is the number of parameters, and $\hat{S}_s$ represents the standard deviation of the conditioning variable. The estimation of the nonparametric correlations is performed by decomposing the conditional covariance matrix H_t into conditional standard deviations and correlations as follows:

$$H_t = D_t R D_t \tag{6}$$

where D_t = diag($h_{1,t}^{1/2}$, …., $h_{N,t}^{1/2}$), with N is the number of indices, and R = [ρ_{ij}] is positive definite with ρ_{ii} = 1, i = 1, …, N. For 1 ≤ i, j ≤ N, the off-diagonal elements of the conditional covariance matrix are defined as:

$$[H_t]_{ij} = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij}, \quad i \neq j, \tag{7}$$

2.2 Parametric Approach

By and large, multivariate models allow for the possibility that some equity volatilities may share common persistent components. Hence, adopting such models will allow the conditional variances and covariances of equity markets to influence each other. In this paper, we use a vector autoregressive multivariate GARCH BEKK (named after Bollerslev, Engle, Kraft and Kroner) model presented by Engle and Kroner (1995). The model is represented as follows:

$$R_t = \alpha + \mu R_{t-1} + \varepsilon_t, \tag{8}$$

$$\varepsilon_t = H_t^{1/2} z_t,$$

where R_t is a Nx1 vector of return between time t-1 and t, H_t is the conditional variance of returns at time t, and z_t are i.i.d innovations, with N being the number of variables.

$$Corr_{t-1}(\varepsilon_t) = \sum_t = D_t^{-1/2}\ H_t D_t^{-1/2}\text{, with } D_t = \text{diag}(h_{11,t}, ..., h_{NN,t}).$$

Engle and Kroner (1995) propose a parametrization that imposes positive definiteness restrictions.

$$H_t = C'C + B'\ H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}'A \tag{9}$$

and where C is a lower triangular matrix of constants, B is a square matrix with parameters b_{ij} that indicate the persistence in conditional volatility between asset i and asset j, A is a square matrix with parameters a_{ij} that measure the degree of innovation from asset i to asset j.

3. Optimal Portfolio Weights and Hedge Ratios

In this section, we calculate the optimal portfolio weights and optimal hedge ratios to identify the appropriate hedging strategies that account for variance-covariance matrix dynamics using the models discussed earlier. Let's consider a one dollar portfolio consisting of two assets at time t and where $h_{12,t}$ represents the conditional covariance between assets 1 and 2, $h_{11,t}$ and $h_{21,t}$ are respectively the conditional variance of the first and the second asset. In order to construct an optimal portfolio design that minimizes risk without lowering expected returns, we apply the methods Kroner and Ng (1998):

$$\omega_{ij,t} = \frac{h_{22t} - h_{12t}}{h_{11t} - 2h_{12t} + h_{22t}} \tag{10}$$

$\omega_{12,t}$ = 0 if $\omega_{12,t}$ < 0 and $\omega_{12,t}$ = 1 if $\omega_{12,t}$ > 1. It is obvious that the weight of the second asset in the one dollar portfolio is 1 $\omega_{12,t}$. Moreover, we construct a risk minimizing hedge ratio as Kroner and Sultan

(1993). In order to minimize risk, a long position of one dollar taken in one asset in a given market should be hedged by a short position of Hedge Ratio_t in another asset in the same market at time t:

$$\text{Hedge Ratio}_t = \frac{h_{12,t}}{h_{22,t}} \tag{11}$$

According to Johnson (1960), the variance of the returns of the hedged portfolio, conditional on the information set available at time t-1 is given by:

$$\text{var}_{Hedged} = h_{11,t} + \text{HedgeRatio}_t^2\ h_{22,t} - 2\text{HedgeRatio}_t\ h_{12,t} \tag{12}$$

and the hedging effectiveness could be measured by the variance reduction for any hedged portfolio compared with the unhedged portfolio. $(\text{var}_{Unhedged} - \text{var}_{Hedged}) / \text{var}_{Unhedged}$. The higher hedging effectiveness the larger risk reduction, and a hedging method with a higher effectiveness is regarded as a superior hedging strategy.

