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Comparison Study of Robust Estimation for (DCC-GARCH) Models in Saudi Stocks Market

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Abstract

Many different techniques address the problem of estimating volatilities of financial assets. Autoregressive conditional heteroscedasticity (ARCH) models and the related generalized ARCH models (GARCH) are popular models for volatilities. In empirical work on multivariate financial time series. In recent research, the tendency has been to reduce the dimensionality of the problem using principal component analysis or by using separate univariate GARCH models for the volatility of each series and a time-varying process for the conditional correlations, such as Engle's Dynamic Conditional Correlation GARCH (DCC-GARCH). The parameters of the DCC-GARCH model are typically estimatedby Maximum Likelihood Estimation (MLE), which is unfortunately greatly affected by deviations from the assumptions of multivariate normality such as outliers or heavy tails distributions. We propose to use modified M-estimators based on bounded influence function for univariate GARCH models that are as efficient (smallest asymptotic variance) as possible. Welinked the robustness estimation and simplicity of univariate GARCH models to estimate dynamic correlation estimator. We showedusing Portfolio from Saudi stock marketthat the maximum likelihood estimate are very sensitive to a small percentage of outlier , while the proposed robust estimates of the DCC-GARCH model will better the estimates of the volatilities and the dynamic correlations of a set of financial assets in the presence of outliers.

Keywords: GARCH, Robust-Estimates, M-Estimates, Saudi stock market.

1. Introduction:

Multivariate GARCH (MGARCH) models are considered as one of the most useful tools for analyzing and forecasting the volatility of time series when volatility fluctuates over time. This feature demonstrates its availability in modeling the co-movement of multivariate time series with varying conditional covariance matrix. Specifically, when analyzing the co-movements of financial returns, it is always essential to estimate, construct, evaluate, and forecast the co-volatility dynamics of asset returns in a portfolio. This task can be fulfilled by MGARCHmodels. The development of MGARCH models could be thought as a great breakthrough against the curse of dimensionality in the financial modeling. MGARCH models can be applied to asset pricing, portfolio theory, VaR estimation and risk management or diversification, which require the volatilities and co-volatilities of several markets [Bauwens *et al.*, 2006]. These models are usually estimated by maximum likelihood assuming that the distribution of one observation conditionally to the past is normal. If the data satisfy the assumption of conditional normality, this procedureis asymptotically efficient.

Moreover, even when the conditional distributionof the observations is not normal, these procedures give consistent and asymptotically normal estimates under certain moment conditions[Muler and Yohai, 2008]. These estimates based on a normal likelihood are very sensitive to the presence of a few outliers in the sample. In fact, a single huge outlier may have a very large effect on the QML-estimate. Estimates that are not muchinfluenced by a small fraction of outliers are called robust estimates. Several authors have proposed robust estimates for ARCH and GARCH models.Huber (1981) considers a stricter concept for a robust estimate. It shouldsatisfy the following two properties:

(H1) The estimate should be highly efficient when all observations ofthe sample follow the assumed model. This condition can be checked bycomparing its efficiency to that of the maximum likelihood estimate for thatmodel.

(H2) Replacing a small fraction of observations of the sample by outliersshould produce a small change in the estimate. This principle allows the use of a robust model in analysis when it is unknown whether outliers are present and they might not be easily detected.

2. Methods of Estimation:

2.1 Conditional Correlation Estimation:

Combinations of univariate GARCH model estimation and multivariate correlation matrix estimation are a less computationally burdensome approach to estimating multivariate GARCH models. This nonlinear combination approach greatly reduces the number of estimated parameters in the model. Bollerslev (1990) proposes a model of this form, where the conditional correlation matrix remains constant. The constant conditional correlation GARCH (CCC-GARCH) model is defined as

$$H_t = D_t \; R \; D_t \qquad \mathrm{D}_t = diag\left(\sqrt{h_{i,t}}\right), \tag{1}$$

Where R is a correlation matrix with conditional correlations and $h_{i,t}$defined as any univariate GARCH model. The most basic GARCH representation is

$$h_{i,t} = \alpha_{i,0} + \sum_{p=1}^{P_t} \alpha_{i,p} r_{i,t-p}^2 + \sum_{q=1}^{Q_t} b_{i,q} h_{i,t-q}. \tag{2}$$

