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Volatility Of AMS Stock Market (Jordan), Through A Comparable models And Approaches (1996 – 2010)

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Abstract

This paper focuses on the performance of various Garch models, were Arch model s not dismissed in term of their ability of delivering volatility forecasts for Amman stock market return data , in this paper a stationary Garch models were estimated , I have assess the performance of the maximum likelihood estimator , finally I have attempt to fit the dynamic of daily Amman stock return , by different models and BL approach , also has been used quantified the day –of – the week effect and the (γ) leverage effect in order to test for asymmetric volatility. This paper attempt to investigate and modules the volatility of Amman stock market using daily observations as the day – of – a week return index for the period from January , 1996 through the period to June , 30 , 2010 , to achieve this purpose I have divided the period of study into two periods , then I have estimated the data by using Arch (1), Garch , E Garch , and the Go –Garch models are employed . Arch and Garch models are used to capture the symmetry effects, whereas the E-Garch are used to capturing the asymmetric effect. Results can be stated as : the E-Garch model is most fitted model to forecasting data of returns volatility between Garch (1,1) and Garch (1,2) as model performance is very small , according to BL approach Alpha of AMS portfolio and frontiers returns is (- 0.6342) , and the risk ratio is (0.5331) .

Key words: Garch, Volatility, leverage effects, Amman stock market (AMS), BL approach,
Jell classifications: C55 , C8 , 016 , P27 , R15 .

1 - brief notes:

ASM (Amman stock market) or some named it Amman stock exchange like any emerging market is characterized by low turnover ratio, low liquidity, low transparency, and the non existence of market decision makers, the turnover ratio for the period of our data under investigation was 17.53%, and the average daily turnover was 0.9593 %, this ratio is too few, and these ratios are considered to be very small, the one of major action that might be effect trading activity. And the average daily turnover is ownership of individual investors and institutional, and government.

Table (1) shows the ownership structure

The ASM has witnessed an increased in the number of listed companies through out the years, which gives an indication of economic growth in Jordan, and stability during the period of 2003 -2010 in ASM. The trading volume increased year to year during the period of study , the results of visibility of AFM is superior than other stock markets in middle east region , it has undergone accelerated growth especially during the last 6 years due to stability and the Arab shares such Iraqi an investors , also Jordan government represented the board of international accounting standard .

Some indicators of ASM , It established 1976 and it is emerging stock market , the capitalization is 9.765m us , and the change 1n 1999-2001 is 8.4% , while it in 1996-2010 is 27.3%, where the capitalization ratio to GNI IS 58.9% , where the turnover is 13.54 m us and the turnover (liquidity)is 18.7%.

2 - introduction :

An efficient capital markets optimize the process of investment through which capital may be transferred from net savers to net borrowers, when this happens we can say that market is efficient, and the share prices must reflects all variables or available information which is relevant for the evaluation of company's future performance and therefore share prices must be the rational explanation for future discounted profits.

Emerging markets have received great attention in recent years due to some factors, such as the fast and quick grew of returns of trading volume, then increasing of number of listed companies in the emerging markets, also market capitalization.

Many previous studies and researches fund a low correlation between developed and emerging markets, which made emerging markets interesting for portfolio diversification, thus the high returns is exceeded which obtain in emerging markets is associated how ever with high risk and high volatility and high autocorrelation, many financial time series such as the returns on stock prices indexes have a certain characteristics which are well cited in the following literature.

A recent development in estimation of standard errors known as "robust standard errors," has also reduced the concern over heteroskedasticity. if sample size is large , then robust standard errors gives quite a good estimate of standard errors , even with heteroskedasticity , but if the sample is small ,the need for a heteroskedasticity correction that does not effect the coefficients .

In this paper the goal of such models is to provide a volatility measure like a standard deviation that can be used in financial decisions concerning risk analysis, portfolio selection and derivative pricing. Engle (1982) proposed to model time- varying conditional variance with auto –regressive conditional heteroskedasticity (Arch) processes using lagged disturbances. Laurent, and lecourt (2000), have used the student's distribution. Similarity to capture skewness and that was later extended to Garch frame work by lambert and Laurent (2000, 2001). Van der wide (2002) was proposed the GO-Garch model as a generalization of the orthogonal Garch model of Alexander (2001). Fan et al (2008) studied a general version of the model by relaxing the assumption of independent factors to conditionally uncorrelated factors. For surveys on multivariate volatility models was refer to Bauwens et al (2006) and for a glossary to volatility models.

