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Volatility Model Estimations of Palm Oil Price Returns via Long-Memory, Asymmetric and Heavy-Tailed GARCH Parameterization

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ABSTRACT

This study attempts to model the volatility of palm oil price returns via a number of Generalized Autoregressive Conditional Heteroskedasticity class of models that capture the long-range memory, asymmetry, and heavy-tailedness phenomena. These models have been estimated in the presence of four alternative conditional distributions: Gaussian, Student *t*, generalized error distribution, and skewed Student *t*. The empirical results indicate that complex model specifications and distribution assumptions do not seem to outperform the simpler ones in terms of standard model selection criteria and numerical convergence. With regard to the conditional distributions, a symmetric fat-tailed distribution has been found to be preferred to Gaussian and asymmetric distribution in many cases.

Keywords: GARCH models, conditional probability distributions, long memory, asymmetry, heavy-tailedness, volatility, palm oil prices.

1. INTRODUCTION

Although the commodity markets have been used for direct physical trading historically, however, over the last few years commodities have become an important part of many investment portfolios (Vivian and Wohar (2012)). Indeed, the scale of investment in commodities has surged considerably as the commodity markets are increasingly viewed as alternative investment areas (see Arouri *et al*. (2012); Kaltalioglu and Soytas (2011)). Thus, due to the considerable growth in financial and commodity markets and the substantial development of complex financial instruments, there is a growing necessity for theoretical and empirical studies on the volatility of commodity prices (see Franses and McAleer (2002); Morimune (2007)). In fact, volatility of asset prices is a fundamentally important concept. A study by Daly (2008), inter alia, discusses the importance of volatility modeling in some depth.

Since the conditional variance (volatility) is not directly observable, there is a need for using models where the volatility measure plays a central role (Morimune (2007)). The commonly employed models for estimating conditional variances are the (Generalized) Autoregressive Conditional Heteroskedasticity, or (G)ARCH, class of models advocated by Engle (1982) and Bollerslev (1986) and stochastic volatility (SV) models initially proposed by (Taylor, 1986). Here it is worth noting that, as an alternative to the GARCH family models, in stochastic volatility models, the conditional variance is specified to follow some latent stochastic process (Kim *et al*. (1998); Tsay (2010)). As noted by Broto and Ruiz (2004), despite an intuitive appeal of stochastic volatility models, their empirical application has been limited mainly because of computational difficulty involved in their parameter estimation. Here, the main issue is that the likelihood function is hard to evaluate because, unlike the estimation of GARCH family models, maximum likelihood (ML) technique has to deal with more than one stochastic error processes. However, unlike SV models, the success of GARCH family models can be attributed largely to their computational tractability and ability to capture a number of stylized facts of financial time series (Morimune (2007)). The examples for usual stylized facts in financial time series are time-varying volatility, volatility clustering and persistence, long-range memory, and asymmetric responses of volatility to negative and positive shocks of a similar magnitude.

In addition, a heavy-tailedness feature of stochastic errors (or return process) can be taken into account by utilizing heavy-tailed conditional densities. The consideration of these stylized facts in return process is important in describing the dynamics of the asset returns adequately which, in turn, is crucial to obtain accurate predictions of the future volatility. Hence, the primary objective of this study is to analyze alternative GARCH class of volatility models for palm oil prices with the consideration of the specific stylized facts in price return process.

The relatively recent studies that use the GARCH family models for the analysis of agricultural commodity price volatility include Yang *et al.* (2001), Jin and Frechette (2004), Dahl and Iglesias (2009), Rezitis and Stavropoulos (2010), Chang *et al.* (2011), Serra (2011), Vivian and Wohar (2012) among others. To the extent of our knowledge, the closest published paper to ours is that of Jin and Frechette (2004). In their paper, the authors attempt to model the volatility of agricultural futures prices via the GARCH and FIGARCH specifications. The model comparison analysis is mainly based on the computed Ljung-Box-Q test statistics. Their finding suggests the validity of the FIGARCH$(1, d, 1)$ model for agricultural futures prices. Here, several differences between our study and that of Jin and Frechette (2004) are worth noting. First, in Jin and Frechette (2004), the quasi maximum likelihood estimations are conducted assuming Gaussian distribution while our study considers four alternative conditional densities including the symmetric and asymmetric heavy-tailed distributions. Second, to model the long-range memory, the authors use the FIGARCH model which has some weaknesses i.e. positivity constraints for the parameters, symmetry of the responses of conditional variances to negative and positive shocks of equal magnitude. In contrast, we have employed the FIEGARCH model that can address the weaknesses of usual FIGARCH model. Third, in addition to the long memory models, we have also considered the standard GARCH, EGARCH, GJR-GARCH, and APGARCH in the estimations with four alternative distributions for each model.