The matrix $\mathbf{H_t}$ is positive definite if all the conditional variances are positive and R is positive definite. The assumption that correlations of assets remain constant over time seems unreasonable in real world applications. Engle (2002) instead assumes a dynamic conditional correlation GARCH (DCC-GARCH) model where the conditional correlation matrix changes over time. The Engle’s DCC-GARCH model is

$$r_t \,|\, \psi_{t-1} \sim N\left(0, D_t R_t D_t\right),$$

$$\begin{aligned}
D_t^2 &= diag\left(\alpha_{0,i}\right) + diag\left(\alpha_{1,i}\right) \circ r_{t-1} r_{t-1}' + diag\left(\beta_{1,i}\right) \circ D_{t-1}^2 \\
\varepsilon_t &= D_t^{-1} r_t \\
Q_t &= R_0\left(1-\alpha-\beta\right) + \alpha\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + \beta Q_{t-1} \\
R_t &= diag\left(Q_t\right)^{-1/2} Q_t diag\left(Q_t\right)^{-1/2}
\end{aligned} \tag{3}$$

Where represents the elementwise product of the matrices. The log likelihood we would maximize toestimate the parameters of the model is

$$L=-\frac{1}{2}\sum_{t=1}^{T}\left[n\log(2\pi)+2\log\left|D_t\right|+r_t'D_t^{-1}D_t^{-1}r_t-\varepsilon_t^{'}\varepsilon_t+\log\left|R_t\right|+\varepsilon_t^{'}R_t^{-1}\varepsilon_t\right] \quad \textbf{(4)}$$

Maximizing this function over the parameters leads to the maximumlikelihood estimates (MLE) of the parameters. Engle suggests splitting the likelihood into the sum of two parts to improve efficiency in calculating the model. The two components are the volatility component, which only depends on the individual GARCH parameters, and the correlation component,which depends on both the correlation parameters and the individual GARCH parameters. Let Ɵdenote the volatility parameters in the *D* matrix and Ødenote the correlation parameters in the *R*matrix. The split is written

$$L(\theta,\phi)=L_V(\theta)+L_C(\theta,\phi) \quad \textbf{(5)}$$

With the volatility part as

$$L_V(\theta)=-\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi)+2\log\left|D_t\right|+r_t'D_t^{-1}D_t^{-1}r_t\right) \quad \textbf{(6)}$$

and the correlation part as

$$L_C(\theta,\phi)=-\frac{1}{2}\sum_{t=1}^{T}\left(\log\left|R_t\right|+\varepsilon_t^{'}R_t^{-1}\varepsilon_t-\varepsilon_t^{'}\varepsilon_t\right) \quad \textbf{(7)}$$

Engle first estimates the volatility parameters with ML estimation. He then places the estimates into the correlation portion of the likelihood to estimate thecorrelation parameters with ML estimation. Observations that deviate from the general pattern of the data, called outliers, affect the accuracy of standard techniques of analysis and estimation.Many different robust estimation techniques have been used to estimatemodels from data when outliers are or are not present. Outliers also affect maximum likelihood estimation (MLE). This is a common method of model parameter estimation used in estimating the parameters in the DCC-GARCHmodel. It is ben SAFCOial to understand outliers in time dependent data because the DCC-GARCH model uses an autoregressive structure in estimating the volatilities and correlations. Time series data, such as financial data, contain greater potential for outliers hindering the estimation process, because of the underlying dependence between observations in the data. In time series data, outliers may occur in patches throughout the data, or in isolation throughout the data. Many different methods have been proposed to handle outliers in time series data, such as robust filter estimation for AR and ARMA models or M-estimationtechniques both of which are described in Maronna et al. (2006).