Generally the model is designed and (asymmetric) volatility spillovers are accommodated which denoted the key stylized facts of multivariate financial data. Moreover, the model is closed under linear transformation; also it is closed under temporal aggregation, which makes the model analytically convenient as Hafner (2008). Vander wide (2002) proposed two step estimation methods that requires joint maximum likelihood (ML) estimation for parameters that feature both in linear transformation and in the univariate Garch specifications for the individual factors .

The overall results are that Garch models are unable to capture entirely the deviations in volatility. A regression of volatility estimates from Garch models on actual volatility produces R2 usually below 8 percent, however, a positive note, the Garch prediction of volatility. The Garch models are not wholly inadequate measures of actual volatility.

My framework in this paper is relatively and closely related to the recent papers by Alexander (2001), lambert and Laurent also Andersen and Bollerslev (1998), Hafner (2008), Diebod and Ebens (1999) and Fan et al (2008). Those papers shows that traditional tests of various volatility models which rely on ex- post squared returns as realized volatility are very noisy although an unbiased . Mackawa et al (2005) demonstrate that most of the Tokyo stock market returns data sets posses' volatility persistence and in many cases it is a consequence of structural breaks in the Garch process. Bauwens and Storti (2007) reported that often volatility goes up proportionally less after out laying shocks that it does after small and moderate shocks , to reduce the effect of outliers on the predicted volatility , my advocate in this paper of M-Garch , is where the effect of out laying returns on volatility predictions is bounded and also the Arch (1,1) has been used and other alternative models of stochastic volatility are implied volatility models from option pricing are not at debate here , in addition , various and other measures of volatility based on volume , price range which effected volatility of return of Amman Stock market . Finally this paper has organized as follows: section one contain introduction, where the second section briefly discussed of Arch model, and Garch models as a literature review of these important models in financial date estimation and the models of the study paper , section three discussed the data sources and methodology, sample tests are conducted on forth section, while section five presents out –of –sample performance is analyzed and the empirical results. Where section six conducted concluded remarks and references.

3 - Literature review of Arch and Garch model:

The purpose of forecasting volatility are for risk management and asset allocation, and for taking bets on future volatility, the risk management is this field is measuring the potential future losses of a portfolio of assets, this can be achieved by estimates of future volatility and correlations, a standard approach Markowitz of minimizing risk for a given level of expected returns is used, in other hand estimate of the variance – covariance matrix is required to measure risk. The simplest approach to estimating volatility to use historical standard deviation. one empirical observation of asset return is that squired returns are positively autocorrelation , if an asset in Amman stock market like a currency , commodity , stock price , or bond price made a big move in a days ago , it is more likely to make a big move to day . The Amman stock market crashed on November 2007, thus we can see anecdotally that large moves in prices lead to more large moves.

Volatility not only spikes up during the financial crisis , but it eventually drops to approximately as the same level of volatility as before crisis , it means that there is periodic spikes in equity volatility due to crisis that caused large market drops . in this option the models we look at will attempt to capture the autocorrelation of squared returns ,the reversion of volatility to the mean , as well as the excess kurtosis .

In this paper the first model I have used it is as a Arch model, which stands for autoregressive conditional heteroskedasticity. The conditional here comes from the fact that in these models, next periods volatility is conditional on information this period heteroskedasticity means non constant volatility (if the variance of residuals is not constant) , when we estimate the variables coefficients in the model by least square method , let us use Arch (1 ,1) model which developed by Engle (1982). We assumes that returns on asset is :

$\sigma_{2t} = C_0 + a1\ a_{2\ t-1}$ .... (1)

Where $C_0 > 0$ and $a1 \geq 0$ to ensure positive variance and $a1 \geq 1$ for stationary under an Arch (1) model, under the model estimate, if residuals returns, a_{2t} is large in magnitude, forecast for next periods conditional volatility, at+1 will be large, we can say in this state that the returns are conditionally normal, and the one period returns are normally distributed , and returns (r_t) are uncorrelated but are not i.i.d also we can notice that a time varying σ2t which lead to fatter tails , this relatively to a normal distribution (Campbell, Lo . and Mackinaly (1997) . the second model is Garch model , we notice in Arch (1, 1) next periods variance only depends on last periods squared residuals , an Arch (1,1) model is an Arama (1,1) model, so the crisis that caused a large residual would not have the sort of persistence this led to an extension of the Arch model to a Garch generalized Arch model which dev eloped by Bollerslev (1986) :

$\sigma_2 = C_0 + a_1\ a_{2t-1} + B\ \sigma_{2t-1}$ .... (2)

Where: $C_0 > 0$, a1>0, B1 >0 and a1+B1 >1, so that our next period forecast of variance is a blend for our last period forecast.

