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MODELING MARKET VOLATILITY IN EMERGING MARKETS: THE CASE OF DAILY DATA IN AMMAN STOCK EXCHANGE 1992-2004

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Abstract
This paper attempts to investigate the volatility of the Jordanian emerging stock market using daily observations from Amman Stock Exchange Composite Index (ASE) for the period from January 1, 1992 through December 31, 2004. Preliminary analysis of the data shows significant departure from normality. Moreover, returns and residuals show a significant level of serial correlation which is related to the conditional heteroskedasticity due to the time varying volatility. These results suggest that ARCH and GARCH models can provide good approximation for capturing the characteristics of ASE. The empirical analysis supports the hypothesis of symmetric volatility; hence, both good and bad news of the same magnitude have the same impact on the volatility level. Moreover, the volatility persists in the market for a long period of time, which makes ASE market inefficient; therefore, returns can be easily predicted and forecasted.
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1. Introduction

The measure of asset's volatility is a measure of its total risk. Risk is one of the features usually analyzed by investors in the process of determining their optimal efficient portfolio. Estimating and forecasting financial market volatility is very important to investors as well as to policy makers. It helps in investment decisions, security valuation, risk management, and in selecting and choosing appropriate hedging instruments (Anderson et al. 2000). In addition,

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understanding, measuring and pricing risk is important for allocative efficiency, which has a great impact on the economy as a whole.

Many financial time series such as the returns on stock price indexes have certain characteristics which are well cited in the literature. Previous research found that asset returns have leptokurtic unconditional distributions (Mandelbrot 1963, Fama 1963, Fama 1965), which is related to the time varying volatility (Corhay & Rad, 1994). They are characterized by volatility clustering (Mandelbrot 1963, Fama 1965). At any time, any causal observation of financial time series reveals high and low volatility episodes (Schwart 1989). This implies that volatility chocks today will influence the expectation of volatility many periods in the future. Skewness can be related to the fact that stock prices tend to cluster; large (small) changes are followed by large (small) changes (Bollerslev, 1987), (Lo, 2000). Another feature of stock returns is mean reversion; hence, there is normal level of volatility to which volatility will eventually return. This implies that current information has no effect on long return forecast. Also one of the major findings in the literature is that different types of news have different impacts on the volatility level. This phenomenon is called the asymmetric or the leverage effect (Black 1976, Koutmos et al., 1993, Anderson et al., 2000). It suggests that stock price movements are negatively correlated with volatility. Empirical evidence reported by Black, Christie (1982), and Schwart 1989), however, suggests that leverage alone is too small to explain the empirical asymmetries observed in security process. Finally, it was found in the literature that volatility is highly persistent.

Emerging markets have received great attention in recent years due to many factors. First, many emerging stock markets grew fast in terms of trading volume, number of listed companies and market capitalization. Therefore, international investors have renewed interest in these markets to get the benefit of their attractive prospects. Second, previous research found a low correlation between the developed and emerging markets, which made emerging markets interesting for portfolio diversification. Although, Bekaert and Harvey (1995) suggested that many emerging markets are becoming more integrated into the global capital market, there still many differences between emerging and developed stock markets. Third, emerging markets are found to provide higher return than those of developed markets. The high return in emerging markets is associated, however, with high volatility and high serial correlation.

Previous literature concentrated on few emerging markets as those of Latin American and Asian markets as good candidates for portfolio diversification. This motivated researchers to study the return and volatility behavior of these markets. Even though the Jordanian Market is considered one of the most important markets in the Middle East, little attention has been given to this market by foreign investors and by researchers. Therefore, this study is interested in capturing stock prices behavior by econometrically modeling volatility of Amman Stock Exchange Composite Index (ASE) for the period January 1, 1992 through December 31, 2004. We will show that the volatility of ASE is high and persists for a long period of time despite the 5% price limit imposed. We will examine if GARCH effects do exist in the volatility of ASE index returns, and whether stock returns in the said market display symmetric or asymmetric volatility. We used the econometric models previously used in the literature, such as ARCH, and GARCH models, to find the most appropriate one that can capture ASE stock index returns.