4. Data and Results

To evaluate the models, we use three sector indices, namely, Financial, Service and Indus-trial, of six GCC markets UAE, Bahrain, Kuwait, Qatar, Saudi Arabia, and Oman. The daily closing prices for these indices for the period April 2, 2012 until March 2, 2017 were obtained from Zawya database and respected stock markets. Due to differences in weekly holidays between the countries for some time period and due to country specific holidays some observations were deleted. Descriptive statistics of daily returns are presented in Table 1. The daily log returns are defined as: $R_{i,t} = \log(p_{i,t} / p_{i,t-1}) * 100$, where $p_{i,t}$ is the daily closing value of the sector index i on day t.

Table 1: Descriptive Statistics for GCC Returns by Sector

Sector	Financial	Service	Industrial
Saudi Arabia			
Mean	0.0022	0.0352	-0.0005
S.D.	1.4751	1.4044	2.0450
Skewness	0.0857	-0.5608	-1.0508
Kurtosis	9.8508	11.7106	9.7569
UAE			
Mean	-0.0042	-0.0722	-0.1142
S.D.	3.2194	1.5025	1.6656
Skewness	0.2648	0.0339	0.3189
Kurtosis	5.8268	6.3576	3.9499
Qatar			
Mean	0.0266	-0.0127	-0.0505
S.D.	1.3777	1.4450	1.4026
Skewness	0.2438	-0.2398	-0.0560
Kurtosis	6.6430	17.4053	10.3935
Bahrain			
Mean	0.0045	0.0212	0.0054
S.D.	0.6459	0.6885	1.2081
Skewness	0.4409	0.6419	0.6793
Kurtosis	4.8534	12.9609	9.8200
Kuwait			
Mean	-0.1439	-0.0211	-0.0250
S.D.	1.0813	0.6569	0.6270
Skewness	-0.6126	0.3698	-0.9090
Kurtosis	6.2202	4.7551	6.7871
Oman			
Mean	-0.0140	-0.0276	-0.0987
S.D.	1.3108	0.6398	0.8664
Skewness	-0.7375	-0.4363	-1.3119
Kurtosis	10.2346	8.8810	13.6937

The highest averages of the daily returns during the sample period are in Saudi Arabia for the Service sector (0.035%) and Qatar for the Financial sector (0.026%). The highest standard deviation is seen in the Financial sector of the Saudi market. According to the sample kurtosis estimates, the daily rate of returns are far from being normally distributed. The lowest kurtosis estimate is 3.95 (Industrial sector of UAE) while the highest is 19.44 (Service sector in Qatar). Based on the sample kurtosis estimates, it may be argued that the return distributions in all sectors are fat tailed. The sample skewness shows that the daily returns have an asymmetric distribution in all the markets. The sample skewnesses are negative for Oman and Kuwait and positive for all other sectors indicating that the asymmetric tail extends more towards negative values than positive ones.

Tables 2, 3, and 4 present the estimation results of the VAR-MGARCH-BEKK model for the variance covariance. There is a relatively large and significant ARCH effect indicating the presence of own-volatility spillovers in all sectors across all GCC markets. With respect to the Financial sector and its sensitivity to past shocks (news), the highest is seen in Saudi Arabia and the lowest in Bahrain and Qatar. This is evident from their interconnectedness with global financial sector as the Saudi market is more open to foreign investors than its counterparts in Bahrain and Qatar. With respect to the Service sector, the highest effects of past shocks or news is in UAE, Bahrain and Qatar, and lowest in Oman. This not surprising as the Service sector in UAE has been in development much earlier than in the other markets.

Table 2: VAR MGARCH BEKK Estimation Results (Saudi Arabia and UAE)