Since at is a stationary process:

Var (at) = $C_0 / 1 - a_1 - B_1$ .... (3)

A Garch (1, 1) model can be written as an Arch (∞)

$\sigma_{2t} = C_0 + a1\ a_{2t-1} + C_0\ B_1 + a_1\ B_1 a_{2\ t-2} + B_1\ 2\ (C_0 + a1a2\ _{t-3} + b_1\ \sigma_{2t-3}$ .... (4)

;

;

$= C_0 / 1 - B_1 + a_1 \sum a_{2t-1} - Ib_{1i}$ ....(5)

We can write the Garch (1,1) equation yet in another way :

$\sigma 2t = (1 - a_1 - B_1)\ E[\sigma_{2t}] + a_1 a_{2t-1} + B_1\ \sigma_{2t-1}$ ....(6)

As this model Garch (1, 1) we can see that next period conditional variance is a weighted combinanation of the unconditional variance of returns. From the 1st – step a head variance forecast we can notice that (a1 + B1) determines how quickly the variance forecast converges to the conditional variance. If the variance spikes up during a crisis , we can measure the half life which given by :

$K = \ln (a_1 + B_1)\ K \quad / LN (a_1 + B_1)$ .....(7)

This indicates for the half way between the first forecast and the conditional variance, where k indicates for number of periods.

The question which rises up how implied volatility react asymmetrically to up and down stock market moves; in this case we should use other index which measure the weighted average of the implied volatility of short term of the stock market.

We can not give a clear interpret for why volatility should increase more than the level of stock market prices drop compared to a stock price rise , in other hand as stocks drop , the debt / equity ratio increased and stock become more volatile with higher leverage ratio , the leverage could be explain the changes in volatility associated with stock market are much larger than that which could be explain by leverage Glosten , Jagannathan and Runkle (1993) has an account the asymmetric model of Garch model called GJR – Garch model , also known as T-Garch

(Threshold) which can be written as:

$\sigma_{2t} = C_0 + a_1\ a_{2t-1} + \gamma_1\ S_{t-1}\ a_{2t-1} + B_1\ \sigma_{2t-1}$ .... (8)

We can estimate γ1 by using maximum likelihood techniques, another variant Garch model to account for a symmetry known as E – Garch (1, 1) model by Nelson (1991), and can be written as:

$\ln (\sigma_{2t}) = C_0 + a_1\ a_{2t-1} + \gamma_1 (a_{1t-1}) + B_1\ \ln (\sigma_{2t-1}) \quad / a_{1t-1}$ ....(9)

Another variation of a Garch model known as Garch (1,1) – M , which tests whether variance can impact the mean of future returns .

4 - The model:

There are several reasons that we may want to model and forecast volatility, first to analyze the risk of holding an asset or the value of an option , second forecast confidence intervals may be time varying , so more accurate intervals can be obtained by molding the variance of the errors , third , more efficient estimators can be obtained if heteroskedastisicty in the errors is handled properly . Thus the variance of the dependent variable is modeled as a function of the past values of the dependent variable and independent or exogenous variables, therefore the Arch model have to consider two distinct specifications one for the conditional mean and one for the conditional variance . We can define the Garch – M model which introduce the conditional variance in mean /(Engle, Lillian , Robins ,1987) as :

$$Y_t = Xt\,\gamma + \sigma_{2t}\,\gamma \qquad \text{………………..(10)}$$

This is a variant of the Arch – M specification, in this model we can use the conditional standard deviation instead of conditional variance, and we often used in financial applications where the expected return on a assets is related to the expected coefficients on the expected risk is a measure of the risk – return trade off ..