The plan of the rest of the study is as follows. First, we describe the data set and provide some discussions on preliminary data analysis. Second, the models under concern and their some theoretical and empirical properties are discussed. Third, the results are presented. The final section offers concluding remarks.

2. DATA AND PRELIMINARY ANALYSIS

This study uses monthly data extending over the period of January 1980 through December 2011. The nominal prices are in US Dollars per metric ton and obtained from the online statistical services of International Monetary Fund.

Table 1 reports summary statistics for the logarithmic returns. The return series are computed by using the first logarithmic differences of monthly palm oil prices. As can be seen, the skewness and kurtosis coefficients show that the unconditional distribution of the returns is negatively skewed with an excess kurtosis. The significant excess kurtosis suggests that the return series are conditionally heteroskedastic. Both Jarque-Bera and Anderson-Darling test statistics reject the null hypothesis of normality. Moreover, the Ljung-Box Q statistics for the returns as well as squared returns indicate that the series exhibit linear dependence and strong ARCH effects respectively. All in all, for the sample size considered in this study, the price returns under study are strongly conditionally heteroskedastic and, therefore, GARCH class of models can be useful in the empirical estimations.

TABLE 1: Summary statistics for palm oil price returns

Mean	0.1493
Median	0.4606
Maximum	29.032
Minimum	-31.582
Standard Deviation	8.0189
Skewness	-0.0932
Kurtosis	4.8564
Jarque-Bera	55.550 [0.000]
Anderson-Darling	2.3007 [0.000]
Q(12)	68.906 [0.000]
$Q^2(12)$	48.470 [0.000]

The figures in the square brackets are *p*-values. The Jarque-Bera and Anderson-Darling tests are for normality. Q(12) and $Q^2(12)$ denote Ljung-Box Q test statistics at lag 12 for returns and squared returns respectively. The BDS test is for series independence. In this test, the embedding dimension is set to 2 whereas the distance between pairs of consecutive observations is set to be 1.

Since adequate GARCH estimations require that the series employed in the models are stationary, we test for a unit root by utilizing a number of usual unit root tests (augmented Dickey-Fuller, Phillips-Perron, and Dickey-Fuller GLS) for the logarithmic price returns. In all cases, the tests reject the null hypothesis of the presence of unit root at one percent significance level and thus the returns follow a stationary process, regardless of whether a trend variable and/or intercept term is incorporated in the model. Hence, in the empirical analysis that follows we treat returns as an $I(0)$ process. The results for unit root tests are not reported here due to space consideration.

3. MODELS

In this section, we describe the statistical models that are used for our statistical estimations.

The Standard GARCH Model

Although the ARCH model of Engle (1982) is simple, it usually requires many parameters to sufficiently describe the volatility process of price returns. For this purpose, Bollerslev (1986) develops a useful specification so-called the generalized ARCH (GARCH) model. For a logarithmic return series r_t , let $\varepsilon_t = r_t - \mu_t$ be the innovation at time t . Then, the GARCH(p, q) model can be expressed as:

$$\varepsilon_t = \sigma_t \epsilon_t, \qquad \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 \tag{1}$$

where ϵ_t is a sequence of independently and identically distributed (iid) random variables with mean 0 and unit variance, $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\sum_{i=1}^{max\{p,q\}}(\alpha_i + \beta_i) < 1$. It can be seen that $\alpha_i = 0$ for $i > p$, $\beta_j = 0$ for $j > q$. The various aspects of theoretical properties of standard GARCH model have been considered in a number of studies (see Bollerslev (1986); Giraitis *et al*. (2009); Jeantheau (1998); Lee and Hansen (1994); Ling and Li (1997); Ling and McAleer (2002a); Ling and McAleer (2003); Lindner (2009); McAleer *et al*. (2007); Robinson (1991) and Zivot (2009)). The Eq. (1) reduces to ARCH(q) model when $p = 0$. The α_i and β_j are called ARCH and GARCH parameters respectively. In Eq. (1), the ARCH (or α_i) effect implies the contribution of shocks to short run persistence, while the GARCH (or β_j) effect shows the contribution of shocks to long-run persistence (McAleer *et al*. (2007)).

It is worth noting that although both theoretical and empirical literature on standard GARCH models is enormous, however, the GARCH model encounters several weaknesses. For instance, it does not capture the possible asymmetries in the financial volatility i.e. it responds equally to positive and negative shocks. In addition, the GARCH model requires that all the parameters in the variance equation must be positive in order to guarantee the strict positivity of conditional variances. The literature proposes a number of alternative formulations to address each of these weaknesses of standard GARCH model. We discuss several of them in next subsections.