Panel A: Saudi Arabia						
	Normal Error Distribution			**Student-t Error Distribution**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
α	-0.0124	0.0695	-0.0049	0.0032	0.0743	0.0249
VAR(1)	0.2184[a]	0.1078[a]	0.1221[a]	0.1898[a]	0.1290[a]	0.1232[a]
$C_{Financial}$	0.2488[a]			0.1443[a]		
$C_{Service}$	0.1749[a]	0.0998[a]		0.0842[a]	0.0721[a]	
$C_{Industrial}$	0.1105[a]	0.0867[a]	0.0671[a]	0.0659[a]	0.0516	0.0427
$ARCH_{Financial}$	0.0964[a]	0.1025[b]	0.0079	0.0969[a]	0.0741	0.0454[c]
$ARCH_{Service}$	0.0788[c]	0.0514[a]	-0.0012	0.0748[c]	0.0598[a]	0.1024[c]
$ARCH_{Industrial}$	0.0514	0.0362[b]	0.0447[a]	0.0620	0.0441[c]	0.0506[a]
$GARCH_{Financial}$	0.7533[a]	0.2552	0.1770	0.865[a]	0.1613	-0.0181
$GARCH_{Service}$	0.7512	0.8825[a]	0.1024	0.8148	0.8760[a]	-0.0659
$GARCH_{Industrial}$	0.8736	0.9023	0.9347[a]	0.8780	0.9025	0.9293[a]
AIC	2244.77			2275.22		
Panel B: UAE						
	Normal Error Distribution			**Student-t Error Distribution**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
α	-0.0631	-0.0575	-0.1536[c]	-0.1365	-0.0682	-0.1608[c]
VAR(1)	-0.1009[c]	-0.1087[c]	-0.066[c]	-0.0610[c]	-0.0387	-0.0518
$C_{Financial}$	0.1109[b]			0.0731		
$C_{Service}$	-0.1769	0.1904		-0.3018	0.5873[b]	
$C_{Industrial}$	0.0401	0.5257	0.7267[a]	0.2115	0.4915	0.6368
$ARCH_{Financial}$	0.0362[a]	0.0264	0.01234	0.0549[a]	0.0981	0.2133[c]
$ARCH_{Service}$	0.0290[c]	0.0866[a]	0.0082	-0.2266[c]	0.1157[c]	0.3566[c]
$ARCH_{Industrial}$	0.0593[c]	0.0223[a]	0.1504[a]	0.0463	0.1130[c]	0.1795[a]
$GARCH_{Financial}$	0.8388[a]	0.1088	0.0325	0.9026[a]	0.1307	-0.0973
$GARCH_{Service}$	-0.0188	0.9585[a]	0.0166	0.0030	0.8459[a]	-0.0915
$GARCH_{Industrial}$	-0.0200	0.0663	0.7838[a]	-0.0160	0.0753	0.7848[b]
AIC	3061.47			3110.48		

[a]= 1% significance level, [b]= 5% significance level, [c]= 10% significance level.

With respect to the Industrial sector, it is considered the least sensitive in all sectors of all GCC countries. In fact, this sector is more dependent on volatilities related to changes in the fundamentals such as the supply and demand for oil and natural gas or petrochemical products. We finally notice a similar sensitivity for all the sectors in Kuwait.

Table 3: VAR MGARCH BEKK Estimation Results (Qatar and Bahrain)

Panel A: Qatar						
	Normal Error Distribution			**Student-t Error Distribution**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
α	0.0653	0.0136	-0.0256	0.1763	0.0523	0.0142
VAR(1)	0.0183	0.1038[c]	0.0768	0.0422	0.1154[c]	0.0812
$C_{Financial}$	0.2809			0.2154		
$C_{Service}$	0.6283	0:1875		0.5249	0.1403	
$C_{Industrial}$	-0.0534	0.3673	0.0200	0.2115	-0.2010	0.1252
$ARCH_{Financial}$	0.0734[c]	0.1840[b]	-0.0711	0.0649[c]	0:0981	0.2133[c]
$ARCH_{Service}$	-0.1603[c]	0.2866[a]	0.0990	-0.2266[c]	0.2157[c]	0.3566[c]
$ARCH_{Industrial}$	-0.0395	0.1699[b]	0.2105	0.0463	0.1130[c]	0.0524[a]
$GARCH_{Financial}$	0.9121[a]	0.2552	0.1770	0.865[a]	0.1613	-0.0181
$GARCH_{Service}$	0.0710	0.6764[a]	0.1024	0.1054	0.7785[a]	-0.0659
$GARCH_{Industrial}$	0.0751	0.1285	0.9240[a]	0.0385	0.0753	0.9089[a]
AIC	2142.05			2123.94		
Panel B: Bahrain						
	Normal Error Distribution			**Student-t Error Distribution**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
α	0.0097	0.0383	0.0046	0.0103	0.0300	0.0153
VAR(1)	-0.0535	0.0050	-0.1883[c]	-0.0450	-0.0005	-0.2242[b]
$C_{Financial}$	0.1751			0.2878[b]		
$C_{Service}$	0.3376	0:1119		0.2609[c]	0.1575	
$C_{Industrial}$	-0.2065	0:4739	0.0014	-0.2194	-0.3076	0.0053
$ARCH_{Financial}$	0.0217[c]	-0.0977	0.0529[c]	0.0253[a]	-0.0039	0.0554[b]
$ARCH_{Service}$	-0.0582	0:2215[a]	0.0140	-0.0772	0.2210[a]	0.0264
$ARCH_{Industrial}$	-0.0638	-0.0685	0:1130[c]	-0.0361	-0.0476	0.0178[a]
$GARCH_{Financial}$	0.9066[a]	0.1238	0.0071	0.8123[a]	-0.0013	0.0481
$GARCH_{Service}$	-0.2455[c]	0.7571[a]	0.1078	-0.2486[c]	0.7752[a]	0.0858
$GARCH_{Industrial}$	0.0598	0.0869	0.8741[a]	0.0087	0.0396	0.9419[a]
AIC	1779.14			1784.19		

