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Forecasting the Jordanian stock index: modelling asymmetric volatility and distribution effects within a GARCH framework

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Abstract: The modelling of market returns can be especially problematical in emerging and frontier financial markets given the propensity of their returns to exhibit significant non-normality and volatility asymmetries. This paper attempts to identify which representations within the GARCH family of models can most efficiently deal with these issues. A number of different distributions (normal, Student t, GED and skewed Student) and different volatility of returns asymmetry representations (EGARCH and GJR-GARCH) are examined. Our data set consists of daily Jordanian stock market returns over the period January 2000 – November 2014. Using both the Superior Predicative Ability (SPA) and Model Confidence Set (MCS) testing frameworks it is found that using GJR-GARCH with a skewed Student distribution most accurately and efficiently forecasts Jordanian market movements. Our findings are consistent with similar research undertaken in respect to developed markets.

Introduction

The global financial crisis of 2007-09 and subsequent shocks in the Euro-area and beyond has led researchers to examine again the ways in which they model stock market returns. It has become increasingly apparent that the 'standard assumptions' made in respect to the ways in which statistical series are distributed are not applicable in financial markets. As the global economy becomes more integrated it is also becoming increasingly important to understand how emerging and frontier markets react in periods of high volatility. In this paper we explore which elements of the GARCH family of models can be used to efficiently and effectively model markets in Jordan from January 2000 to November 2014.

The paper begins with a brief review of the literature in the second Section. This is followed in the subsequent section by a description of the data and methodology. The most efficient model is then identified using the Superior Predictive Ability (SPA) and Model Confidence Set (MCS) prediction frameworks before, finally, some brief conclusions are drawn.

Literature: volatility modelling in the GARCH framework

The GARCH model was first introduced by Bollerslev (1986). Much of the subsequent research in this area has focused on developing the model to better reflect the data found in real-world settings, such as, for example, financial markets. The finance-related literature focuses principally on modelling (i) the structure of the volatility (ii) the nature of the distribution of the returns.

Much of the work on modelling the structure of volatility relates to the asymmetries found in stock market returns. For example, Engle and Ng (1993) found evidence supporting the Quadratic-GARCH model. Others, such as Brailsford and Faff (1996), found evidence to support GJR-GARCH and Heynen and Kat (1994) argued that EGARCH has a superior predictive ability. Although the literature does not show one individual asymmetry specification as being clearly superior to others, Awartani and Corradi (2005) argue that they generally outperform non-asymmetric specifications in financial market prediction. However, it can be noted that the evidence is not unequivocal; McMillan, Speight, and Apgwilym (2000) found GARCH, moving average and exponential smoothing models to provide marginally superior daily volatility forecasts. Their work also strongly suggested that EGARCH does not necessarily outperform simple GARCH model in forecasting market volatility.

For the purposes of our paper methodologies with the greatest out-of-sample forecasting accuracy are the most desirable. Balaban (2004) tested a series of both symmetric and asymmetric models (included ARCH, GARCH, GJR-GARCH and EGARCH). Their results suggest that all models are biased and generally over-predict volatility. Model performance in these latter respects was best for GARCH and worst for GJR-GARCH. However, they also noted that if avoidance of under-prediction was the key decision criteria, ARCH was the preferred model.

A further issue that is important to consider is that the nature of volatility in emerging and frontier markets differs considerably from that found in developed markets (Andrikopoulos, Niklewski and Rodgers forthcoming). Given that the focus of this paper is Jordan, it is important to consider how different GARCH specifications perform in these market-types. Gokcan (2000) examined seven emerging market (Argentina, Brazil, Colombia, Malaysia, Mexico, Philippines, Taiwan) and found that GARCH(1,1) outperformed EGARCH everywhere with the exception of Brazil.

The most compelling conclusion we draw from the literature in respect to modelling volatility structure is that it is difficult to identify one single model that is clearly superior to others. This indicates to us that it may be necessary to test a number of volatility specifications.