Preliminary analysis of the data shows significant departure from the normality. Moreover, returns and residuals show a significant level of serial correlation which is related to the conditional heteroskedasticity due to the time varying volatility. Since heteroskedasticity makes the estimation of asset pricing relationships inefficient, therefore, appropriate econometric techniques should be implemented to control for heteroskedasticity in our model. Our preliminary results suggest that ARCH-type models can provide a good approximation for capturing the characteristics of ASE. The empirical analysis supports the hypothesis of symmetric volatility; hence, both good and bad news of the same magnitude have the same impact on the volatility level. Moreover, the volatility persists in the market for a long period of time, which makes ASE market inefficient; therefore, returns can be easily predicted and forecasted. The paper is organized as follows. Section 2 will provide an overview of the main characteristics of Amman Stock Exchange. Data and methodology will be presented in section 3. Section 4 will provide an empirical analysis and shows the results of our analysis. In this section, preliminary results will be provided first which will pave the way to the volatility analysis. Finally, the last section will summarize and concludes the paper.

2. Characteristics of Amman Stock Exchange

The temporary law No. 31 of the year 1976 gave the permeation to establish a market known as Amman Financial Market (AFM), and operation were officially started on the 1st of January, 1978. AFM was established to regulate the issuance of securities, a place that could ensure safe, speedy and easy trading for suppliers and demanders and to protect small savors through a mechanism that would define a fair price based on supply and demand. Moreover, two major tasks were given to AFM; first to take the role of Security and Exchange Commission (SEC), and the role of a traditional Stock Exchange. In March 1999 AFM was legally split up to create Jordan Security Commission (JSC) and Amman Stock Exchange, or the security market.

ASE is considered to be one of the most important markets in the Meddle East, which currently lifted all restrictions on foreign investments. It consists of two markets; the primary and the secondary markets, and four major sectors: Banking, Services, Insurance and Industries. The secondary market in ASE is subdivided into six major markets; first market, second market, third market, bonds market, mutual funds market and transactions off the trading floor. The ASE market has witnessed an increase in the number of listed companies through out the years, which gives an indication of an economic growth in Jordan. Market capitalization also increased since the establishment of the ASE market. At the end of 2004, 192 companies were listed on the market with a total market capitalization of 13033.8 million JDs (Key Statistics of the ASE).

ASE, like any emerging market, is characterized by low turnover ratio, low liquidity, low transparency, and the nonexistence of market makers. The turnover ratio for the period under investigation was 15.77% and the average daily turnover was 0.064%. These ratios are considered to be very low and the trading activity in ASE market is considered to be very thin (Chandrasekhar, 2001). One of the major actions that might affect the trading activity and by then the average daily turnover is the ownership structure of the market. The ASE market ownership is a composite of individual investors (Jordanian and foreign investors), institutional, and government. Table 1 presents the ownership percentage on average for the period from 1992 to 2003.

As can be seen from the table below, that individual investors own the highest percentage of securities. But still the average daily turnover is very low and can not be attributed to the ownership structure. It can be said that ASE is a shallow market and the idea of investment in the stock market is not popular yet especially to individual investors.

Table 1. Ownership structure

	Average ownership percentage
Foreigners	1.9%
Arabs	9.2%
Jordanian	88.9%
Total	100%
Individuals	53.6%
Companies	28.9%
Government Agencies	4.6%
Government	6.4%
Others	6.5%
Total	100%

In addition, ASE imposes daily price limits on the stock prices. These limits are stated in terms of plus or minus a specific percentage of the previous day's closing price. This action is taken to protect small investors from big investors who can influence stock prices by selling and buying large quantities in the trading session. These limits were changed through the years, it was 10% before the Gulf War, and was reduced to 2% during the Gulf War on 1991. After 1991 until now the price limit are set at 5%. The two main restrictions of 5% daily price limits along with the restriction on short selling have major implication on stock prices, such as producing high correlation between stock prices, making future prices predictable and reducing the efficiency of the market. The results from the previous literature about price limit is, however, controversial (Kim and Sweeney 2002), while some argue that price limits reduce the market volatility and investor's overreaction (Ma et al. (1989)), others found that price limits neither reduce market volatility nor the investor's overreaction (Kim and Rhee 1997)

3. Data and Methodology

3.1.Data and variables definition. The data used in this study is the daily closing prices of the weighted index of ASE, from which the daily rates of returns are calculated as the first difference in the logarithmic closing prices for the period form January 1, 1992 through December 31, 2004. At the end of 2004 the number of companies that were included in the weighted index is 70. The rate of return on the index is calculated by:

$$R_t = (\log P_t - \log P_{t-1}) * 100 \tag{1}$$

where: R_t: is the return index at time *t*. P_t, P_{t-1}: are closing index price at the current day and previous day respectively.