[a]= 1% significance level, [b]= 5% significance level, [c]= 10% significance level

Looking at the own volatility spillovers, the Financial sector displays a high spillover in Qatar and Bahrain and low in Saudi Arabia. This could be interpreted as there is more regulations and bank supervision implemented in Saudi Arabia than its counterparts. On the other hand, the Service sector displays a high spillover in UAE, Kuwait and Oman, and a low spillover in Qatar. Whereas for the Industrial sector, the highest spillover is in Qatar, and the lowest is in Kuwait and Oman. Finally, and looking at the inter-sector volatility spillover, we observe a moderate spillover between sectors in Bahrain and Oman, and no spillover between sectors in the other markets.

Table 4: VAR MGARCH BEKK Estimation Results (Kuwait and Oman)

Panel A: Kuwait						
	Normal Error Distribution			**Student-t Error Distribution**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
α	-0.0734	-0.0171	0.0130	-0.1101[c]	-0.0101	-0.0168
VAR(1)	0.0586	-0.0142	0.0129	0.0991[b]	0.0124	0.0286
$C_{Financial}$	0.0821[b]			0.1001[b]		
$C_{Service}$	0.1349	0.2282		0.5249	0.0820	
$C_{Industrial}$	-0.0521	0.1825	0.0573[b]	0.2115	-0.2010	0.0912[b]
$ARCH_{Financial}$	0.0891[a]	0.0986	-0.0878	0.0727[b]	0.0259	-0.0804
$ARCH_{Service}$	0.0343	0.0852[a]	0.0997	0.0317	0.0820	0.0342
$ARCH_{Industrial}$	-0.0017	0.1376[c]	0.0747[b]	0.0449	0.1130[c]	0.1173[a]

Panel A: Kuwait						
	Normal Error Distribution			Student-t Error Distribution		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
GARCH$_{Financial}$	0.8293[a]	-0.1067	0.1675	0.8459[a]	0.0527	0.2324[c]
GARCH$_{Service}$	0.0057	0.8863[a]	0.0395	-0.0102	0.9642[a]	-0.0016
GARCH$_{Industrial}$	0.0367	0:1194	0.7871[a]	-0.0182	0.0326	0.6497[a]
AIC	1489.74			1583.87		
Panel B: Oman						
	Normal Error Distribution			**Student-t Error Distribution**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
α	0.1036[c]	0.0155	-0.0274	0.0253	0.0073	-0.0519
VAR(1)	0.1436[a]	0.2363[a]	0.3769[a]	0.1193[b]	0.2931[a]	0.5096[a]
C$_{Financial}$	0.1391[a]			0.1443[a]		
C$_{Service}$	0.0534	0.0235[a]		0.1479[b]	0.275[a]	
C$_{Industrial}$	-0.0489	0:1681	0.0437[a]	0.1859[c]	-0.0754	0.0399[a]
ARCH$_{Financial}$	0.1552[a]	-0.2954	-0.4500[b]	0.2177[a]	0.5624[c]	0.2133[c]
ARCH$_{Service}$	0.2880[a]	0:0878[a]	0.0990	0.0774	0.1042[a]	0.3566[c]
ARCH$_{Industrial}$	0.2003[b]	-0.3049[a]	0.2266[a]	-0.0808	0.4264[b]	0.2853[a]
GARCH$_{Financial}$	0.7296[a]	0.3626	0.2767[c]	0.6674[a]	0.2878	0.0614
GARCH$_{Service}$	-0.1580	0.8287[a]	0.1816[c]	-0.1177[c]	0.7943[a]	0.0974
GARCH$_{Industrial}$	0.0449	0.0231	0.6760[a]	-0.1441[c]	0.0942	0.6396[a]
AIC	1076.58			1219.4		

[a]= 1% significance level, [b]= 5% significance level, [c]= 10% significance level

The AR-GARCH-FHS model results in Table 5 confirm the existence of a highly significant GARCH effects in all sectors of all the GCC markets indicating the presence of own-market volatility persistence. The own-market volatility spillover effects are high for all the markets ranging from 0.415 for the Service sector in Qatar to 0.985 for the Service sector in Kuwait. This shows that all individual sectors in all GCC markets show positive sensitivity to past own volatility.