The Exponential GARCH Model

To address some of the aforementioned weaknesses of the standard GARCH model in handling financial time series, Nelson (1991) proposes so-called the EGARCH model. To allow for asymmetric responses of conditional variances to positive and negative shocks of a similar magnitude, the author relies on the following weighted innovation:

$$g(\epsilon_t) = \theta_1\epsilon_t + \theta_2[|\epsilon_t| - E(|\epsilon_t|)] \tag{2}$$

where θ_1 and θ_2 are real constants. Both sequences ϵ_t and $[|\epsilon_t| - E(|\epsilon_t|)]$ are iid with zero mean. Thus, $E[g(\epsilon_t)] = 0$. One may see an asymmetry by rewriting the Eq. (2) as:

$$g(\epsilon_t) = \begin{cases} (\theta_1 + \theta_2)\epsilon_t - \theta_2 E(|\epsilon_t|) \text{ if } \epsilon_t \geq 0, \\ (\theta_1 - \theta_2)\epsilon_t + \theta_2 E(|\epsilon_t|) \text{ if } \epsilon_t < 0 \end{cases} \tag{3}$$

where $E(|\epsilon_t|)$ depends on the assumption made on the conditional probability density function of ϵ_t. Similar to the ARMA representation, Nelson (1991) expresses the general form of EGARCH(p,q) model as follows:

$$\ln(\sigma_t^2) = \omega + \frac{1 + \beta_1 B + \cdots + \beta_{p-1}B^{p-1}}{1 - \alpha_1 B - \cdots - \alpha_q B^q}\, g(\epsilon_{t-1}) \tag{4}$$

where ω constant, B is a lag operator, and $1 + \beta_1 B + \cdots + \beta_{p-1}B^{p-1}$ and $1 - \alpha_1 B - \cdots - \alpha_q B^q$ are polynomials with zeros outside the unit circle and have no common factors. Nelson (1991) has observed that stationarity and ergodicity for EGARCH(1,1) are ensured when $|\beta| < 1$. In addition, Shephard (1996) argues that the QMLE for EGARCH(1,1) is consistent if inequality $|\beta| < 1$ holds.

The GJR-GARCH Model

The GJR-GARCH model of Glosten et al. (1993) is another extension of standard GARCH model that accommodates possible differential effect of positive and negative shocks on conditional volatility. This model can be specified as

$$h_t = \omega + \sum_{j=1}^{q}\{\alpha_j + \gamma_j I(\varepsilon_{t-j} > 0)\}\varepsilon_{t-j}^2 + \sum_{j=1}^{p}\beta_j h_{t-j} \quad (5)$$

where $\omega > 0$, $\alpha_j \geq 0$, $\alpha_j + \gamma_j \geq 0$, $\beta_j \geq 0$, and $I(\varepsilon_{t-j} > 0)$ is an indicator function which obtains the value of one when $\varepsilon_{t-j} > 0$ and takes zero when the argument is not true. As can be seen, an asymmetric effect in the series is captured by the parameter γ_j. Moreover, as McAleer *et al.* (2007) note, γ_j measures the contribution of shocks to short-run and long-run persistence. The necessary and sufficient condition for the existence of second moment of ε_t for GJR-GARCH(1,1) model is given in Ling and McAleer (2002b).

The Asymmetric Power GARCH Model

Ding *et al.* (1993) proposed an asymmetric power GARCH model which includes seven other ARCH extensions as particular cases. The APGARCH model is given by:

$$\varepsilon_t = \eta_t\sqrt{h_t}, \quad \sigma_t^{\delta} = \omega + \sum_{i=1}^{p}\alpha_i\,(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^{\delta} + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^{\delta} \quad (6)$$

where δ is the power parameter and γ is an asymmetric parameter. Indeed, the power term can obtain any positive value in the variance equation and the financial returns still demonstrate the volatility clustering. As we have seen from the models discussed earlier, the preference is usually given to squared terms and a power of one. This is due to the fact that the returns are traditionally assumed to follow a normal distribution. As commonly noted, the first two moments can fully describe the Gaussian distribution and squared or absolute residuals can be employed as a proxy for the volatility process if the data is normally distributed (Ané and Ureche-Rangau (2006)). However, over the last few decades, a vast literature which followed by the pioneering work of Mandelbrot (1963) suggests that the empirical distributions of financial return series display the heavy-tailed feature. As noted by Ané and Ureche-Rangau (2006), other power transformations might be adequate rather than squared or absolute terms if an underlying return process is heavy-tailed. Here one may note that squared or absolute terms in the second moments of general GARCH class of models may not necessarily be optimal. Thus, the APGARCH model of Ding *et al.* (1993) might be useful parameterization as it allows an optimal power to be estimated directly from data rather than imposed. In addition, by considering a special APGARCH model, Ling and McAleer (2002a) showed the necessary and sufficient conditions for the existence of moments.