Two measures of volatility are used in the literature: historical also known as realized volatility, and implied volatility. While implied volatility represents the market expectations of a stock future price, historical volatility is the measure of a stock movement based on historical prices. It measures how a specific stock or an index moves over a certain period of time (Active trader, 2001). In this paper we will use historical volatility, measured by the standard deviation of the stock returns.

$$HV=\sqrt{\frac{\sum_{t=1}^{n}(R_t-R_m)^2}{n-1}} \quad (2), \qquad R_t=\log\left(\frac{S_t}{S_{t-1}}\right) \quad (3), \qquad R_m=\frac{\sum_{t=1}^{n}R_t}{n} \quad (4)$$

where HV: historical volatility; R_t: stock return; R_m: average stock return; S_t: stock's price at current day: S_{t-1}: stock's price at previous day. To annualize historical volatility, we multiply it by the square root of the average number of trading days.

3.2. Methodology. In order to estimate and forecast the volatility of stock index return in Amman Stock Exchange (ASE) market, four different ARCH-type models will be used, two models for *testing the symmetric volatility*; the ARCH and GARCH models and two models for *estimating the asymmetric volatility* which are the EGARCH and GJR-GARCH models. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model that can capture most of the stock prices behavior. ARCH model was generalized by Bollerslev in 1986 into the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH). This generalization allowed for a more flexible lag structure by including autoregressive terms of the volatility (Sharma et al., 1996). To capture the asymmetric effect in stock prices, we will apply the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model introduced by Nelson (1991); this model can capture the asymmetric effect because the conditional variance depends on the sign of the lagged residuals (Helan, 2002). Another asymmetric model was introduced by Golsten, Jagannathan, and Runkle in (1993); the GJR-GARCH model, in which contrary to the GARCH model the squared residuals have different values depending on whether they are positive or negative (Helan, 2002). Finally, we will apply the Threshold ARCH (TARCH) model introduced by Zakoian (1990) which is the same as the GJR-GARCH model, but instead of modeling the conditional variance, it accounts for modeling the standard deviation.

ARCH model introduced by Engle (1982) is as follows (Sharma et al., 1996):

$$R_t = X_t\beta + \varepsilon_t \qquad \varepsilon_t \big| \Omega_{t-1} \sim N(0, h_t) \tag{5}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 \tag{6}$$

where: Y_t: is a random variable, the stock returns. $X_t\beta$: is the conditional mean of the random variable, representing a linear combination of lagged endogenous and exogenous variables in the information set Ω available at time *t-1*, the residual is normally distributed with zero mean and conditional variance h_t. p: is the order of the ARCH process, the number of lags. α_0, $_I\alpha_1$ and β: coefficients to be estimated using maximum likelihood estimation. $p > 0$, $\alpha_0 > 0$ and $\alpha_i > 0$ must be assured to get a conditional variance $h_t > 0$. The conditional variance h_t in financial literature is called volatility (Lo, 2000).

The ARCH model was extended by Bollerslev in 1986, because it was found that the ARCH model needed long lag length to be able to capture and explain the financial data (the excess kurtosis in data), in which GARCH model allows for a more flexible lag structure. That GARCH model is presented as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{7}$$

Where $p \geq 0, q \geq 0 \quad \alpha_0 \geq 0, \alpha_i \geq 0 \quad \beta_j \geq 0$

These conditions are needed as in ARCH model so the conditional variance $h_t > 0$. The main difference between GARCH and ARCH is that GARCH model allows the conditional variance to be dependent on its past values. The coefficient of α_i represents the impact of current news on the conditional variance process (volatility), β_j shows the impact of old news on the volatility, or the persistence of volatility to a shock. The level of persistence of volatility as was shown by Engle and Bollerslev (1986) depends on the sum of α+β. If the sum equals or higher than unity, then the persistence of volatility to a shock will last in the future and it is said to be an integrative GARCH (IGARCH) process. However; if the sum is less than a unity then the persistence of volatility is not expected to last in the long future, volatility response to shocks diminishes by time. The existence of GARCH effects in stock returns requires that α and β to be more than zero and significant (Sharma et al., 1996). ARCH and GARCH models could not capture the asymmetric effect in the financial data, which is different type of news have different impact on future stock market volatility. To solve this problem, Nelson (1991) introduced a model that can capture the stock market behaviour including the asymmetric effect. This model is the exponential GARCH (EGARCH) model with the following equation:

$$\log h_t = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta\log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{8}$$

Where ω, α, β and δ are coefficients to be estimated, and δ is the measure for the asymmetric effect, where the sign of yesterday's shock enters the model in contrast to simple GARCH. The advantage of using the logarithmic construction on the EGARCH model is that the conditional variance will be positive, so there will be no need to impose a restriction of non-negative coefficients. If δ is less than zero or greater than zero and significant, then the data is said to have a leverage effect. However, if the asymmetric coefficient (δ) is equal to zero then both positive and negative shocks of the same magnitude will have the same effect on market volatility. The persistence of shocks to the volatility is given by β (Lilien et al., 1995).