The simplest model is an Arch model , let us assume that the return of stock market on asset is :

$$Rt = \mu + \sigma_{2t\acute{e}t} \qquad \text{………………………………(11)}$$

Where: έt is a sequences of N(0,1) i.i.d random variables , we can define the residual returns as :

$$\acute{\alpha}_t = \sigma_{2t\acute{e}t} \qquad \text{……………………….(12)}$$

Engle (1982) has developed Arch (1) model , which can be written as :

$$\sigma_{2t} = \acute{\alpha}_0 + \acute{\alpha}_1\acute{\alpha}_{2t-1} \qquad \text{………………… (13)}$$

The kurtosis of άt is defined in normal distribution, the kurtosis of 3:

$$\text{Kurtosis (at)} = 3\ E\ \{ \sigma t4 \} / \ \ E\{ \sigma 2t\}2 \qquad \text{……………(14)}$$

And since is a stationary, the var (at) = var (at -1) = e (a2t-1) .so

$$Var\ (a_t) = a_t / 1\text{-}a_1 \qquad \text{…………………….. (15)}$$

If we consider that just as an Arch (1) model, is an AR (1) MODEL on sequenced residuals, an Arch (1) model is an ARMA (1,1) model on squared residuals which can be written as :

$$a_{2t} = C_0 + (a_1 + B_1)_{t-1} + vt - B_t v_{t-1} \qquad \text{………………… (16)}$$

And since at is a stationary process

$$Var\ (a_t) = C_0 / 1 - a_1 - B_1 \qquad \text{…………………..(17)}$$

The ARMA (1,1) can be considered as AR (∞), a Garch (1,1) , and it can be written as Arch (∞) as :

$$\sigma_{2t} = C_0 + a_1\, a_{2t-1} + B_1\, \sigma_{2t-1} \qquad \text{…………………… (18)}$$

And as the substitution:

$$C_0 / 1\text{-}B_1 + a_1 \sum a_{2\,t-1} - iB_i \qquad \text{…………………. (19)}$$

From this model it is easy to see the next periods conditional variance is weighted combination on the conditional variance of returns. Where last periods squared residuals (a_{2t-1}) , and last periods conditional variance (σ_{2t-1}) , it is clear that not only does the magnitude of (a_{2t}) effect future volatility , but the sign of (a_t) , also effect of future volatility at least for equities also it is not clear why volatility should increase more when the level of stock prices rise, and when stock prices drop, the debt / equity ratios increases and stocks becomes more volatile with higher leverage ratios .

The threshold Garch (T- Garch) model can be written as (Golsten et al, 1993) as follows:

$$a_{2t} = C_0 + a_1\, a_{2t-1} + \gamma_1\, S_{t-1}\, a_{2t-1} + B_1\, \sigma_{2t-1} \qquad \text{…………… (20)}$$

Where: {1, if at -1 < 0} or {0, if at -1 >0}

Another variation of Garch model tests whether variance can impact the mean of future returns, these models are referred as Garch – M, which represented as:

$$\sigma_{2t} = C_0 + a_1\, a2_{t-1} + B_1\, \sigma_{2t-1} \text{ …………………………….. (21)}$$

in some specifications , the volatility rather than the variance .

5 - Data and methodology:

The data related to Amman stock market daily observation of Amman stock index from 21/ 12/1992 ton31/6 /2010 which represents daily observation to estimate and forecast these results of observation indices , E-views5 is used as a package who proposed to estimate Arch and Garch models and many of it is extensions Parameters were estimated using the QML technique which proposed by Bellerslev and Wooldridge (1992), the conditional heteroscedasticity may be caused by a time dependence in the rate of information arrival to the market, therefore we can use the daily trading volume of stock market of Amman stock market as a proxy for such information arrival, and confirm it is significant as Johnston and Dinardo (1997) , who suggest a simple

test for the presence of Arch problem , we can named step –by –step as :
1- Regress Y on X BY OLS obtains the residuals {et}.
2- Compute the OLS regression:

$E_{t\,2} = a_0 + a1^{e}_{t-1} + a1e_{2t-1} + \ldots\ldots + ape2t\text{-}p + error.$