The Fractionally Integrated GARCH Models

As usually noted (see, among others, Fantazzini (2011) and Tsay (2010)), there exist some time series processes whose ACF (autocorrelation function) decays slowly to zero at a polynomial rate as the lag increases. In Econometrics literature, these processes are referred to as long-memory feature.

A vast literature on conditional volatility suggests that the GARCH model of Bollerslev (1986) and EGARCH model of Nelson (1991) have been found to be successful parameterizations for characterizing asset return volatility. The usual finding in many studies with both of these models concerns the high persistence of the conditional volatility processes (Bollerslev and Mikkelsen (1996)). For this purpose, Engle and Bollerslev (1986) proposed so-called Integrated GARCH (IGARCH) class of models. As noted in Bollerslev and Mikkelsen (1996), in the IGARCH model, a shock to a conditional volatility remains crucial for the optimal forecasts of the conditional variances for all future horizons. At this stage, it is useful to show the difference between IGARCH and the fractionally integrated GARCH (FIGARCH) model proposed by Baillie *et al.* (1996).

The IGARCH(p,q) formulation can be expressed as:

$$\phi(L)(1-L)\varepsilon_t^2 = \omega + [1-\beta(L)]\eta_t \tag{7}$$

The FIGARCH model can be obtained from this equation by replacing the $(1-L)$ operator with the fractional differencing operator $(1-L)^d$:

$$\phi(L)(1-L)^d\varepsilon_t^2 = \omega + [1-\beta(L)]\eta_t \tag{8}$$

It is important to emphasize that the covariance-stationary standard GARCH model and the IGARCH formulation are naturally analogues to the I(0) and I(1) type processes for conditional mean respectively (Bollerslev and Mikkelsen (1996)). In addition, literature generally suggests that an added flexibility can be obtained by allowing I(d). The shocks die out at an exponential rate in I(0) process whilst there is no mean reversion in I(1) process. In contrast, in fractionally integrated, I(d), process with $0 < d < 1$, shocks dissipate at a slow hyperbolic rate (Tsay (2010)).

To increase the flexibility of fractionally integrated models, Bollerslev and Mikkelsen (1996) extended the EGARCH model of Nelson (1991) to allow for fractional orders of integration. The resulting model is called a fractionally integrated exponential GARCH (FIEGARCH) model. As we have mentioned earlier, the EGARCH model with the use of lag polynomials can be written as:

$$\varepsilon_t = \sigma_t \epsilon_t, \;\; \ln(\sigma_t^2) = \omega + [1 - \alpha(L)]^{-1} \, [1 + \beta(L)] g(\epsilon_{t-1}) \qquad (9)$$

By factorizing the autoregressive polynomial $[1 - \alpha(L)] = \varphi(L)(1 - L)^d$, one may obtain the FIEGARCH (p, d, q) model by Bollerslev and Mikkelsen (1996).

$$\ln(\sigma_t^2) = \omega + \varphi(L)^{-1}(1 - L)^{-d} \, [1 + \beta(L)] g(\epsilon_{t-1}) \qquad (10)$$

This specification includes EGARCH model when $d = 0$ and integrated EGARCH (IEGARCH) model when $d = 1$ as particular cases. An important feature of this formulation is that in contrast to FIGARCH model, the parameters for the FIEGARCH models do not require the non-negativity constraints in order for the model to be well-defined.

In the empirical examination, four conditional distributions for the standardized residuals of returns innovations have been used: (i) a standard normal (N), (ii) a standardized Student t (ST), (iii) a generalized error distribution (GED), (iv) a skewed Student t distribution (SST). Accordingly, five competing model specifications in modeling volatility of the palm oil price returns are constructed in the comparative analysis: GARCH, EGARCH, GJR-GARCH, APGARCH, FIEGARCH.

4. RESULTS AND DISCUSSIONS

In this section, the estimation results for four aforementioned models are discussed. For space considerations, the estimation results for the EGARCH-N, EGARCH-ST, EGARCH-GED, APGARCH-ST, APGARCH-GED, APGARCH-SST, and FIEGARCH-SST are not discussed due to the numerical convergence failure. The quasi maximum likelihood estimates are obtained by using the numerical algorithm so-called BFGS (Broyden, Fletcher, Goldfarb, Shanno) quasi-Newton method described in Press *et al.* (2007). As noted in Bollerslev and Mikkelsen (1996), discontinuous trading in the markets may result in significant serial dependence in the returns. Hence, in order to account for such serial dependence, following Bollerslev and Mikkelsen (1996), we have parameterized the conditional mean for all the estimated models as an unrestricted AR(3) model. We begin the analysis by first discussing the standard GARCH model estimations that are reported in Table 2. All the parameters in both conditional mean and variance equations are statistically significant at conventional levels except for a few cases. Turning to the goodness-of-fit tests, our results suggest that we do not reject the null hypothesis of an adequate model specification for palm oil price returns since the computed Ljung-Box and ARCH test statistics at different lags show no serial correlation and no remaining ARCH effects in standardized ($\hat{\varepsilon}_t\hat{\sigma}_t^{-1}$) and squared standardized ($\hat{\varepsilon}_t^2\hat{\sigma}_t^{-2}$) residuals.