Table 5: AR-GARCH-FHS Estimation Results

	Saudi Arabia			UAE		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
φ	0.0215	0.0135	0.0812	-0.1152	-0.0738	-0.1480[c]
AR(1)	0.2788[a]	0.1168	0.1791[b]	-0.1251[b]	-0.1859[a]	-0.1302[b]
W	0.1206[a]	0.0636[b]	0.1063[c]	0.5536[a]	0.2152[c]	0.9277[c]
α	0.1780[b]	0.2837[a]	0.1536[b]	0.3529[a]	0.0483[c]	0.0806[c]
β	0.7853[a]	0.7684[a]	0.8510[a]	0.6382[a]	0.8537[a]	0.5734[a]
	Qatar			**Bahrain**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
φ	0.0739	0.0094	0.0139	-0.1152	-0.0738	-0.1480[b]
AR(1)	0.0837	0.1772[b]	0.1182	-0.0256	-0.1258[b]	-0.0679[c]
W	0.3828[b]	0.4055[a]	0.3823[a]	0.5536[a]	0.2743	0.4674[c]
α	0.2127[a]	0.3233[a]	0.3342[a]	0.1608[a]	0.0655[b]	0.0523[c]
β	0.5871[a]	0.4153[a]	0.4646[a]	0.7456[a]	0.8537[a]	0.7520[a]
	Kuwait			**Oman**		
Coefficient	**Financial**	**Service**	**Industrial**	**Financial**	**Service**	**Industrial**
φ	-0.0703	-0.0268	-0.0122	0.0817[c]	-0.0085	-0.0247
AR(1)	0.0.1376[c]	-0.0054	0.0733	0.3200[a]	0.2659[a]	0.2189[b]
W	0.0552[c]	0.0039	0.0197	0.0851[a]	0.0198[b]	0.0128[a]
α	0.1108[b]	0.0013[c]	0.0500[c]	0.1552[a]	0.1808[b]	0.2266[a]
β	0.8470[a]	0.9859[a]	0.9024[a]	0.7296[a]	0.7605[a]	0.6701[a]

[a]= 1% significance level, [b]= 5% significance level, [c]= 10% significance level.

The average values of optimal weights for the sectors in each GCC country are reported in Table 6. For instance, the average value of optimal weights of a portfolio comprising the Financial and

Service sector indices in Saudi Arabia is 0.466 using BEKK-Normal, 0.470 using BEKK-Student-t, and 0.478 using FHS model. This suggests that the optimal holding of the Financial index in one dollar of Financial/Service index portfolio for Saudi Arabia is between $0.46 and $0.48, compared with $52 to $54 for the Service index. Consequently, this may recommend investors in Saudi Arabia to own more Service stocks than Financial stocks in their portfolios. This finding is opposite to the result in Hammoudeh and Al-Gudhea (2006). The case is different for UAE, Oman and Kuwait, where a portfolio of Service/Industrial dominates the Financial/Service portfolios, possibly due to the highest own volatility and shock spillovers in the Service sector in these markets.