3- List the joint significant of a1, …., ap .
Green (1997) provided a straight forward method of estimation as:
1- Regress Yon X using LS (Least square method) to obtain B and e t vectors.
2- Regress e2t on a constant and e2t-1 to obtain the estimates of C0, and a1, note that the whole sample should by used in regression
3- compute: $Et = a_0 + a1e_{2t-1}$
4- re compute Et using a, compute and estimate B = B +db , where db is least squares coefficients vector in the regression .
The method of estimation of Garch as :
1- generate a series of N values from the standard normal distribution that is zt ~~N (1,)) .
2-Generate an equal number of values {et }t =1 by et = 2t √h2t .
3- repeat step one (1)and (2) 100 times to obtain data series .
4- Generate N bootstrap of (et1, j , ….,e100j) , j=1, …..,N
For each sample data are order from smallest to largest.
5- the 5^{th} step and 95^{th} values represents the lower and upper limits of 95 percent confidence interval . Other method can be used, such as the BL approach is selected to measure Alpha , risk , and tracking error , implementing the BL approach requires the specification of on other hand a suitable weight –on view to calibrate the confidence level of the perior belief (γΩ) . Also the matrix contains the uncertainty of the views. Black and Litterman (1992) and Leo (2000) suggests a solution to this practical problem by imposing (γ) to close to zero due to the uncertainty of the means is less than one of expected returns . therefore the calibration used the covariance matrix is assumed to be proportional to variance of the viewed portfolio according the equation is :
Si / γ = piΩ pi-
Where Si as ith diagonal eliminate in matrix S , piΩ pi- is the variance of the viewed portfolio and pi is ith raw in matrix . a unit root test has been justified the data to insure of stationarity of data also autocorrelation of squared residuals of portfolio returns to have the state of normal distribution and autoregressive state , then I have plot values at risk of Amman stock market (ASM) portfolio , lastly I have estimated the volatility of ASM returns , in both cases reduce or increase , then I have estimated the volatility regime . To obtain stationary series , I have used returns rt =100(ln (pt) – ln (pt -1) ,where pt is the closing value of index at date (t) . the sample kurtosis is greater than 3 , it means that return distribution have excess kurtosis for both indices . also excess skewness is observed , due to high Jarque – Bera statistics which indicating non – normality . In table (2) , shows descriptive statistics for logarithm differences of data . We simulate stock prices pt from the relation pt = e rt pt -1 is return series generated from the fitted models by taking boot strap steps 1 ,2 also we present the parameter estimates of Garch (1,1) and Garch (1, 2) . Table (3) shows the results as stationary condition holds for the models.

6 – empirical results :

. Respectively to table results , it can be observed that both Garch (1,1) and Garch (1,2) models fit the data , while Garch (1,1) does not exhibit clearly detectable superior performance to Garch (1,2) , thus we fund Garch (1,1) was adequate to capture most of the conditional heteroskaedsiticity .As daily stock returns may be correlated with the day – of – the week effect , therefore I have filtering the daily means and variances using the OLS method to fitted value of rt from regression results , hence we can write the the model as :

Rt = a1 Sunt +a2 Mont + a3 Tuet + a4 Went + a5Thurt + et ……………(22)

Returns of Sunday, Monday, Tuesday, Wednesday, Thursday. per t are the dummy variables for Sunday . the result of regression are stated in table (4) .
Unit root test to data has done to analyzed the data to insure of normal distribution, thus table (5) shows the results .In the table results two test for a unit root were carried out , the ADF and PP test , the lag length in the ADF case and the truncation lag in the PP case are chosen on the basis of the sample of autocorrelation function of returns , the lag is chosen as the highest one , for which this autocorrelation is significant provided this is less than √N . from the table results clearly rejected the null hypothesis of a unit root in favor of the trend – stationary alternative . table (6) shows the autocorrelation of squared standardized residuals of Amman stock market returns , the standardized residuals are examined for autocorrelation in table (6) , the autocorrelation are dramatically reduced from that observed in ASM portfolio returns , therefore applying the

test to find p-values at level 5 % of significant to insure of hypothesis as to accept the l hypothesis or no residual of Arch , forecast standardized deviation for the next day is 0. 0246 which almost double the average standard deviation , which are not very closed to normal distribution , and reflects the fat tails of the return distribution. Table (6) shows the autocorrelation of squared portfolio returns, that it dies quickly to zero from the 5^{th} lags and all observations are significant due to prob level, the value of risk has shown in figure (1) , as the figure the lower level in this year and a quarter , the value of risk exceeded only once ; this mean a slightly conservative estimation of the risk . According to table (7) the sample kurtosis rt's are 3.2578 and 5.01342, the skewness are – 0.3272 and -0.5663.