A standard feature of most financial markets is that their returns are non-normal with distributions exhibiting 'fat-tailed' characteristics (Mittnik, Paolella, and Rachev 2000). This appears to be particularly an issue in emerging markets. Brooks (2007) studied a set of such markets (including MENA region countries) using the Asymmetric Power ARCH model. He found that unlike developed markets, where non-normal conditional error distributions appear to fit the data well, there were a set of emerging markets where estimation problems arise using a conditional t distribution. It was also found that the degree of volatility asymmetry appears to vary across markets, with the Middle Eastern and African markets having very different volatility asymmetry characteristics to Latin American markets.

Brooks (2007) found that a fat-tailed t-distribution was needed to model the distribution of returns in most MENA markets. However, there were differences. For example, Turkey, Egypt and Morocco display much larger kurtosis and exhibit fatter tails than Jordan. Likelihood ratio tests were found to clearly favour the APARCH with t-distribution rather than a normal distribution. It is possible that such differences may reflect the Islamic nature of these markets. For example, Al-Hajieh, Redhead, and Rodgers (2011) found that the month of Ramadan (Islamic holy month) shows high level of volatility and the overall impact of Ramadan on returns is statistically significant in most Middle East countries.

We conclude the literature review by identifying that we are aware of no studies of volatility forecasting in emerging markets that have examined the combined issues of the distribution of returns and the GARCH model specification. We have also identified from the literature that (i) no single GARCH model specifications clearly outperforms other forms in all circumstances and (ii) evidence to suggest that the distribution of returns in emerging markets (like Jordan) can follow a number of possible forms and that these can interact with volatility models in different ways. In this paper we therefore test a number of possible distribution-types (Normal, Student-t, GED, and Skewed Student) and GARCH model types (GARCH, GJR-GARCH and EGARCH) in order to identify the most efficient volatility forecasting model for Jordan.

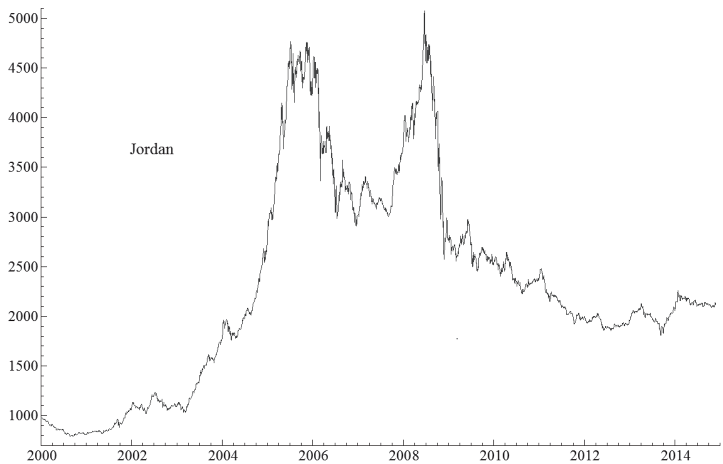
Data description

The empirical investigation is undertaken in respect to daily closing price data for the Jordanian Amman Stock Exchange Index (ASE) covering the period 2nd January 2000 to 27th November 2014. The data source is the Thomson-Reuters Eikon database and the dataset comprises of a total of 3655 trading days. Daily returns computed as the log-difference of the daily closing prices:

$$R_t = \ln P_t - \ln P_{t-1} \quad [1]$$

ASE Index closing prices are presented in Figure 1 and the daily returns in Figure 2. A number of volatility clusters can be observed in the returns data; for example, a cluster corresponding to the 2007-09 global financial crisis.

Figure 1. Daily Jordanian Price Index January 2000–November 2014



Source: created by the authors using OxMetrics™ 7 software and data from Thomson Reuters Eikon™.

A preliminary statistical analysis of the daily returns is presented in Table 1. It can be noted that average daily returns are small relative to the standard deviation. The series also displays negative skewness and strong positive kurtosis; these are indicative of a heavy tailed non-Gaussian distribution.