Another asymmetric model is the GJR-GARCH model, which was introduced by Golsten, Jagannathan and Runkle in 1993:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \delta d_{t-1}\varepsilon_{t-1}^2 \tag{9}$$

d_{t-1}: is a dummy variable that is added to capture the asymmetric effect in data. This dummy variable takes the value of one if ε_{t-1} less than zero, and zero otherwise (Lilien et al., 1994, 1995). α shows the impact of good news, while α+δ the impact of bad news. The leverage effect exists if δ is significantly greater than zero. β measures the persistent in the conditional variance, the sum of α + β+ δ/2 provide the persistence of shocks on volatility. If the sum is less than one then the shock is not expected to last for a long time, close to one means that the shock will affect volatility and the volatility can be predicted for some time. However, if the sum of the coefficients is one then shock is to affect volatility for the indefinite future. Like the GARCH model when coefficients are equal to one the model will be (IGARCH) (Helan, 1993).

4. Empirical Results

4.1. Preliminary Results: Table 2 shows descriptive statistics for the data, stock price index and for the return on the index. It is obvious from this that neither the stock price index nor return index are normally distributed. They are both significantly skewed to the right and have an excess kurtosis, and the series are leptokurtic. The Jarque-Bera statistic test for normality confirms the results based on skewness and kurtosis; the hypothesis of normality is rejected at the level of 1% for both price and return index. Ljung-Box test is used to test for the autocorrelation between data by taking the first-order up to the twenty second-order.

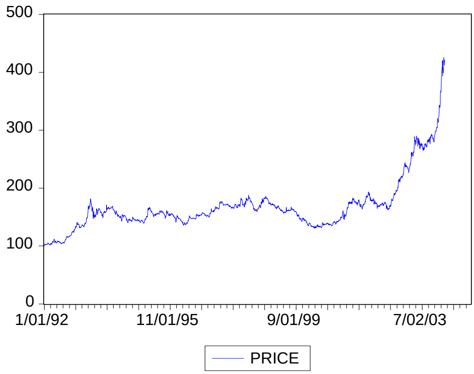
Table 2. Statistics for Price Index and the Return Index

		Price Index	Return Index	
N		3180	3179	
Mean μ		168.62	0.019	
Sta. Dev. σ		47.176	0.324	
Skewness		2.312	0.282	
Kurtosis		9.895	7.499	
Jarque-Bera		9132.608***	2724.12***	
Q(1)	$Q^2(1)$	3149.3***	194.09***	449.63***
Q(2)	$Q^2(2)$	6265.2***	194.25***	657.92***
Q(6)	$Q^2(6)$	18404***	196.85***	878.68***
Q(10)	$Q^2(10)$	30011***	198.12***	1203.5***
Q(12)	$Q^2(12)$	35632***	202.35***	1292.6***
Q(22)	$Q^2(22)$	61886***	249.30***	1427.9***

Notes: Q (1-22) is Ljung-Box test for serial correlation in the price index and return, Q^2 (1-22) is the Ljung-Box test in the squared return index. Jarque-Bera is the test for normality. *** denote significance at the 1% level. Critical range of skewness for price index and return index are ± 0.0869, ± 0.0174 respectively, as for the critical range of kurtosis for price and return index; ± 3.1737,± 3.1738 respectively.

The hypothesis of no serial correlation is significantly rejected at the level of 1% implying high level of autocorrelation. The price index showed higher autocorrelation than the return, this is due to the fact that the returns are calculated by using the first differences of the logarithmic price index, and differencing data reduces the serial correlation. Moreover; the autocorrelation for the squared returns are much higher than those of raw return data which is consistence with the literature for the characteristics of financial series data suggesting the presence of conditional heteroskedasticity (Lo, 2000) and the persistence of volatility. The high level of autocorrelation can be caused by the imposition of daily price limits on stock prices on ASE (Chiang & Doong, 2001). Figure 1 shows price index.