Suppose that we have two models, how do we know which models is better fit to data? Simply to answer this question, if the two models have the estimation of parameters, we could compare the maximum values of their likelihood functions, but if the models differ in their parameters we can use the Akaike information criterion (A IC) , which makes adjustment to the likelihood function .

Aic (p) = 2 ln (maximum likelihood) – 2p …………………… (23)

Where: p is the number of parameters in the model. The OLS estimate of two regression models shows that the indices have significantly positive daily mean on Sunday and significant daily variations for Sunday through week, I have estimate the effect by standardized the daily returns using the below function :

Rt = (rt rt) √π1 ………………(24) .

Where: π1 is the fitted value of (rt –rt)2 rom the regression 2 at date .

Table (7) shows the descriptive statistics for standardized yearly returns of ASM.

Returns rt are thus the normalized to zero mean and unit variance. According to table results of Jarque – Berra it indicates to normal distribution.

The second criterion attributed to Schwartz criterion (SBC), it demonstrated in our research here as:

SBC (P) = 2 ln (maximum likelihood) – p ln (T) ……………. (25) .

Where: P: is the number of parameters in the model, and T: is the number of observations of data in analysis. A common test has performed on et is the portmanteau test, which jointly test whether several squared autocorrelations of et are zero. The test statistics are proposed by Box and Pierce (1970) which preformed as:

Q (M) = T ∑ P I 2 …………………………(26)

And a modified version for smaller sample size proposed by Ljung and Box (1978) as :

Q (M) = T (T+2) ∑ P I 2 / (T-1) …………..(27) .

Where : m : is the number of autocorrelations , and T is the number of observation in data .when we are looking at Garch models , it is more relevant to test the autocorrelations of squared residuals of the model so p is the autocorrelations of et 2with et2 -1 rather than the autocorrelation of et with et -1 , therefore I have analyzed the densities setting these quantities of data to their unconditional expected values to avoid the recursive evaluation of maximum likelihood on the un observed values . results are available in table (8) , and table (9) as comparable between models .

The models above in table are described the dynamic of the two moments of the series which proposed by Box – Pierce statistics for residuals and squared residuals , the stationirty constraints are observed for each model . According the results of table we can demonstrated that CO –Garch is the best choice due to small amount results in AIC and SBC also as the skewed. Forecasting analysis for return index is made in table (9) to compare densities. And for every density all models are non significant at 5 percent level , these values suggests long persistence of the volatility for the indices , the skewed student – distribution shows results that are superior to the symmetric t – student and log likelihood ratio is too large scale , thus it is necessary to add a symmetric Garch models . compare between densities Most measures in the variance equation , the E-Garch model out performs the CO-Garch model and provides poorest forecasts , while Garch model provides much less satisfactory results , where E-Garch gives better forecasts than other models , and in models skewed distribution , it most successful in forecasting ASM conditional variance , thus we can concluded that the skewed student densities is more appropriate for molding the ASM , and it seems to be the best for forecasting series .

Table (10) shows respectively the resulting portfolio and frontiers updated according to mean – variance paradigm and the manager's view with fixed TE = 5%.

Table (10) : forecast ASM portfolio by using BL Approach .

. Finally I have presents the parameters estimate of Garch (1,1) and Garch (1,2) in table

p (11) . as for the stationarity discussed ∑ά1 + B1 in both model are all less than one , though rather close to , the stationarity condition holds for the fitted model

The comparative plots of two simulated models almost coincide , conforming again , thus the difference between models performance is too small , thus mainly I decided to choose Garch (1, 1) in analysis the volatility . Finally I should estimate the volatility, this is presented in table (12).

According to results of table the single regime model of volatility has a negative sign thus the relationships is inverse relation, when the volatility increases and also when there is reduction, also in single regime model threshold is 29.3, the average of return has inverse relation with the effected variables when the volatility increases, but proportional relationship when the volatility reductions. Lastly I have estimated the Sunday effect in ASM using the mean equation and the variance equation through comparison of analysis the week of ASM which start on Sunday and end on Thursday , the result is stated in table (13) . The model which used to determined the results is Garch model (1, 2)-M, as results the effect of Sunday as opening day of sell and buy clearly has negative sign but not largely than other days due to aware of dealer in ASM, and they are not deal to much in first day of their week, they are wait to other days as individual expectations and waiting for more information of good news or bad news.