Table 6: Optimal Hedging Strategies

	Normal Error Distribution				**Student-t Error Distribution**			
Portfolio	**Weight**		**Hedge Ratio**		**Weight**		**Hedge Ratio**	
	BEKK	**FHS**	**BEKK**	**FHS**	**BEKK**	**FHS**	**BEKK**	**FHS**
Saudi Arabia								
Financial/Service	0.466	0.478	0.559	0.558	0.470	0.478	0.570	0.558
Financial/Industrial	0.653	0.636	0.401	0.442	0.430	0.636	0.461	0.442
Service/Industrial	0.671	0.658	0.371	0.437	0.493	0.658	0.449	0.437
UAE								
Financial/Service	0.337	0.340	0.012	0.028	0.360	0.340	0.003	0.028
Financial/Industrial	0.361	0.358	0.155	0.151	0.355	0.358	0.149	0.151
Service/Industrial	0.545	0.533	0.046	0.000	0.511	0.533	0.000	0.000
Qatar								
Financial/Service	0.465	0.431	0.436	0.564	0.473	0.431	0.439	0.564
Financial/Industrial	0.497	0.441	0.566	0.640	0.430	0.441	0.671	0.640
Service/Industrial	0.530	0.528	0.363	0.410	0.493	0.528	0.406	0.410
Bahrain								
Financial/Service	0.517	0.498	0.156	0.092	0.498	0.498	0.097	0.092
Financial/Industrial	0.689	0.693	0.118	0.152	0.693	0.693	0.154	0.152
Service/Industrial	0.652	0.644	0.047	0.000	0.675	0.644	0.000	0.000
Kuwait								
Financial/Service	0.330	0.338	0.339	0.392	0.314	0.338	0.347	0.392
Financial/Industrial	0.000	0.050	1.000	0.920	0.000	0.050	1.000	0.920
Service/Industrial	0.514	0.492	0.327	0.394	0.522	0.492	0.284	0.394
Oman								
Financial/Service	1.000	0.576	1.000	0.576	0.500	0.576	1.000	0.576
Financial/Industrial	0.000	0.095	1.000	0.947	1.000	0.095	1.000	0.947
Service/Industrial	0.534	0.522	0.929	1.000	0.186	0.522	1.000	1.000

Table 6 also reports the average values of Hedge Ratio for the GCC markets. Adopting the same hedging strategy, one dollar long in the Financial index, for example in the Saudi market, should be shorted by $0.55 to $0.57 in the Service sector. The most expensive hedge in the other GCC markets is by hedging the Service index with short positions in the Financial or Industrial sector. As shown in the optimal portfolio weight columns in Tables 6, there are no big differences among the BEKK models, which are in return slightly different than the FHS model. Similar conclusions could be drawn with the results of the Hedge Ratios. However, we should look closely at how much gain in minimizing the variance of the hedged portfolio using each of the models studied.

Table 7 displays one example of the hedging effectiveness calculated for Bahrain, the highest hedging effectiveness to hedge long positions is between the Service and Industrial in Bahrain, and the Financial and Industrial in Kuwait. However, the FHS model provides the highest hedging effectiveness than its counterpart the BEKK model (with both Normal and Student-t distributed errors). In fact, the variance reduction of the hedged portfolio, Service/Industrial for Bahrain and Financial/Industrial for Kuwait, is much higher than the one provided by the BEKK model. This suggests that the nonparametric approach leads to superior hedging strategies than the parametric approach.

Table 7: Optimal Hedging Effectiveness for Bahrain

Portfolio	BEKK		FHS	Unhedged
	Normal	Student		
Financial/Service	0.290	0.290	0.288	0.489
Hedging Effectiveness	40.7%	40.7%	41.1%	
Financial/Industrial	0.593	0.590	0.578	0.726
Hedging Effectiveness	16.9%	17.3%	19%	
Service/Industrial	0.366	0.367	0.391	0.714
Hedging Effectiveness	49.5%	49.4%	46.2%	

Notes: Hedging Effectiveness is the variance reduction of the hedged portfolio compared to the unhedged portfolio. $(var_{Unhedged}\ var_{hedged})=var_{Unhedged}$. A higher hedging effectiveness indicates a larger variance reduction and hence a superior hedging strategy

6. Summary and Concluding Remarks

This paper reiterates the importance of measuring conditional variances and covariances of asset returns in hedging strategies. In doing so, two approaches are adopted, one parametric and based on a multivariate GARCH model, and one nonparametric based on Filtered Historical Simulation. The findings show that the VAR-GRACH-BEKK with Normal and Student-t errors provide similar results in terms of hedging ratios, portfolio variance reduction and hedging effectiveness, which suggests that dynamic asymmetry may not be crucial empirically. Moreover, the FHS approach performs better in terms of portfolio variance reduction and hedging effectiveness. This suggests that the nonparametric approach leads to superior hedging strategies than the parametric approach. Future research will consider pitting the nonparametric approach against the parametric one in an all-sector-portfolio context and investigating the hedging strategies in holding long positions in different markets in terms of hedging effectiveness.

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