2.2 Deviance Robust Estimation

Other approaches include working with deviances instead of likelihoods and developing a measure of observation influence and trying to bound these measures. Pregibon (1982) approaches the problem of sensitivity by switching between likelihood functions and deviance functions. The log of the likelihood function transforms to a similar deviance function;

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$$d\left(g\left(x'\beta\right);y_i\right)=-2\left[L\left(y_i,x_i;\beta\right)-L\left(y_i,x_i;\hat{\beta}_{MLE}\right)\right] \quad \textbf{(8)}$$

Where g $(x'\beta)$ is the link function of the generalized linear model. The link function provides the relationship between the linear predictor and the mean of the distribution function. Converting the log of the likelihood to the deviance does not alter the results because maximizing the log of the likelihood function is the same as minimizing the deviance function. This makes the deviance function as sensitive to outliers as the likelihood function. Pregibon proposes a new less sensitive estimator that minimizes

$$\sum_{i=1}^{n}\lambda\left\{d\left[g\left(x'\beta\right);y_i\right]\right\} \quad \textbf{(9)}$$

Where λis a strictly increasing Huber loss function defined in Huber (1973) and the estimate $\hat{\beta}_\lambda$ exists and is unique. Pregibon'sλfunction is:

$$\lambda_P\left(t\right)=\begin{cases} t, & t\le c \\ 2\sqrt{tc}-c & t>c \end{cases} \quad \textbf{(10)}$$

With*c*an adjustable tuning constant. However, Pregibon suggests that this is not the only option forthe λ function. The modified deviance approach is defined for many different λ functions Such as in Bianco and Yohai (1996),Croux and Haesbroeck (2003) and Muler and Yohai (2008).

2.3 The Proposed Robust Estimation for DCC-GARCH

The proposed robust method for the DCC-GARCH takes the bounded deviance function approach.This approach will limit the observational effects of unexpectedly large magnitude in the data, but not affect observations that are not unexpectedly large in magnitude.DCC-GARCH estimation involves the split estimation of two components of a linear equation. Since the volatility and correlation components are a linear combination andthe -function adjustment is nonlinear, the λ function is not applied to each individual component.Instead it is applied to the sum of both components. For this reason, a multiple iteration approach is needed for the estimation of the proposed robustmethod for the DCC-GARCH. Before the iteration process, estimate the unconditional correlationmatrix for an initial value of R_0. The sample correlation matrix will be used. The first iteration involves estimation of only the volatility parameters by assuming the parametersin the correlation component are constant, using the MLE values

$$\sum_{t=1}^{T}\lambda[d(\theta,\phi)]=\sum_{t=1}^{T}\lambda\{-2[L_V(\theta)+L_C(\hat{\theta}_{MLE},\hat{\phi}_{MLE})-L_{V+C}(\hat{\theta}_{MLE},\hat{\phi}_{MLE})]\} \quad \textbf{(11)}$$

From this modified deviance function, the robust estimates of the volatility parameters are calculated by

$$\hat{\theta}_R=\arg\min\sum_{t=1}^{T}\lambda[d(\theta,\hat{\phi}_{MLE})] \quad \textbf{(12)}$$

The second iteration involves estimation of only the correlation parameters by assuming the volatilityparameters are constant, using the previously calculated robust values:

$$\sum_{t=1}^{T} \lambda[d(\theta,\phi)] = \sum_{t=1}^{T} \lambda\{-2[L_V(\hat{\theta}_R) + L_C(\hat{\theta}_R,\phi) - L_{V+C}(\hat{\theta}_{MLE},\hat{\phi}_{MLE})]\} \qquad \textbf{(13)}$$

The robust correlation parameters are estimated by

$$\hat{\phi}_R = \arg\min \sum_{t=1}^{T} \lambda[d(\hat{\theta}_R,\phi)] \qquad \textbf{(14)}$$