Table 1. Descriptive Statistics of Daily Returns January 2000–November 2014

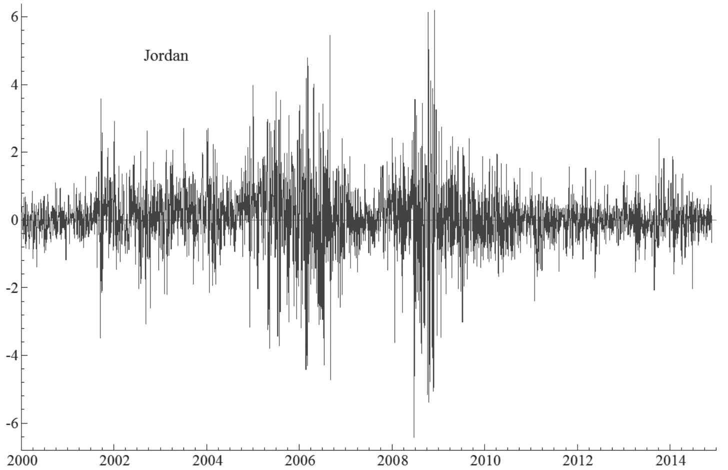
Mean	Std. Dev	Min	Max	Skewness	Excess Kurtosis	J-B Test	ARCH Test[1]	L-B Test[1]	ADF Test
0.025	0.946	-6.428	6.198	-0.363	6.167	5872.2**	107.9**	2571**	-32.8**

** Significant at 1%.

[1]Both the Ljung-Box and the ARCH tests use 10 lags.

Source: estimated by the authors using OxMetrics™ 7.

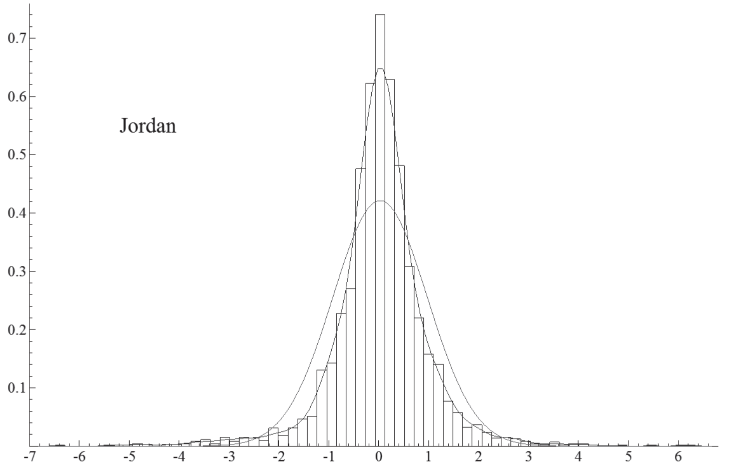
Figure 2. Jordanian Daily Percentage Returns January 2000–November 2014



Source: created by the authors using OxMetrics™ 7.

This is confirmed by the Jarque-Bera test which rejects unconditional normality and further confirmatory evidence is provided in the related histogram (Figure 3).

Figure 3. Histogram of Jordanian Daily Returns January 2000–November 2014



Source: created by the authors using OxMetrics™ 7.

The Ljung-Box Q-test and the ARCH tests suggest autocorrelation and hetroskedasticity within the data and the ADF (Augmented Dickey-Fuller) unit root test rejects the null hypothesis of data non-stationary.

The research methodology

A total of 12 GARCH-model-specification/distribution pairs are tested with the results being presented in Tables 3–7. The models tested are: GARCH-based specifications (GARCH-N, GARCH-T, GARCH-GED and GARCH-ST)[1]; and two sets of asymmetry-type specifications: (i) EGARCH (EGARCH-N, EGARCH-T, EGARCH-GED and EGARCH-ST) and (ii) GJR-GARCH (GJR-GARCH-N, GJR-GARCH-T, GJR- GARCH-GED and GJR- GARCH-ST).

The alternative models are subsequently evaluated by: (i) an evaluation of model parameters and (ii) an evaluation of model forecasting performance. For robustness, the latter undertakes a series of tests using both the Superior Predictive Ability (SPA) test Hansen (2005) and the Model Confidence Set (MCS) test (Hansen, Lunde, and Nason 2011). Both are available in the OxMetrics™ 7[2] software package used in this paper. The forecast-based tests use a 'loss-function' to identify the most efficient model. The loss function can be estimated using Mean Squared Error (MSE) and Mean Absolute Deviation (MAD) statistics. SPA identifies the 'best' model in terms of predictive ability and MCS identifies the 'best' model set.

The model specifications and the distributions tested are identified below. They consist of three different conditional volatility specifications and four different statistical distributions.