Importantly, the positivity constraint for the parameters of the variance equations is satisfied in all the estimated standard GARCH models. In addition, all estimated GARCH(1,1) models with four conditional densities do not fail to satisfy the second ($\hat{\alpha}+\hat{\beta}<1$) and fourth moment ($(\hat{\alpha}+\hat{\beta})^2+2\hat{\alpha}^2<1$) conditions. Interestingly, all the models have high estimated $\hat{\alpha}$ values, and relatively low estimated $\hat{\beta}$ values, which reflect high levels short-run persistence. All in all, the estimated standard GARCH models have been found to describe the volatility phenomenon in palm oil price returns adequately. Nevertheless, both selection criteria (AIC and SIC) reported in Table 2, give slight preference to the GARCH(1,1) with generalized error distribution. In this model, the estimates of tail-thickness parameter, υ, has been found to be highly significant and less than two indicating that the innovations have thicker tails than the normal distribution. Another advantage of assuming the heavy-tailed generalized error distribution in GARCH estimations is that the empirical validity of normality can be tested (Bali and Theodossiou (2007)). Moreover, the results indicate that the double exponential or Laplace distribution with tail-thickness parameter $\upsilon=1$ is likely to be more appropriate than the Gaussian distribution with a degree of freedom $\upsilon=2$.

TABLE 2: Estimates for standard AR(3)-GARCH (1,1) model

	GARCH-N	GARCH-ST	GARCH-GED	GARCH-SST
μ_0	0.3188 [0.500]	0.3806 [0.395]	0.4459 [0.354]	0.3008 [0.523]
μ_1	0.4310 [0.000]	0.3987 [0.000]	0.3987 [0.000]	0.3983 [0.000]
μ_2	-0.3049 [0.000]	-0.2852 [0.000]	-0.2826 [0.000]	-0.2880 [0.000]
μ_3	0.1639 [0.001]	0.1560 [0.004]	0.1483 [0.012]	0.1573 [0.004]
ω	3.5387 [0.068]	3.1222 [0.071]	3.3536 [0.069]	3.1682 [0.066]
α	0.1169 [0.009]	0.1064 [0.015]	0.1093 [0.013]	0.1055 [0.015]
β	0.8202 [0.000]	0.8416 [0.000]	0.8323 [0.000]	0.8413 [0.000]
υ (Tail)	-	6.9473 [0.007]	1.3537 [0.000]	6.9304 [0.007]
ξ (Asy.)	-	-	-	-0.0359 [0.549]
AIC	6.7706	6.7505	6.7425	6.7551
SIC	6.8434	6.8337	6.8256	6.8486
$Q(10)$	11.725 [0.109]	12.895 [0.075]	12.849 [0.075]	12.951 [0.073]
$Q(20)$	21.836 [0.191]	23.361 [0.137]	23.428 [0.136]	23.337 [0.138]
$Q^2(10)$	4.3455 [0.825]	4.8001 [0.778]	4.6847 [0.791]	4.7444 [0.784]
$Q^2(20)$	10.187 [0.925]	10.087 [0.929]	10.021 [0.931]	9.9298 [0.934]
ARCH 1-2	0.7927 [0.453]	0.9328 [0.394]	0.8851 [0.413]	0.9044 [0.405]
ARCH 1-5	0.7195 [0.609]	0.8287 [0.529]	0.8165 [0.538]	0.8073 [0.545]

The Table reports Quasi Maximum Likelihood Estimates (QMLE) for the monthly returns on the palm oil prices from February, 1980 through December, 2011, for a total of 383 observations. Figures inside the square brackets are p-values. AIC and SIC refer to the Akaike and Schwarz Information Criterion, respectively. The values of Ljung-Box portmanteau test statistics for up to kth order serial correlation in the standardized residuals, $\hat{\varepsilon}_t\hat{\sigma}_t^{-1}$, and squared standardized residuals, $\hat{\varepsilon}_t^2\hat{\sigma}_t^{-2}$, are denoted by $Q(k)$ and $Q^2(k)$, respectively. The ARCH test inspects the presence of heteroscedasticity.