7 - Concluded remarks:

This paper enriched the empirical work by accommodating the following issues , first it adjusts for sample size and long period of study which extended from January 1996 up to June of 2010 , also changing of volatility of time-series shocks , autocorrelation and /or fat tails in the distribution of average ASM returns , second I have analyze the daily return pattern and Sunday effect , thirdly , it utilized from some measurement errors hypothesis in different models as compression to choose the best model for analysis the data . Therefore this paper is an attempts to investigates and model the volatility of ASM emerging stock market using the daily returns for the period under investigation, for achieving this purpose, the Arch, Garch, CO-Garch are employed to data analysis in hence of the procedure I have used Arch and Garch models to capture symmetric effects , whereas the other models are employed to capture the asymmetric effects , the data of returns as daily returns or yearly returns showed both of them a significant departure from normality and the existence of conditional heteroskadesticity (volatility clustering), this paper was built on four hypothesis, the first hypothesis was to examine the volatility through using different models, second hypothesis was to capture a symmetric effect through these models, thirdly was to check whether the BL approach can determined the volatility and asymmetric volatility, the forth hypothesis is to determined which model is the best model to fit the data. I have fund that returns are volatile and that has a positive shocks on daily data and yearly returns , also I have fund that volatility response to shocks tends to positive in ASM . Although the Garch model (1,1) and Garch (1,2) are fund that it can display asymmetric effects , and it was better than other models , due to the log likelihood ratio and to other diagnostic test such as kurtosis , skewed ,and lower statistics of Jerque and Berra statistics .

The ASM not follow a random walk over the period Jan , 1996 to- June , 2010 , this can be explain the market capitalization and liquidity , capitalization average gives an evidence as 128% than the last periods (1990-1996) , also we can add that due to non – restricted movement of capitalization as ASM an opening –up of the market . In addition to these results the daily returns and yearly exhibit significant non – linear decency, while the daily returns from the ASM do not confirm to a random walk.

These results is consistent with previous studies results documented in the literature , such as the positive significant of Sunday effect of daily return , and the ASM do not confirm to a random walk .

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Index :

Table (1) shows the ownership structure

Owners	%
Foreigner	3.7
Arab citizens	43.8
Jordanian	52.5
Total	100%
Individuals	57.3
Companies	38.8
Government agencies	3.9
Total	100%

Table (2) : descriptive statistic for logarithm differences . 100 (ln pt - ln pt-1) .

Index	Average	Min	max	Std .dev	kurtosis	skewness	Jerque – Bera statistics
ASM	0.0653	- 9.2535	8.435	1.2361	3.3051	- 0.3144	412.36

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Table (3) : two periods of data Garch tests results

Period one	γ	Ά1	Ά2	B1	Ά1 +B1∑
Garch (1,1)	3.612e-04	1.673e-01	--------	6.223e-01	0.9301
Garch (1, 2)	5.843e-04	1.026e-01	9,807e-02	6.0183e-01	0.9135
Period two					
Garch (1,1)	6.453e-05	8.432e-02	-------------	7.498e-01	0.8765
Garch (1,2)	6.0132e-05	5.631e-02	2.123e-01	7.8113e-01	0.8923

Table (4) : OLS result of daily return for the sample period of ASM .

Days	mean	S,Error	Variance	S,Error
Sunday	0.173*	0.014	3.5371*	0.267
Monday	0.086	0.127	0.986**	0.265
Tuesday	0.043	0.126	1.7742**	0.273
Wednesday	0.0167	0.126	1.9324**	0.273
Thursday	- 0.0387	0.127	1.3489*	0.273

Significant * at 5 percent level , ** significant at 10 percent level .

Table (5) : results of unit root tests by ADF and PP.