(i) *GARCH*

The GARCH model, as introduced by Bollerslev (1986), is a generalisation of the ARCH specification of Engle (1982). The model specifies that the conditional variance is a function of the lagged squared residuals as well as of its past conditional variances. Although the equation may be specified with a number

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[1] N stands for the Normal distribution, T the Student t distribution, GED the Generalised Error Distribution and ST the Standardised Skewed Student distribution.

[2] The MULCOM 3.0 package running SPA and MCS was developed by Hansen and Lunde (2014).

of lags in each term a single lag in each is usually adequate in financial market data. We follow this conversion in this paper.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad [2]$$

(ii) *EGARCH*

It is often observed that volatilities associated with downward movements in financial markets are greater than the volatilities observed by upward movements of the same magnitude. In such circumstances the symmetry imposed on the conditional variance structure in the GARCH model may not be appropriate. To address this issue, Nelson (1991) proposes the exponential GARCH (EGARCH) model. The specification for the conditional variance is:

$$\log \sigma_t^2 = \omega + [1 - \beta(L)]^{-1}[1 + \alpha(L)]g(z_{t-1}) \qquad [3]$$

$$\text{where } g(z_t) \equiv \underbrace{\theta_1 z_t}_{sign\ effect} + \underbrace{\theta_2[|z_t| - E|z_t|]}_{magnitude\ effect}$$

The log specification implies that the asymmetric effect is exponential, rather than quadratic, and that forecasts of the conditional variance that are generated are non-negative. The presence of asymmetry effects is tested in terms of the sign and magnitude effects identified above.

(iii) GJR-GARCH

This variation on the GARCH model was proposed by Glosten, Jagannathan, and Runkle (1993) as an alternative way of dealing with asymmetric shocks in financial series. Its generalized version is:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \gamma_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad [4]$$

Where S_t^- is a dummy variable that take the value 1 when $\varepsilon_{t-i} < 0$, and 0 when $\varepsilon_{t-i} \geq 0$. A feature of the GJR model is that the null hypothesis of no leverage (asymmetry) effect is simple to test. Indeed, $\gamma_1 = \ldots = \gamma_q = 0$ implies that the impact of a shock is symmetric, i.e., past positive shocks have the same impact on today's volatility as past negative shocks.

Four different statistical density functions are tested. The use the Gaussian or normal distribution is potentially appropriate as the conditional distribution of the residuals would account for some non-normality in returns. The second and third density functions can more fully account for 'fat-tail' effects; however, they do have a drawback in that they are symmetric. Our preferred option is therefore the skewed-Student density proposed by Fernández and Steel (1998).

(iv) *Gaussian (normal) distribution*

Where the log-likelihood function of the distribution is:

$$L_{norm} = -\frac{1}{2}\sum_{t=1}^{T}[\log(2\pi) + \log(\sigma_t^2) + z_t^2] \qquad [5]$$

(v) *Student-t distribution*

Where the log-likelihood function of the distribution is:

$$L_{stud} = T\left\{\log\Gamma\left(\frac{\nu+1}{2}\right) - \log\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\log\left[\Pi(\nu-2)\right]\right\}$$
$$-\frac{1}{2}\sum_{t=1}^{T}\left[\log(\sigma_t^2) + (1+\nu)\log\left(1+\frac{z_t^2}{\nu-2}\right)\right] \qquad [6]$$

(vi) *Generalized Error distribution (GED)*

Where the log-likelihood function of the distribution is:

$$L_{GED} = \sum_{t=1}^{T}\left[\log\left(\frac{\nu}{\lambda_\nu}\right) - 0.5\left|\frac{z_t}{\lambda_\nu}\right|^{\nu} - (1+\nu^{-1})\log(2) - \log\Gamma\left(\frac{1}{\nu}\right) - 0.5\log(\sigma_t^2)\right] \qquad [7]$$

(vii) *Standardized (zero mean and unit variance) skewed-Student distribution*

Where the log-likelihood function of the distribution is:

$$L_{SkSt} = T\left\{\log\Gamma\left(\frac{\nu+1}{2}\right) - \log\Gamma\left(\frac{\nu}{2}\right) - 0.5\log\left[\Pi(\nu-2)\right] + \log\left(\frac{2}{\xi+\frac{1}{\xi}}\right) + \log(s)\right\}$$

$$-\,0.5\sum_{t=1}^{T}\left\{\log\sigma_t^2 + (1+\nu)\log\left[1+\frac{(sz_t+m)^2}{\nu-2}\xi^{-2I_t}\right]\right\} \qquad [8]$$

Results: model evalutation

We evaluate the alternative models by (i) an assessment of the parameters associated with each model set (ii) an evaluation of each model set's forecasting performance.