The estimation results for GJR-GARCH(1,1) are presented in Table 3. Here also the positivity constraint for the coefficients of the second moment equations is satisfied in all the estimated GJR-GARCH(1,1) models. Moreover, all estimated GJR-GARCH(1,1) models with four conditional densities satisfy the second $(\hat{\alpha} + \hat{\beta} + 0.5\hat{\gamma} < 1)$ and fourth moment $(\hat{\beta}^2 + 2\hat{\alpha}\hat{\beta} + 3\hat{\alpha}^2 + \hat{\beta}\hat{\gamma} + 3\hat{\alpha}\hat{\gamma} + 1.5\hat{\gamma}^2 < 1)$ conditions. With respect to standardized and squared standardized residuals, the computed Ljung-Box Q statistics give clear indication of no serial dependence, and the Engle's (1982) Lagrange multiplier statistics offer significant evidence of no remaining ARCH effects. Hence, these statistics imply that the GJR-GARCH models assuming four conditional densities are well specified.

TABLE 3: Estimates for AR(3)-GJR-GARCH (1,1) model

	GJR-GARCH-N	GJR-GARCH-ST	GJR-GARCH-GED	GJR-GARCH-SST
μ_0	0.2909 [0.542]	0.3538 [0.431]	0.4230 [0.389]	0.2718 [0.566]
μ_1	0.4297 [0.000]	0.3972 [0.000]	0.3973 [0.000]	0.3972 [0.000]
μ_2	-0.3057 [0.000]	-0.2838 [0.000]	-0.2819 [0.000]	-0.2865 [0.000]
μ_3	0.1666 [0.001]	0.1563 [0.004]	0.1494 [0.013]	0.1580 [0.004]
ω	3.5443 [0.059]	3.1277 [0.057]	3.3512 [0.056]	3.1684 [0.052]
α	0.1049 [0.052]	0.0853 [0.125]	0.0917 [0.080]	0.0842 [0.127]
β	0.8218 [0.000]	0.8451 [0.000]	0.8348 [0.000]	0.8451 [0.000]
γ	0.0195 [0.754]	0.0333 [0.565]	0.0284 [0.623]	0.0336 [0.559]
υ (Tail)	-	6.8371 [0.007]	1.3524 [0.000]	6.8136 [0.007]
ξ (Asym.)	-	-	-	-0.0364 [0.544]
AIC	6.7756	6.7550	6.7472	6.7595
SIC	6.8587	6.8485	6.8407	6.8634
$Q(10)$	11.610 [0.114]	12.707 [0.079]	12.671 [0.080]	12.731 [0.079]
$Q(20)$	21.681 [0.197]	23.153 [0.144]	23.221 [0.142]	23.095 [0.146]
$Q^2(10)$	4.3532 [0.824]	4.9680 [0.761]	4.7786 [0.781]	4.9377 [0.764]
$Q^2(20)$	10.312 [0.921]	10.394 [0.918]	10.248 [0.923]	10.274 [0.923]
ARCH 1-2	0.6697 [0.512]	0.7037 [0.495]	0.6900 [0.502]	0.6791 [0.507]
ARCH 1-5	0.7331 [0.599]	0.8859 [0.490]	0.8538 [0.512]	0.8691 [0.502]

The Table reports Quasi Maximum Likelihood Estimates (QMLE) for the monthly returns on the palm oil prices from February, 1980 through December, 2011, for a total of 383 observations. Figures inside the square brackets are p-values. AIC and SIC refer to the Akaike and Schwarz Information Criterion, respectively. The values of Ljung-Box portmanteau test statistics for up to kth order serial correlation in the standardized residuals, $\hat{\varepsilon}_t\hat{\sigma}_t^{-1}$, and squared standardized residuals, $\hat{\varepsilon}_t^2\hat{\sigma}_t^{-2}$, are denoted by $Q(k)$ and $Q^2(k)$, respectively. The ARCH test inspects the presence of heteroscedasticity.

However, the asymptotic t-ratio for the γ estimate in all GJR-GARCH models is not significant. In addition, the magnitude of γ estimates is much smaller than the α estimate, which indicates that negative shocks do not seem to have a significant impact on the conditional variances than positive shocks. Importantly, the models satisfy the condition that $\hat{\alpha} + \hat{\gamma} > 0$ in all cases which implies that the positivity of the conditional variances associated with the negative shocks is guaranteed.

Similar to the standard GARCH models, both reported selection criteria suggest that GJR-GARCH(1,1) model under generalized error distribution is favored over the rest of estimated models assuming Gaussian, Student t and skewed Student t distributions.

The estimated tail-thickness parameter of generalized error distribution has been found to be statistically highly significant. This strongly indicates that the stochastic errors of return process follow the heavy-tailed distribution rather than the normal distribution. This fact is also supported with the estimated degree of freedom of Student t distribution. Furthermore, although there is an evidence of fat-tailedness in the return process, however, there seems to be negligible evidence for skewness features. Skewness characteristics of innovations can be seen from the significance levels of estimated skewness parameter $\ln(\xi)$ when the GARCH models estimated assuming skewed t distribution.