Figure 1. Price Index



For the price index and by applying both unit root tests, the hypothesis of non-stationarity is rejected implying that the price series is not highly stationary. However, when applying the same tests to the return index (by taking the first differences of the price index), the hypothesis of non-stationarity is strongly rejected by having a large negative *t*-statistics for the ADF and PP test, these findings are supportive to the martingale process for stock prices. Until this point of analysis and after testing data for normality and unit root, the data is shown to be not normally distributed, and the existence of conditional heteroskedasticity. The next step is to make sure that data displays heteroskedasticity through testing the unpredictable part of stock returns, the error (residual) term. This is done by running an Autoregressive regression for the return series by taking the sixth-lag order and test the standardized residual for excess skewness and kurtosis. Results showed that the standardized residual is not normally distributed, although the skewness coefficient is small, still significantly skewed to the right. However, the kurtosis coefficient is significantly larger than three so the residuals display excess kurtosis thus, the residual is leptokurtic. The Jarque-Bera statistics rejects the hypothesis of normality at the level of 1%. The serial correlation, using the Ljung-Box, shows that the standardized residuals are not correlated up to the twenty second-order, but the squared residuals is highly correlated; the hypothesis of no serial correlation for the squared residuals is rejected at the level of 1%. This result indicates the existence of time-varying volatility (volatility clustering) in stock prices (Chiang & Doong, 2001).

Table 3. Unit Root Test

	Price Index	Return Index
ADF	4.420438	-24.21482
PP	4.569682	-43.32784

Notes: ADF stands for the Augmented Dickey-Fuller test for the presence of unit root. PP stands for Phillips-Perron unit root test. The critical values for ADF and PP statistics are taken form Mackinnon (1991). Critical values: -3.9664 at 1%, -3.4139 at 5% and -3.1287 at 10%. Lag length: 4 for ADF and 8 for PP.

At this stage it is clear that ASE data are not normally distributed and the existence of conditional heteroskedasticity (volatility clustering) can not be rejected. These characteristics therefore, suggest that the ARCH-type models provide a good approximation that captures the time-series characteristics of the daily returns in the Jordanian stock market during the period under consideration (Corhay & Rad, 1994).

4.2. Volatility Results: Table 4 presents the results for the four different ARCH-type models for the period from January 1, 1992 through December 31, 2004. The mean equation in all models includes AR (1) to remove any serial correlation in the returns which may be caused by non-synchronous trading in the stocks (Schwert, 1989). The first lag order in the mean equation was selected based on the statistical significance of autocorrelations (Chiang & Doong, 2001). Since return series showed significant autocorrelations from the first lag, we will include one lag in the mean equation. Moreover, the number of lags order of the mean equation must be selected based on the lowest Schwartz (SIC) and Akaike (AIC) information criteria (Corhay & Rad, 1994), which was also achieved by the first lag order. The SIC and AIC criteria are also the main determinant of the optimal lag structure in the ARCH-type models.

Table 4. Estimates of ARCH-Type Models

	ARCH (1)	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH (1,1)
μ	0.0106 (1.7267)*	0.0057 (0.9971)	0.0127 (2.1712)**	0.0097 (1.6875)*
γ	0.2380 (8.1087)***	0.2646 (11.8415)***	0.2714 (11.7915)***	0.2651 (11.4817)***
ω	0.0672 (16.1533)***	0.0068 (5.5384)***	-0.5100 (-8.3169)***	0.0067 (5.5293)***
α	0.3098 (7.9988)***	0.2174 (9.1114)***	0.3916 (10.4047)***	0.2444 (7.3272)***
β	-	0.7249 (25.9444)***	0.9138 (52.6966)***	0.7274 (26.7538)***
δ	-	-	0.0358 (1.2196)	-0.0624 (-1.2223)
Log likelihood	-627.98	-426.00	-418.65	-422.98
SIC	-2.3048	-2.3014	-2.2994	-2.2994
AIC	-2.3124	-2.3109	-2.3108	-2.3109

Notes: SIC and AIC are the Schwartz and Akaike information criteria respectively. The numbers in the parentheses are Bollerslev and Wooldridge robust *t*-values. *, **, *** significant at 10%, 5% and 1% respectively.

Results showed that p=1 for the ARCH model, and p=1 and q=1 specifications for the conditional variances of the GARCH, EGARCH and GJR-GARCH is optimal in term of SIC and AIC criteria.