The iteration process does not need to continue past this point because the estimation of the volatilitycomponent does not depend on the correlation parameters. The modified deviance approach is defined for many different λfunctions. The λfunction selected is the bounded function described by Muler and Yohai (2008). They develop a robust estimation technique for the GARCH model thatadapts the quasi-maximum likelihood function.They mention that all ofthe previous attempts to robustify the univariate GARCH framework do not follow a strict definitionof a robust estimate where replacing a small number of observations by outliers should only leadto small changes in the estimate. They create an estimation procedure that follows thisdefinition and remains highly efficient and asymptotically normal. They adapt the quasi-maximum likelihood estimate by modeling the log of the squared returns,similar to Peng and Yao (2003). Under theassumption of conditional normality of $r_t \mid \psi_{1\le t\le \upsilon} \sim N(0,h_t)$with $\upsilon \ge \max(p,q)$ the conditionaldensity function of $r_{\upsilon+1},\ldots\ldots\ldots,r_T$ is proportional to

$$\left(\prod_{t=\upsilon+1}^{T} h_t\right)^{-1/2} \exp\left(-\frac{1}{2}\sum_{t=\upsilon+1}^{T}\frac{r_t^2}{h_t}\right) \qquad \textbf{(15)}$$

Maximizing this quantity leads to the quasi-maximum likelihood estimates of the GARCH model with

$$\hat{\theta}_{MLE} = \arg\min_{\theta} \sum_{t=\upsilon+1}^{T}\left(\frac{r_t^2}{\hat{h}_t} + \log \hat{h}_t\right) \qquad \textbf{(16)}$$

Where $\hat{h}_t$ is an $r_1, \ldots, r_t$ based approximation of h_t defined in Peng and Yao (2003).Theyreparametrize the returns so that the squared returns now have a median equalto 1 instead of the variance of the returns equaling 1. They also adjusted the structure of the returnsfrom $r_t = \sqrt{h_t}\,\varepsilon_t$ to

$$\log\left(r_t^2\right) = \log\left(h_t\right) - \log\left(\varepsilon_t^2\right) \qquad \textbf{(17)}$$

This leads to the creation of their quasi-maximum likelihood based on least absolute deviations estimator

$$\hat{\theta}_{PY} = \arg\min_{\theta} \sum_{t=\upsilon+1}^{T}\left|\log\left(r_t^2\right) - \log\left(\hat{h}_t\right)\right| \qquad \textbf{(18)}$$

Sincemedian ($\log \varepsilon_t^2$) = logmedian(ε_t^2) = 0. They show that this estimator is both unbiased and asymptoticallynormal under certain conditions. Their estimation technique out-performs the maximumlikelihood estimates when the normality assumption is broken, but performs worse than the MLEunder normality with no outliers.

Muler and Yohai generalizethe previous minimizing equationas an M-estimation structure of

$$M_T = \frac{1}{T-p}\sum_{t=p+1}^{T}\rho(\log(r_t^2) - \log(h_t)) \quad \textbf{(19)}$$

Minimizing this quantity leads to the M-estimates, $\hat{\gamma}_1$ for the GARCH model where γ is a vector ofthe parameters $(\alpha_0, \alpha_1, ..., \alpha_p, \beta_1, ..., \beta_p)^T$. When the function ρis unbounded, but the derivative ofρis bounded, the estimates are robust in the presence of a heavy tailed residual distribution, but still affected by outliers.

When both the function ρand its derivative are bounded, the estimates arerobust to any form of outlier. However, even when both ρand its derivative are bounded, outliers may still affect the quasimaximumlikelihood estimation, because outliers at time *t* may affect estimates of the conditionalvariance at time $t+i$with $i>0$. Muler and Yohai correct this problem with the use of robust filteringsimilar to their approach inMuler and Yohai (2002). They replace $h_t$in the calculation of$M_T$with a filtered version defined by

$$h_t^* = \alpha_0 + \sum_{i=1}^{p}\alpha_i h_{t-i}^* g_k\left(\frac{r_{t-i}^2}{h^*_{t-i}}\right) + \sum_{i=1}^{q}\beta_i h_{t-i}^* \quad \textbf{(20)}$$

Where the function$\mathbf{g_k}$is defined

$$g_k(U) = \begin{cases} U & \text{if } u \le k \\ K & \text{if } u > k \end{cases} \quad \textbf{(21)}$$