(i) Parameter Based Evaluation

Tables 2, 3 and 4, present the parameter values and associated significance tests for the GARCH, EGARCH and GJR-GARCH specified model sets. For the first and third model sets the constants in the mean equations and the variance parameters are positive and statistically significant for all distributions. For the EGARCH model set the constants for the mean equations are not statistically significant.

The alpha coefficient for all models and distributions is statistically significant at the 99% level of confidence. This implies the existence of the ARCH process in the residuals term. The returns exhibit time-varying volatility clustering; this indicates that periods of volatility are followed by periods of relative calm.

The beta coefficients of the three models in all distribution are also statistically significant at the 99% level of confidence. This indicates that the variance is dependent on its moving average. In a subset of the models the sum of alpha and beta is close to unity, which implies in these cases that volatility shocks are quite persistent and suggests that a large positive (or negative) return will lead future forecasts of the variance to be high for an extended period.

The GARCH coefficient (beta) is larger than the ARCH term (alpha) in all three model sets. This is a further indication that the conditional variance will exhibit long persistence of volatility.

The GJR models show no evidence of asymmetry effects being statistically significant. EGARCH models however, indicate significance in the magnitude effect but not in the sign effect.

Table 2. The GARCH model set

Distribution		Const. (M)$^{\alpha}$	Const. (V)$^{\beta}$	ARCH (Alpha)	GARCH (Beta)	Student (DF)$^{\mu}$	GED (DF)$^{\mu}$	Asymm.	Tail
Normal	Coefficient	0.02	0.01	0.11	0.89	NA	NA	NA	NA
	p-value	0.05	0.02	0	0	NA	NA	NA	NA
Student	Coefficient	0.02	0.01	0.14	0.86	6.23	NA	NA	NA
	p-value	0.02	0.02	0	0	0	NA	NA	NA
GED	Coefficient	0.02	0.01	0.12	0.88	NA	1.36	NA	NA
	p-value	0.02	0.02	0	0	NA	0	NA	NA
Skewed Student	Coefficient	0.02	0.01	0.14	0.86	NA	NA	-0.01	6.22
	p-value	0.05	0.02	0	0	NA	NA	0.69	0

$^{\alpha}$ Mean equation, $^{\beta}$ Variance equation, $^{\mu}$ Degrees of freedom.

Source: estimated by the authors using OxMetrics™ 7.

Table 3. The EGARCH model set

Distribution		Const. (M)$^{\alpha}$	Const. (V)$^{\beta}$	ARCH (Alpha)	GARCH (Beta)	Student (DF)$^{\mu}$	GED (DF)$^{\mu}$	Asymm.	Tail	EGARCH (Theta1)	EGARCH (Theta2)
Normal	Coefficient	0.01	0.12	-0.53	0.99	NA	NA	NA	NA	0	0.39
	p-value	0.16	0.74	0	0	NA	NA	NA	NA	0.8	0
Student	Coefficient	0.02	-0.59	-0.52	0.99	6.47	NA	NA	NA	-0.01	0.43
	p-value	0.17	0.02	0	0	0	NA	NA	NA	0.55	0
GED	Coefficient	0.02	-0.68	-0.53	0.99	NA	1.38	NA	NA	0	0.41
	p-value	0.11	0	0	0	NA	0	NA	NA	0.93	0
Skewed Student	Coefficient	0.01	-1.11	-0.53	0.99	NA	NA	-0.02	6.44	-0.01	0.43
	p-value	0.15	0.15	0	0	NA	NA	0.48	0	0.65	0

$^{\alpha}$ Mean equation, $^{\beta}$ Variance equation, $^{\mu}$ Degrees of freedom.

Source: estimated by the authors using OxMetrics™ 7.