As far as the APGARCH models are considered, to simplify the layout of the Table 4, we only report the results pertaining to the APGARCH model assuming Gaussian distribution that has achieved the numerical convergence in the maximum likelihood optimization. Note that, based on serial dependence tests, AR(3) specification has been selected for the conditional mean of palm oil price returns. Several points are worth mentioning. The magnitude of parameter $\hat{\beta}$ is close to 1 but statistically different from 1 which indicates that a high degree of volatility persistence.

Moreover, the estimated APGARCH model is stationary in the sense that $\alpha_1 E(|\eta_t| - \gamma\eta_t)^\delta + \beta_1$ is less than 1. The power parameter δ is close to 1 and statistically different from 2. For palm oil price returns, γ is positive but not statistically different from zero. Thus, negative returns do not seem to lead to higher subsequent volatility than positive returns. The AR(3)-APGARCH assuming normal distribution succeeds in accounting for all the dynamical structure exhibited by the returns and the conditional variance of returns as the computed Ljung-Box test statistics on the standardized residuals and the squared standardized residuals are nonsignificant at 5% significance levels. And, there are no further signs of heteroskedasticity according to the ARCH LM test statistics. As shown in Table 4, the β estimate from AR(3)-EGARCH(1,1) for palm oil price returns is less than one in absolute value, which indicate that all moments exist. As we have mentioned earlier, there is no parametric restriction for the conditional variance to be positive, as EGARCH is model of the logarithm of the conditional variances. The numerical convergence has been achieved only in AR(3)-EGARCH assuming skewed Student t distribution.

One may note that neither sign (θ_1) nor size (θ_2) effect parameters seem to have a statistically significant impact on conditional variances. In fact, the values of computed Ljung-Box and ARCH LM test statistics at various lags support the adequacy of both specified conditional mean and variance equations. With regard to the parameters of skewed t distribution, although the tail parameter υ has been found statistically highly significant, asymmetric parameter $\ln(\xi)$ is not significant. This indicates that heavy tailed asymmetric conditional distribution (skewed t) does not seem to be fully adequate for EGARCH(1,1) model.

TABLE 4: Estimates for AR(3)-APGARCH (1,1)-N and EGARCH-SST models

	APGARCH-N	EGARCH-SST
μ_0	0.2946 [0.531]	0.2220 [0.606]
μ_1	0.4311 [0.000]	0.3985 [0.000]
μ_2	-0.3177 [0.000]	-0.2783 [0.000]
μ_3	0.1699 [0.001]	0.1483 [0.004]
ω	0.6382 [0.636]	3.9681 [0.000]
α	0.1205 [0.012]	-0.0533 [0.931]
β	0.8304 [0.000]	0.9036 [0.000]
γ	0.0908 [0.669]	-
δ	1.0659 [0.358]	-
θ_1	-	-0.0387 [0.473]
θ_2	-	0.2124 [0.146]
υ (Tail)	-	4.9141 [0.004]
ξ (Asym.)	-	-0.0346 [0.602]
AIC	6.7769	6.7449
SIC	6.8705	6.8592
$Q(10)$	10.317 [0.171]	8.2088 [0.314]
$Q(20)$	20.366 [0.256]	18.337 [0.367]
$Q^2(10)$	4.7528 [0.783]	4.7444 [0.784]
$Q^2(20)$	10.305 [0.921]	9.9298 [0.934]
ARCH 1-2	0.6791 [0.507]	0.9044 [0.405]
ARCH 1-5	0.7968 [0.552]	0.8073 [0.545]

The Table reports Quasi Maximum Likelihood Estimates (QMLE) for the monthly returns on the palm oil prices from February, 1980 through December, 2011, for a total of 383 observations. Figures inside the square brackets are p-values. AIC and SIC refer to the Akaike and Schwarz Information Criterion, respectively. The values of Ljung-Box portmanteau test statistics for up to kth order serial correlation in the standardized residuals, $\hat{\varepsilon}_t\hat{\sigma}_t^{-1}$, and squared standardized residuals, $\hat{\varepsilon}_t^2\hat{\sigma}_t^{-2}$, are denoted by $Q(k)$ and $Q^2(k)$, respectively. The ARCH test inspects the presence of heteroscedasticity.

Table 5 provides the estimation results of AR(3)-FIEGARCH(1, d ,1) assuming normal, Student t, and generalized error distributions.