Minimizing the new filtered M_T^* leads to the robust estimate $\hat{\gamma}_2$. The final BM-estimate ofMuler andYohai combines $\hat{\gamma}_1$ and $\hat{\gamma}_2$ as

$$\hat{\gamma}^B = \begin{cases} \hat{\gamma}_{1,T} \text{if} M_T(\hat{\gamma}_{1,T}) \le M_T(\hat{\gamma}_{2,T}) \\ \hat{\gamma}_{2,T} \text{if} M_T(\hat{\gamma}_{1,T}) > M_T(\hat{\gamma}_{2,T}) \end{cases} \quad \textbf{(22)}$$

Muler and Yohai (2008) prove this estimator is highly efficient and asymptotically normal. Theyalso compare their estimator to Peng and Yao's estimator, the traditional QMLE, and the maximumlikelihood estimator with a *t* -distribution with 3 degrees of freedom. Their model outperforms eachof these estimates with regards to MSE.

3. Data

The models detailed above are estimated using daily returns data for Portfolio of 3 daily time series returns from Saudi stock market[Savola Group (Savola-2050, Saudi Arabia Fertilizers Co.(SAFCO-2020) and Saudi Basic Industries Corp.(SABIC-2010)] .Five models in addition to quasi maximum likelihood (QML) are estimated shown in table 1 on a period from January, 1st 2011 until December, 31th 2016 for 1225 Trading days to assess the efficiency of the compared methods for estimating the volatility and correlation parameters in DCC-GARCH (1,1).

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Table1: Five models estimates and weighted functions

Estimate	ρ(u) weighted function
QML	-ln(g(u))
LAD	|u|
M1	m_1(-ln(g(u)))
M2	0.8 m_1(-ln(g(u))/0.8)
BM1	min(m_1(-ln(g(u))),MLE)
BM2	min(0.8m_1(-ln(g(u))/0.8),MLE)

Descriptive statistics are provided in Table2.The average daily spreads are almost always positive. The high levels of standard deviations show that our data is widely spread and not centered around the mean. The Jarque-Bera test confirms the non-normality of the data distribution at the 1% significancelevel. These findings are reaffirmedby the significant excess kurtosis and the positiveskewness coefficients. As expected, the Augmented Dickey-Fuller test confirms the null hypothesis of the unit-root presence.Returns are non-stationary. TheARCH-LM test and the Q statistics of Ljung-Box both confirm the presence of ARCH effectand reject the null hypothesis of no serial correlation inreturns.

Table 2: Descriptive statistics for returns, Normality test ,unit-root and ARCH Effect

	SAVOLA-Return	SAFCO-Return	SABIC-Return
Min.	-11.8454	-13.12139	-11.87655
1st Qu.	-1.1739	-1.3535	-1.47643
Median	0.1218	-0.04297	-0.04651
Mean	0.1639	0.02821	0.02826
3rd Qu.	1.39	1.49	1.3
Max.	33.72	26.93	47.37
S.D.	3.302303	3.449047	3.550349
standard Sk.	0.26	0.3	0.046
robust Sk.	0.008	0.077	0.028
standard Kr.	14.76	10.56	8.5
robust Kr.	0.53	0.29	0.61
jb.test stat.	11119.52	5708.464	3681.828
& p-value	0.00	0.00	0.00
ljung.box.test	5971.048	6048.365	5859.576
& p-value	0.00	0.00	0.00
Box-Pierce test stat. & p-value	11.3375	40.266	13.7948
	0.00302	3.813e-08	0.00798

Table 3 reports Lagrange multiplier and constant correlation assumption which reject the null hypothesis of no serial correlation in returns at significance level 1%.

Table 3Lagrange multiplier and constant correlation

Test	test Stat.	p-value
Hafner and Herwartz	73.83	6.11E-11
Engle and Sheppard	4812.95	0.00

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Hafner and Herwartztest for Causality in Conditional Variance confirm that GARCH models are suitable for data and Engle and Sheppard test reject the null hypothesis for constant conditional correlation assumption at 1%.