Table 4. The GJR-GARCH model set

Distribution		Const. (M)$^{\alpha}$	Const. (V)$^{\beta}$	ARCH (Alpha)	GARCH (Beta)	Student (DF)$^{\mu}$	GED (DF)$^{\mu}$	Asymm.	Tail	GJR (Gamma)
Normal	Coefficient	0.02	0.01	0.11	0.89	NA	NA	NA	NA	-0.01
	p-value	0.03	0.03	0	0	NA	NA	NA	NA	0.53
Student	Coefficient	0.02	0.01	0.14	0.86	6.22	NA	NA	NA	0.01
	p-value	0.03	0.02	0	0	0	NA	NA	NA	0.6
GED	Coefficient	0.02	0.01	0.12	0.88	NA	1.36	NA	NA	0
	p-value	0.02	0.03	0	0	NA	0	NA	NA	0.92
Skewed Student	Coefficient	0.02	0.01	0.14	0.86	NA	NA	-0.01	6.21	0.01
	p-value	0.05	0.03	0	0	NA	NA	0.75	0	0.62

$^{\alpha}$ Mean equation, $^{\beta}$ Variance equation, $^{\mu}$ Degrees of freedom.

S o u r c e : estimated by the authors using OxMetrics™ 7.

We turn now to the issue of identifying the most efficient model(s) from the groups that have been tested. The diagnostic tests of the standardized residuals (Table 5) give us little help in this respect. Both ARCH(10) and $Q^2(10)$ statistics indicate that hetroskedasticity has not been fully accounted for by the models which means the estimated volatility equations have to be treated with some degree of caution. Furthermore, Log likelihood and Akaike information criteria based tests all have approximately similar results; this suggests they provide minimal help in distinguishing between model sets on the basis of model fit. We can conclude from this that alternative forecasting-based testing procedures will be required. It can be noted as a caveat to the above conclusion however, that for all model sets, Akaike indicates that the normal distribution produces the worst performance. From this it can possibly be concluded that this distribution can probably be discounted at the outset.

Table 5. Diagnostic Tests Of The Standardised Residuals

Model	Distribution	Log Likelihood	$Q^2(10)^\alpha$	$ARCH(10)^\alpha$	Akaike
GARCH	Normal	-4044.15	37.14 (0)	3.49 (0)	2.22
	Student	-3963.3	31.31 (0)	2.92 (0)	2.18
	GED	-3966.62	33.86 (0)	3.15 (0)	2.17
	Skewed Student	-3963.22	31.29 (0)	2.92 (0)	2.17
EGARCH	Normal	-3980.23	21.62 (0)	2.14 (0.01)	2.18
	Student	-3893.84	21.01 (0)	2.11 (0.02)	2.13
	GED	-3900.81	21.28 (0)	2.12 (0.01)	2.13
	Skewed Student	-3890.96	21.04 (0)	2.11 (0.02)	2.13
GJR-GARCH	Normal	-4043.82	38.11 (0)	3.57 (0)	2.22
	Student	-3963.12	30.56 (0)	2.86 (0)	2.17
	GED	-3966.62	34.01 (0)	3.17 (0)	2.17
	Skewed Student	-3963.07	30.59 (0)	2.86 (0)	2.17

$^\alpha$ The p-values are shown in brackets.

Source: estimated by the authors using OxMetrics™ 7.

(ii) Forecasting Based Evaluation

The Superior Predictive Ability test can be used for comparing the performances of two or more forecasting models. Forecasts are evaluated using a pre-specified loss function with the ‘best’ forecast model being the one producing the smallest expected loss. An important issue that researchers face is identifying what the loss function is estimated against. For the purposes of this paper losses are estimated relative to the observed returns.

The two potential loss functions used by SPA are the Mean Squared Error (MSE) and Mean Absolute Deviation (MAD). The losses estimated from the chosen function are then compared against a benchmark model. Identifying an appropriate benchmark to use is another important issue in respect to this methodology. In this paper we benchmark against a random walk.

The result presented in Table 6 below identify that GJR-GARCH with Skewed distribution produces the smallest loss and is therefore the best fitting model. These findings are consistent with those of Marcucci (2005) and Awartani and Corradi (2005). The latter found GARCH-N to be outperformed by both EGARCH and GJR-GARCH models across different forecast horizons.