TABLE 5: Estimates for AR(3)-FIEGARCH (1,1) model

	FIEGARCH-N	FIEGARCH-ST	FIEGARCH-GED
μ_0	-0.1069 [0.813]	0.3239 [0.437]	0.2953 [0.557]
μ_1	0.4672 [0.000]	0.4002 [0.000]	0.4198 [0.000]
μ_2	-0.3651 [0.000]	-0.2802 [0.000]	-0.3051 [0.000]
μ_3	0.1682 [0.008]	0.1477 [0.003]	0.1617 [0.010]
ω	2.9483 [0.045]	4.0575 [0.000]	2.8074 [0.154]
d	0.8724 [0.001]	0.1462 [0.654]	0.8193 [0.011]
α	0.6683 [0.211]	-0.1778 [0.758]	0.6943 [0.048]
β	-0.8851 [0.000]	0.8876 [0.000]	-0.8755 [0.000]
θ_1	0.0216 [0.726]	-0.0331 [0.524]	-0.0059 [0.922]
θ_2	0.4248 [0.002]	0.2013 [0.177]	0.4087 [0.000]
υ (Tail)	-	5.0787 [0.000]	1.3472 [0.000]
ξ (Asym.)	-	-	-
AIC	6.7943	6.7447	6.7611
SIC	6.8982	6.8590	6.8753
$Q(10)$	11.565 [0.116]	8.8659 [0.262]	11.372 [0.123]
$Q(20)$	23.340 [0.138]	19.156 [0.319]	24.645 [0.103]
$Q^2(10)$	7.7058 [0.463]	0.9348 [0.998]	8.6967 [0.368]
$Q^2(20)$	12.874 [0.799]	3.2315 [0.999]	14.128 [0.721]
ARCH 1-2	1.4694 [0.231]	0.1075 [0.898]	1.4915 [0.226]
ARCH 1-5	0.8087 [0.544]	0.1342 [0.897]	1.1725 [0.322]

The Table reports Quasi Maximum Likelihood Estimates (QMLE) for the monthly returns on the palm oil prices from February, 1980 through December, 2011, for a total of 383 observations. Figures inside the square brackets are *p*-values. AIC and SIC refer to the Akaike and Schwarz Information Criterion, respectively. The values of Ljung-Box portmanteau test statistics for up to kth order serial correlation in the standardized residuals, $\hat{\varepsilon}_t\hat{\sigma}_t^{-1}$, and squared standardized residuals, $\hat{\varepsilon}_t^2\hat{\sigma}_t^{-2}$, are denoted by $Q(k)$ and $Q^2(k)$, respectively. The ARCH test inspects the presence of heteroscedasticity.

However, the model with the skewed Student t does not achieve the numerical convergence. The FIEGARCH models under Gaussian and GED densities are able to capture the long memory feature of palm oil price return volatilities as the long-memory parameters (d) reject null hypothesis $(d = 0)$ at 5% significance level. With reference to the AIC and SIC, the estimation results show that the FIEGARCH model with Student t innovations seems to perform better than that with GED. Turning to the goodness-of-fit tests, our results suggest that we do not reject the null hypothesis of a correct model specification for palm oil price returns because Ljung-Box Q and ARCH LM tests show no serial correlation and no remaining ARCH effects.

In addition, the tail parameters of Student t, and GED are statistically highly significant indicating that the innovations' distribution is leptokurtic. Like all other estimated asymmetric models above, asymmetries in the volatility are not detected since the asymmetric parameter θ_1 is not found to be significantly different from zero.

5. CONCLUSION

Modeling agricultural commodity prices remains one of the stubborn challenges in economics and finance as it becomes important in hedging models, option pricing, and computations of value-at-risk measures. For this reason, we have attempted to model the conditional volatility of palm oil prices by taking into consideration a number of stylized facts in the return process. To accomplish this, five competing models are estimated: the standard GARCH, EGARCH, GJR-GARCH, APGARCH, and FIEGARCH. The quasi maximum likelihood estimations are based on four alternative conditional densities such as normal, Student t, GED, and skewed Student t. Several findings emerge from this study. First, the estimated standard GARCH(1,1) models have been found to describe the volatility dynamics of palm oil prices adequately. The selection criteria give slight preference to the GARCH(1,1) under GED distribution. Second, the estimated GJR-GARCH(1,1) models assuming four alternative conditional densities have been found to be well-specified. According to two selection criteria considered in this study, the GJR-GARCH(1,1) model with GED is favored over the rest of the GJR-GARCH(1,1) models. Third, the likelihood function faces the numerical convergence problems in APGARCH assuming Student t, GED, skewed Student t distributions, EGARCH assuming skewed t density, and FIEGARCH with skewed t distribution. Asymmetric model estimates suggest that there is a very little evidence for asymmetric effects in palm oil returns. Lastly, as far as the conditional distributions are concerned, the symmetric fat-tailed distributions (Student t or GED) are found to be preferred to Gaussian and skewed t distributions.

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