4.Empirical Results

The different estimator return different values for the model parameters.Since the MSE is not applicable in this context, one way to evaluate the goodness of fit of the model is through the estimated innovations

$$\hat{z} = \frac{x_t}{\sqrt{\hat{h}_t}}$$

For a M-estimate

$$\hat{h}_t = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} b_i h_{t-i}$$

and for the BM-estimate

$$\hat{h}_t^* = a_0 + \sum_{i=1}^{p} a_i \hat{h}_{t-1}^* r_k \left(\frac{x_{t-1}^2}{\hat{h}_{t-1}^*} \right) + \sum_{i=1}^{q} b_i \hat{h}_{t-1}^*$$

If the time series x_t follow a GARCH model, than it should hold for the estimated innovations

$$\sum_{t=1}^{T} (\hat{z}_t) = 0 \quad \sum_{t=1}^{T} \frac{(\hat{z}_t^2)}{T} = 1$$

Moreover they should be uncorrelated Muler and Yohai [2008]. Tables 4 to 7 summarizesvolatility and correlation estimates, mean, standard deviation, Kendall and Spearman'scorrelation coefficients of standardized returns.

Table 4: Volatility and Correlation Estimates

Method / Estimate	ML	LAD	M1	M2	BM1	BM2
a_0SAVOLA	0.0168	0.0257	0.4482	0.5147	0.0179	0.0146
a_1SAVOLA	0.1413	0.1447	0.1408	0.1475	0.1433	0.1312
b_1SAVOLA	0.8587	0.8553	0.7551	0.7641	0.8565	0.8524
a_0SAFCO	0.0085	0.2005	0.1296	0.3101	0.0142	0.0121
a_1SAFCO	0.1604	0.1258	0.1317	0.2308	0.1607	0.152
b_1SAFCO	0.8396	0.8742	0.8232	0.6874	0.8393	0.829
a_0SABIC	0.0674	0.0113	0.1511	0.0863	0.0053	0.061
a_1SABIC	0.0783	0.1245	0.1022	0.1015	0.1198	0.0945
b_1SABIC	0.9217	0.8755	0.8463	0.8767	0.8802	0.8937
alpha	0.0127	0.0147	0.0106	0.0112	0.0136	0.0124
beta	0.9628	0.9656	0.9591	0.9559	0.9622	0.9602

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Table 5: Means of standardized returns

Method	MeanSAVOLA	MeanSAFCO	MeanSABIC
QML	0.050078	0.022612	-0.00544(1st)
LAD	0.048687(3rd)	0.012448(1st)	-0.00799
M1	0.041285(2nd)	0.019172	-0.00601(2nd)
M2	0.035618(1st)	0.017349(2nd)	-0.00678(3rd)
BM1	0.050244	0.022095(3rd)	-0.00829
BM2	0.057587	0.025382	-0.00697

From table 5 we noted that The best performance was achieved with the M1 and the M2-estimators in the three time series of stocks. They have values of means very closed to zeroThey outperform slightly the BM1, respectively the BM2 estimators.

Table 6 : Variances of standardized returns

Method	VarSAVOLA	VarSAFCO	VarSABIC
QML	0.883227	0.579775	0.655229
LAD	0.872564	0.627925	0.877528
M1	0.97288(2nd)	0.98110(2nd)	1.037347(1st)
M2	0.859221	1.045779(3rd)	0.900778(2nd)
BM1	0.885296(3rd)	0.880804	0.881490(3rd)
BM2	1.001589(1st)	1.009644(1st)	0.848025

From table 6 we noted thatThe best performance was achieved with the BM1 and the M1-estimators. They have values of variances very closed to one.

Table 7 : Kendall-tau correlation coefficient of standardized returns

Method	tauSAVOLA	tauSAFCO	tauSABIC
QML	0.036924	0.04933	0.099523
LAD	0.035802(3rd)	0.06715	0.072719(1st)
M1	0.031996(1st)	0.0458(3rd)	0.075825(3rd)
M2	0.036303	0.00775(1st)	0.079939
BM1	0.036266	0.04899	0.074184(2nd)
BM2	0.034758(2nd)	0.045045(2nd)	0.085437

Table 8. Spearman correlation coefficient of standardized returns

Method	rhoSAVOLA	rhoSAFCO	rhoSABIC
QML	0.055414	0.075361	0.147822
LAD	0.053983(3rd)	0.101639	0.108902(1st)
M1	0.048542(1st)	0.069787(2nd)	0.11286(3rd)
M2	0.05492	0.012159	0.119102
BM1	0.054464	0.074754(3rd)	0.11103(2nd)
BM2	0.052277(2nd)	0.069033(1st)	0.126932

From tables 6 and 7 we noted that The performance of all models was very close and the differences in values of correlation coefficient were very small.