ADF	PP	Lags	10%	5%
-3.987**	-15.634 **	30	-2.860	-3.0796

** Significant at 5 percent and 10 percent level.

Table (6) : Autocorrelation of squared standard residuals of AMS returns .

lags	AC	Q- Stat	Prob
1	0.0138	0.05177	0.798
2	0.029	3.0192	0.265
3	- 0.012	4.3275	0.227
4	-0.018	4.9382	0.298
5	0.0127	5.2763	0.310
6	- 0.0254	5.10463	0.408
7	- 0.0134	5.8876	0.574
8	- 0.0327	6.1224	0.552
9	- 0.0072	6.9382	0.623
10	- 0.0325	7.3874	0.687
11	- 0.0154	7.8959	0.521
12	-0.013	9.5443	0.635
13	-0.005	10.038	0.715
14	- 0.008	11.4346	0.758
15	-0.021	13.0523	0.761

Data Autocorrelation used 15 lags.

Table (7): descriptive statistics for standardized yearly returns of ASM.

	St / dev	Kurtosis	Sekwness	Jarque-Berra stat
ASM	0.7866	3.2578	- 0.3272	29.21

Table (8) ASM portfolio data analysis

	Normal	Students	skewed
	Arch	Garch	Co-Garch
Q (20)*	28.639	28.625	28.214
Q 2 (20)*	29.052	30.741	29.877
P (100)**	68.332	51.297	44.318
Prob (1)	0.064	0.427	0.537
Prob (2)	0.032	0.239	0.218
AIC ***	2.693	2.584	2.584
SBC ***	3.215	3.108	3.107
Log likelihood	- 2950.936	- 2863.050	- 2845.693

* Q (20) and Q2 (20): respectively the Box- pierce statistics at lag 20 of the standardized and squared standardized residuals.
P (100) **: Pearson's goodness of fit with 100 cells.
*** AIC: Akiake information criterion.
*** SBC: Schwartz Bayesian Criterion.

Table (9): Forecasting analysis for returns of ASM

	Garch student –t	Garch skewed	E – Grach t-student	E – Grach Skewed	CO-Garch t-student	CO-Garch skewed
MSE (1)	0.214	0.215	0.267	0.260	0.263	0.260
MSE (2)	0.438	0.438	0.317	0.309	0.428	0.420
Med SE (1)	0.0452	0.0452	0.0435	0.4035	0.0398	0.0394
Med SE (2)	0.296	0.251	0.282	0.279	0.248	0.249
MAE (1)	0.289	0.287	0.288	0.287	0.291	0.290
MAE (2)	0.543	0.541	0.556	0.543	0.548	0.547
RMS (1)	0.517	0.517	0.522	0.522	0.517	0.518
RMS (2)	0.693	0.690	0.672	0.668	0.698	0.693
AMA PA (2)	0.873	0.872	0.869	0.867	0.824	0.829
TH.I (1)	0.872	0.861	0.869	0.868	0.873	0.870
TH.I (2)	0.538	0.529	0.532	0.541	0.529	0.528

(1): indicates to mean equation.
(2): indicates to variance equation.

Table (10) : forecast ASM portfolio by using BL approach

Portfolio indicators	Ratios %
Returns	0.8971
Alpha	- 0>6342
Risk	0.5331
Sharp ratio	1.0927
Tracking error	2.4236

Table (11) : parameters estimate of Garch (1,1) and Garch (1,2).

Models	ω	ά1	ά2	в1	+B1∑ά 1
Garch (1,1)	3.825E-04	1.502E-01	....	6.5432E-01	0.8703
Garch (1,2)	5.473E-04	1.023E-01	0.8972E-02	6.123E-01	0.8124

Table (12): volatility as single regime model and restricted regime model.

	Single regime model	Low volatility regime	Average return
Volatility increases	- 0.876	....	....
Volatility reductions	-0.896	....	....
Threshold	29.3	......	......
Low volatility regime			
Volatility increases		- 0.763	- 1.216
Volatility reductions		0.481	0.923
Restricted regime (one regime)	142.2		659.4

Table (13) : test for the Sunday effect in ASM daily returns .

Day of week	Sunday ά1	Monday ά2	Tuesday ά 3	Wednesday ά 4	Thursday ά5	ω	γ	в1
Mean equation						Variance	Equati	on
Coefficient	- 0.063	- 0.07	- o.083	-0.094	- 0.068	0.02	0.18	0.53
Standard Error	0.31	(0.09).	0.07	0.00	0.29	0.00	0.00	0.27

Are the coefficients of variance equation. ω , B1 , and γ