Mean Equation: $R_t = \mu + \gamma AR(1) + \varepsilon_t$

Variance Specifications:

GARCH (1, 1): $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$

EGARCH(1,1): $\log h_t = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta\log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$

GJR-GARCH (1, 1): $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \delta d_{t-1}\varepsilon_{t-1}^2$

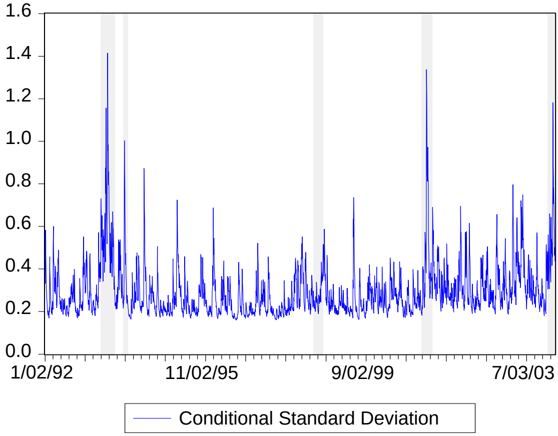
Starting with the mean equation, the AR (1) coefficient for all specifications are highly significant implying that even after taking into account the impact of non-synchronous trading, return series still exhibit serial correlation. From the ARCH (1, 1) model, the coefficient that represents the impact of current news on volatility α is highly significant. This result implies that the level of volatility is directly affected by the impact of news that enters the market. ARCH model does not capture or measure the impact of old news on volatility (the persistence of volatility). In GARCH (1, 1) model, both the ARCH and GARCH coefficients (α and β respectively) are positive and highly significant, thus the first null hypothesis is rejected against the alternative which means that the return series in ASE market is volatile and symmetric (ASE data displays GARCH effects). However, the persistence of the volatility to a shock is tested by the sum of the ARCH and GARCH coefficients. Results showed that the sum is equal to 0.940 which is less than a unity; however, it is very close to one which indicates a long persistence of volatility in ASE market (Corhay & Rad, 1994).

In order to test for the asymmetric effect; two models are used; EGARCH (1, 1) and GJR-GARCH (1, 1). From the EGARCH (1, 1) model, both current news and old news have great impact on the volatility level. Moreover, the persistence of volatility given by β is 0.9138 and highly significant at the level of 1% indicating a long memory in variance. The asymmetric effect coefficient (δ) is not significantly different from zero, which means that different types of news have the same impact on the volatility level. The asymmetric coefficient (δ) for GJR-GARCH (1, 1) model is also not significantly different from zero. Based on these empirical results, the volatility of ASE market is not asymmetric i.e. good and bad news has the same impact on future volatility. The persistence level of volatility is given by the sum of $\alpha+\beta+\delta/2$ in the GJR-GARCH (1, 1) model, and it is equal to 0.9406, less than unity but very close to one. This result is not different from the results found from the GARCH (1, 1) and EGARCH (1, 1) models. This means that shocks in ASE market affect the volatility for a quite time in the future and will not be forgotten in a short time, this is consistence with the results of Corhay and Rad (1994).

4.3. Which Model Fits Data Best? In order to examine which one of the four models used fit data best, one must look at the Schwartz (SIC) and Akaike (AIC) information criteria and the log likelihood value. The best model must have the lowest SIC and AIC and the highest log likelihood value. The Schwartz information criteria ranks ARCH (1) first with the lowest value, followed by GARCH (1, 1), and the highest values are given EGARCH (1, 1) and GJR-GARCH (1, 1) with the same values. As for the Akaike information criteria, ARCH (1) also shows the lowest value followed by GARCH (1, 1) and GJR-GARCH (1, 1) with the same value and EGARCH (1, 1) is the highest value. Although SIC and AIC rank ARCH (1) first, the log likelihood value ranks it in the last place with the lowest value. The first place based on the log likelihood is to be given to EGARCH (1, 1) followed by the GJR-GARCH (1, 1) and GARCH (1, 1) models. Until this point it is not obvious which model can capture best the characteristics of ASE returns. So the determining point will be by looking at the diagnostic tests for the standardized residuals for each model and compare it with the standardized residuals for the autoregressive for the raw data. The best model will be the model that can reduce the kurtosis of the data and shows the highest level of normality. Results showed that the ARCH (1) model has the highest Jarque-Bera test which indicate that the residual from ARCH (1) is not normally distributed. Moreover, this model has the highest level of kurtosis. This result is similar to what was found in the literature that ARCH model can not capture high excess kurtosis (Bera & Higgins, 1993). As for the autocorrelation, it was found that all researchers were interested in the Ljung-Box *Q*-statistic for the twelfth order for the daily frequency (Sharma et al., 1996), (Chiang & Doong, 2001); so it will be appropriate to use *Q* (12) as the benchmark for comparing between models in terms of autocorrelation. Ljung-Box statistic for ARCH (1) for the raw residuals and squared are significant at 1% level which implies that this model could not capture the time-varying volatility in ASE data; so this model will be excluded from the comparison process. For the other models, the Jarque-Bera statistic test for normality ranks GJR-GARCH (1, 1) first with the lowest value, followed by EGARCH (1, 1) and then GARCH (1, 1). And by comparing them with the values from table 4, the Jarque-Bera is lower for all models but still significant and the hypothesis of normality is rejected at the level of 1%. Furthermore; GJR-GARCH (1, 1) reduced the kurtosis level the most but still significantly higher than 3.As for the serial correlation GARCH (1, 1) and GJR-GARCH (1, 1) could capture the time-varying volatility of the data, since the squared values of the Ljung-Box for the twelfth order are not significant. On the other hand, EGARCH (1, 1) which gave the highest value of the log likelihood could not capture this feature. From the discussion above, ARCH (1) show the lowest values for SIC and AIC but the lowest value of the log likelihood and is excluded from the comparison as mentioned above. The highest log likelihood value is given by the EGARCH (1, 1) model followed by GJR-GARCH (1, 1) and the GARCH (1, 1). Although of these facts, the EGARCH (1, 1) is thought to capture the volatility clustering in ASE data, which will lead to the second highest log likelihood, the GJR-GARCH (1, 1). The GJR-GARCH model show the lowest Jarque-Bera statistic value and is the model that could reduce the kurtosis values the most, and moreover could capture the time-varying volatility of the market under study.