Table 6. Superior Predictive Ability Tests

Performance	Model	Sample Loss (MSE*10^3)	t-statistic	p-value
Most Significant	GJR-GARCH-Skewed Student	0.00039	16.75819	0
Best	GJR-GARCH-Skewed Student	0.00039	16.75819	0
Model_25%	GJR-GARCH-Student-t	0.00043	16.75729	0
Median	GARCH-GED	0.00049	16.75627	0
Model_75%	EGARCH-Normal	0.02761	16.63402	0
Worst	EGARCH-Skewed Student	0.03208	16.59516	0

Source: estimated by the authors using OxMetrics™ 7 and MULCOM 3.0 package (Hansen, and Lunde 2014).

Forecasts can also be tested using the model confidence set (MCS) procedure. This uses the same loss function as SPA but requires no benchmark. It identifies efficient model sets at different levels of confidence. Hansen and Lunde state “the set,, that consists of the ‘best’ model(s) from a collection of models,; where ‘best’ is defined in terms of a criterion that is user-specified. The MCS procedure yields a model confidence set,, that is a set of models constructed to contain the best models with a given level of confidence. The models in are evaluated using sample information about the relative performances of the models in ”. (Hansen and Lunde 2014, 16). The result of MCS presented in Table 7 identifies that the 90% confidence model set consists of a single model; namely, GJR-GARCH with Skewed Student distribution.

Table 7. Model Confidence Set Tests

Model	MSE*10³	p-value
GARCH-Normal	0.00041	0
GARCH-Student-t	0.00047	0
GARCH-GED	0.00049	0
GARCH-Skewed Student	0.00041	0
EGARCH-Normal	0.02761	0
EGARCH-Student-t	0.03117	0
EGARCH-GED	0.02926	0
EGARCH-Skewed Student	0.03208	0
GJR-GARCH-Normal	0.00047	0
GJR-GARCH-Student-t	0.00043	0
GJR-GARCH-GED	0.0005	0
GJR-GARCH-Skewed Student	0.00039	1.0000*

* 90% model confidence set.

Source: estimated by the authors using OxMetrics™ 7 and MULCOM 3.0 package (Hansen, and Lunde 2014).

Discussion of findings and conclusions

Given the large differences between developed and emerging markets, it is possibly a little surprising that the result of our study, made in respect to Jordan, are consistent with previous studies made of developed markets. For example, Engle and Ng (1993), examining Japanese stock return also found strong support for the GJR-GARCH model. Similarly, Bentes, Menezes, and Ferreira (2013) examining NIKKEI 225, S&P 500 and STOXX 50 from 1987–2013 found all stock index returns tested exhibited asymmetry.

Further similarities can be identified between our results and other studies. Liu & Hung (2010) investigated the performance of one-step-ahead forecasting using asymmetric GARCH models with different distribution assumptions. Their work, in respect to United States data, concluded that GJR-GARCH generated volatility forecasts were more accurate that those produced by their EGARCH counterparts. Furthermore, their results indicated that modelling the asymmetric component was much more important than specifying the correct error distribution when it came to improving volatility forecasting. This was especially the case in the presence of fat-tails, leptokurtosis, skewness and the leverage effect.

A number of other studies have examined volatility in MENA countries like Jordan. Assaf (2015), for example, examined the forecasting performance of the Value-at-Risk (VaR) models in Egypt, Jordan, Morocco, and Turkey. Their results suggested that returns had a significantly fatter tails than the normal distribution and that Student APARCH model produced more accurate results than those generated using Normal APARCH models.

The considerable variety of results found in these different studies suggests to us that it is difficult to conclude that there is a 'one size fits all' model that can be used to model asymmetry affects in stock market returns.

We believe that our study contributes significantly to the literature by examining the relative forecasting performances of different distribution-type (Normal, Student-t, GED, and Skewed Student) and asymmetry-type (GJR-GARCH and EGARCH) GARCH models. Both our Superior Predictive Ability and Model Confidence Set results identify that GJR-GARCH with Skewed Student distribution is the best fitting model for Jordan. The finding in our research chimes with the findings of similar studies undertaken in different market contexts; such as Liu & Hung (2010) work in respect to the United States.

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