5. Conclusion

The effects of outliers have been studied for many years. It has been shown that outliers affect the estimation of models with an autoregressive structure. Both additive and innovation outliers lead to estimation problems in these types of models. Outliers also affect models that have heteroscedasticity.The DCC-GARCH model structure is constructed with each of these components as assumptions or parts of the model. This makes the DCC-GARCH model inherently affected by outliers.Since modeling correlation is of a paramount importance in assessing diversification risk, indynamic stocks returns and in optimization of portfolio allocation.Even though no model clearly outperforms all the others, our results show that our proposed Robust DCC-GARCH model seems to better fit the studied data. The best performance is achieved with the M1- and the M2-estimators. They outperform slightly the BM1, respectively the BM2 estimators. The BM-estimator show a robust behavior, in the sense, that they are not influenced very much by outliers. For these reasons, A robust estimation method for the DCC-GARCH model using the technique of bounded deviance estimation is proposed to solve the estimation problems of the DCC-GARCH model in the presence of outliers or heavy tailed distributions. However, results are differ sample to another which implies that no multivariate volatility model should be selected in an arbitrary way. The model selection should rather be based on the particular features of the data used.

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References

Bauwens, L., Laurent, S. and Rombouts, J. (2006) Multivariate GARCH models: A survey. Journal of Applied Econometrics, 21:79–109.
Bianco, A. and Yohai, V. (1996) Robust Statistics, Data Analysis, and Computer Intensive Methods, chapter Robust Estimation in the Logistic Regression Model, pages 17–34. Springer, New York.
Bollerslev, T. (1986) Generalized autoregressive conditional heteroscedasticity. Journal of Econometrics. 31:307-327.
Boudt, K. andCroux, C. (2010) Robust M-estimation of multivariate GARCH models, Computational Statistics and Data Analysis, Vol.54:2459-2469.
Croux, C. and Haesbroeck,G.(2003) Implementing the Bianco and Yohai estimator for logistic regression Computational Statistics and Data Analysis, 44:279–295.
Engle. R (2002) Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticityA models. Journal of Business and Economic Statistics, 20(3):339–350.
Engle, R. (1982) Autoregressive conditional heteroscedasticity with estimates of the variance of the United Kingdom inflation. Econometrica, 50:987–1007.
GianPieroAielli. Dynamic conditional correlation: on properties and estimation. Journal of Business & Economic Statistics, 31(3):282–299, 2013.
Huber, P. J., 1981, Robust Statistics, Wiley, N. Y.
Maronna, R., Martin, R. and V Yohai. (2006)" Robust Statistics: Theory and Methods " New York: Wiley.
Muler, N. and Yohai, V. (2002) Robust estimates for ARCH processes. Journal of Time Series Analysis, 23(3):341–375.
Muler, N. and Yohai, V. (2008) Robust estimates for GARCH models. Journal of Statistical Planning and Inference, 138:2918–2940.
Peng, L. and Yao, Q. (2003) Least Absolute Deviations Estimation for ARCH and GARCH models. Biometrika, 90:967–975.
Pregibon, D. (1982) Resistant fits for some commonly used logistic models with medical applications. Biometrics, 38(2):485–498.
Tse, Y. and Tsui, A. (2002) A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business and Economic Statistics, 20(3):351–362.
Xiao Jing Cai, ShuairuTian, and Shigeyuki Hamori. Dynamic correlation and equicorrelation analysis of global financial turmoil: evidence from emerging east asian stock markets. Applied Economics, 48(40):3789–3803, 2016.
Christian Walter. Les origines du modèle de marche au hasard en finance. Le modèle de marche au hasard en finance, pages xx–xx, 2013.