Since it was found that the GJR-GARCH model was the best to capture ASE return characteristics, the estimated conditional volatility using this model is shown in figure 2. The shaded areas in this figure represent the periods with highest level of volatility through out the interval under investigation. The first shaded area is around the Oslo treaty between Palestine and Israel which were signed in the white house on 13/9/1993.

Figure 2. Conditional Volatility



As shown on figure 3 this period had high level of volatility in the Jordanian market. The second shaded area represents the period surrounding the signing of the peace treaty between Jordan and Israel on 25/7/1994 which also shows high level of volatility, but the volatility level is lower than the level the market showed surrounding the Oslo treaty. The third shaded area shows the period surrounding the death of his Majesty King Hussein which surprisingly shows very low level of volatility. The period from 11/9/2001 through 22/11/2001 is the period of the aftermath of the eleventh of September which was a shock to the entire world. And more recently the Jordanian market was affected by the death of the Palestinian President Yasser Arafat on 11/11/2004 which is marked as the last shaded area in figure 3.

As it is clear the Jordanian market shows higher level of volatility around the international events which means that the Jordanian market shows stability when it comes to the national event. Furthermore, each shaded area is more than two months which means that the volatility level persists for a quite time in the future and shocks are not forgotten quickly, which is consistent with the findings of the study.

5. Summary and Conclusions

This paper attempts to investigate and model the volatility of the Jordanian emerging stock market using daily observations from Amman Stock Exchange Composite Index (ASE) for the period from January 1, 1992 through December 31, 2004. For achieving this purpose, the ARCH, GARCH, EGARCH and the GJR-GARCH models are employed. The first two models are for capturing the symmetry effect whereas the second group is for capturing the asymmetric effect. ASE data showed a significant departure from normality and the existence of conditional heteroskedasticity (volatility clustering). Therefore, the ARCH-type models were used because it was found in literature that they are able to capture many of the financial data characteristics, such as thick tails of the observations, volatility clustering and the asymmetric effect i.e. different type of information has different impacts on volatility level (Corhay & Rad, 1994).

This study was built on two main hypotheses, the first was to examine if ASE return display symmetric volatility and the second was to investigate if good and bad news have different impact on the future volatility at ASE market (asymmetric effect). Empirical analysis came supportive to the symmetric volatility hypothesis, which means that ASE returns are volatile and that positive and negative shocks (good and bad news) of the same magnitude have the same impact and effect on the future volatility level. Also, it was found that the volatility response to a shock tend to persist in the market and not forgotten quickly.

Although ASE return data do not display asymmetric effect; the best model that could capture the characteristics of the said market was the GJR-GARCH model which is an asymmetric model. The GJR-GARCH model was the best according to the log likelihood value and to the diagnostic test of the model's residuals. The GJR-GARCH model reduced the kurtosis level the most and had the lower Jarque-Bera statistic value. Furthermore, this model captured the time-varying volatility in the data; the squared residual was not correlated

References

Active Trader. 2001. www.activetrader.com

Al-Fayyoumi, N. A. 2003. Stock Returns and Conditional Risk: An Empirical Investigation of the Amman Stock Exchange. *Mu'tah Lil-Buhuth wad-Dirasat, 18*, 49-72.

Andersen, T. G., Bollerslev, T., Diebold F. X. and Ebens, H. 2000. The Distribution of Stock Return Volatility. *National Bureau of Economic Research NBER Working papers*, *7933*,

Bautista, C. C., 2004. How volatile are East Asian Stocks During High Volatility periods. www.up.edu.ph/~cba/bautista

Bekaert, G. and C. R. Harvey, 1997."Emerging Equity Market Volatility," *Journal of Financial Economics,* 43, 29-77.

Black (1976). Studies in Stock Price Volatility Changes, *Proceedings of the 1976 Business Meeting of the Business and Economics Statistics Section*, American Statistical Association, 177-181.

Bollerslev, T. 1987. A Conditional Heteroskedastic Time Series Models for Speculative Prices and Rates of Returns. *The Review of Economics and Statistics*. *69*, 542-547.

Carr, P., Geman, H., and Yor, M. 2002. The Fine Structure of Asset Returns: An Empirical Investigation. *Journal of Business. 75*, 305-332.

Chandrasekhar, C. P., 2001. Financial Fraud and the Ethos of Liberalization. www.macroscan.com

Ching, T. C., Doong, S. 2001. Empirical Analysis of Stock Return and Volatility: Evidence from Seven Asian Stock Markets Based on TAR-GARCH Model. *Review of Quantitative Finance and Accounting*. *17*, 301-318.

Christie, Andrew A. 1982. The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects, *Journal of Financial Economics*, 10, 407-432.

Cohary, A. and Rad, A. T. 1994. Statistical Properties of Daily Returns: Evidence from European Stock Markets. *Journal of Business Finance and Accounting*. *21*, 271-282.

Depken, C. A., 2002. Good News, Bad News and GARCH Effects in Stock Return Data. *Journal of Applied Economics*. *4*, 313-327.

Directives for trading in securities. Issued by virtue of the provision of article 67 (c) of the securities law No. 76 of 2002.

Fama, E. F. 1963. Mandelbrot and the Stable Paretian Distribution, *Journal of Business* 36, 420-429.

Fama, E. F. 1965. The Behavior of Stock Market Prices, *Journal of Business* 38, 34-105

Gazda, V. and Výrost, T. 2003. Application of GARCH Models in Forecasting the Volatility of the Slovak Share Index (SAX). *Economic Focus*. *6*, 17-20.
Gujarati, D. N., 1995. *Basic Econometrics*, third edition, McGraw-Hill, Inc. Singapore.
Haugen, R. A. 2001. *Modern Investment Theory*, fifth edition, Prentice Hall International, INC. Upper Saddle River, New Jersey.
Helan, M. 2002. Asymmetric GARCH models for Jordanian Stock Returns. *Abhath Al-Yarmouk, Basic Sciences and Engineering*. *11*, 155-181.
Internal By-Law of the Amman Stock Exchange. Issued by virtue of Article (65) and the Securities Law NO. 76. Article 6 A. of 2002.
Kim, K. A. 2001. Price Limits and Stock Market Volatility. *Economic Letter*. *71*, 131-136
Kim, K. A. and Sweeney, R. J. 2002. Effects of Price Limits on Information Revelation. www.ascu.bufalo.edu
Koutmos, G., Negakis, C and Theodossiou, P. 1993. Stochastic Behaviour of the Athens Stock Exchange. *Applied Financial Economics*. *3*, 119-126.
Lamoureux, C. and Lastrapes, N., 1990. Heteroskedasticity in Stock Return Data: Volume Versus GARCH Effects. *Journal of Finance*. *45*, 221-229.

Lilien, D. L., Statz, R., Ellsworth, S., Noh, J., Engle, R., Hall R. E., Sueyoshi, G. and Johnston, J. 1994, 1995. *Eviews User Guide*. Version 2.0. Quantitative Micro Software (QMS). Irvine, California.

Lo, M. S. 2000. *Generalized Autoregressive Conditional Heteroscedastic Time Series Models.* Department of Statistics and Actuarial Science, Simon Fraser University, British Columbia, Canada.
Mandelfrot, B.B . 1963. The Variation of Certain Speculative Prices, *Journal of Business* 36, 394-416.
Phylaktis, K., Kavussanos M. and Manalis G., 1999. Price Limits and stock market Volatility in the Athens Stock Exchange. *European Financial Management. 5*, 69-84 .
Schwert, G. W., 1989. Why Does Stock Market Volatility Change Over Time? *Journal of Finance. 44*, 1115-1154.
Schwert, G. W., 1990. Stock Market Volatility. *Financial Analysts Journal*. *46*, 23-34.
Sharma, J. L., Mougoue, M. and Kamath, R., 1996. Heteroscedasticity in stock market indicator return data: volume versus GARCH effects. *Applied Financial Economics*. *6*, 337-342.

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