Arab Journal of Administrative Sciences

2004, Vol. 11, No. 3, 395 - 422

Aktham I. Maghyereh

The Hashemite University, Jordan

PRICE LIMITS AND STOCK MARKET VOLATILITY: EVIDENCE FROM THE AMMAN STOCK EXCHANGE

Key Words

Price Limits, Stock Market Volatility, GARCH Models, Amman Stock Exchange.

Abstract

This paper provides empirical evidence on effect of price limits policy on stock price volatility in the Amman Stock Exchange (ASE) during the period between 1998 and 2002. Seventeenth Jordanian individual stocks are adopted here. These stocks were selected based on their liquidity and trading volume. Based on our cross-section of stocks, the results show that the price limits policy does not have the desired effect on stock price volatility in the ASE. The policy implication of this empirical finding suggests that the market should consider either reducing the existing distortions by making the price limits more binding (i.e., by narrowing the current range of permissible price changes), or introducing an alternative type of circuit breaker, such as trading halts adopted for index declines in several mature markets.

Introduction

Financial markets and institutions play a key role in the economy by channeling funds from saver to investors. It is widely argued that some volatility in the prices of financial assets is a normal part of the process of allocating investable funds among computing uses. Extreme volatility of financial assets prices (i.e., interest rates, exchange rates and stock prices) may be detrimental, however, because such volatility may impair the smooth functioning of the financial system and aversely affect economic performance (Camplell *et al*., 2001; and Schwert, 2002).

Like volatility in interest rates and exchange rates, stock market volati-

Submitted May 2003, accepted November 2003.

lity can lead to a negative future for stock markets in that it can undermine the financial system as a whole. Volatility also discourages risk-averse investors and savers, and stock market fluctuations may raise the cost of capital to corporations[1] and may also increase the value of the ''option wait'' hence delaying investments. Excess volatility would also tend to discourage firms from seeking a stock market listing or attempting to raise funds by new issues. Thus, a high level of market volatility will impede investment and slow overall economic growth (De Long *et al.*, 1989). Garner (1988), Starr-McCluer (1998) and Poterba (2000) also argue that stock price volatility may adversely affect real economic activity through several possible channels. It may adversely affect consumer spending through wealth and by consumer confidence changes. In addition, a weakness in consumer confidence could contribute to a further spending reduction. Finally, if extreme stock price volatility causes a financial system crisis, financial intermediation could break down, causing monetary and credit problems in the economic system[2].

Following the 1987 major stock markets crash in the United States, many questions have been raised concerning its causes and whether the microstructure of the stock market had to be redesigned to protect the market from such large fluctuations. Recommendations were made to circuit breakers as one form of price fluctuation limits. Consequently, in the last decade, the price limit regulation has received a lot of attention. In the United States, for example, price limits were imposed on the trading of futures and options, while in many exchanges around the world as in Italy, Greece, France, Spain, Austria, Belgium, Mexico, Taiwan, Japan, Thailand and Korea[3], Turkey and Jordan, price limits were imposed on the movements of stock prices. In spite of the strong existence of price limits worldwide, there is no much information regarding the effects of price limits on volatility which has important policy implications for the regulators.

In the Jordanian capital market (Amman Stock Exchange, ASE), the price limit regulation has been imposed since the markets inception in 1978. Naturally, the purpose of this regulation is to avoid listed stocks

1 See for example Bekaert and Wa (2000), Singh (1992, 1997, 1999), Glen, *et al.*, (2000); Singh, *et al.*, (2000) and Kim and Singal (2000).

2 This argument is also mentioned by Singh *et al.*, (2000).

3 Roll (1989).

price movements from excessive volatility and to protect investors by limiting potential daily losses to a maximum. The price limit allows each listed stock to fluctuate on any given trading day within the pre-specified percentage level above or below its previous days closing price. Trading (if any) may well continue at the ceiling (floor) price or move below (above) it.

This study examines the effects of price limits on volatility in stock prices using data from the ASE. A commonly cited benefit ascribed to price fluctuations limits is that such measures provide a cooling-off period allowing investors to re-evaluate market information so that investment strategies can be formulated. Its also allows order imbalances to be publicized to attract value traders that could bring back equilibrium (see Harris, 1998). According these pints of view, stock price volatility should be less with price limits rule. Thus, the testable question in this paper is:

-Does the price limit regulation that exists in the ASE contribute to reduce the volatility of stock prices?

Answering the above question has some important implications for the feasibility of the imposition of price limits. Furthermore, since the price limit regulation has been imposed since the markets inception in 1978, the price limit system of the ASE provides a rare opportunity for examining the relationship between price limits and stock market volatility.

In this study, we examine the effects of price limits on volatility using daily prices of 17 individual stocks from January 1998 through December 2002. We use the exponential generalized autoregressive conditional hetroscedasticity (EGARCH) of Nelson (1991) to investigate the price limits effect. The EGARCH model is well-suited for modeling the behavior of financial time series. This model is able to capture a number of common empirical observations in daily returns data; fat tails due to time-varying volatility, skewness that result from mean non-stationarity, and asymmetry volatility.

The results indicate that the price limit regulation in the ASE does not have the desired effect. The policy implication of this empirical finding is clear. The market should consider either reducing the existing distortions by making the price limits more binding (i.e., by narrowing the current range of permissible price changes), or introducing an alternative type of circuit breaker, such as trading halts adopted for index declines in several mature markets.

The rest of the paper is organized as follows. In section II, we provide some basic information about the capital market in Jordan. In Sections III, we provide a review of the literature on price limits. IV and V, we discuss the methodology and the statistical properties of the data respectively. The empirical results are presented and discussed in Section VI. Finally, Section VII provides a summary and conclusions.

The Jordanian Stock Exchange: Some Descriptive Statistics and Information

The ASE is the only stock market in Jordan. Since its establishment in 1978, the ASE has developed and expanded greatly, and has become one of the most sophisticated and active stock markets among the emerging markets (World Bank, 1994; Cobham, 1995; Demirguc-Kunt and Huizinga, 2000; and others). For instance, El-Erian and Kumar (1995) pointed out that, "Jordan has a relatively highly developed equity market which plays an important part in the economic life of the country" (p.146).

Table (1) reports the number of listed companies and the ratios of market capitalization to GDP.

Table 1
Amman Stock Exchange: Number of Listed Companies and Market Size

Year	Total Number of Companies	Market Capitalization ($ billion)	Capitalization / GDP
1978	57	0.408	36.7
1980	71	0.707	41.9
1982	86	1.411	58.1
1984	103	1.266	44.7
1986	103	1.253	40.5
1988	107	1.550	47.9
1990	102	1.830	48.0
1992	94	3.243	64.9
1994	99	4.618	76.1
1996	98	4.614	68.5
1998	98	5.478	74.0
1999	99	4.041	53.4
2000	101	4.509	59
2001	102	4.476	76
Mean			54.5

Source: Various ASE Annual Reports

When judged by the ratio of market capitalization to GDP, the increase from about 37% in 1978 to 76% in 2001 indicates the importance of the market in the national economy. However, the performance of ASE is less impressive if we consider the market value of traded shares. As Table (2) indicates, the market experienced sharp fluctuations (falls) in 1990-1996. Moreover, it must also be pointed out those only 10 companies in each year account for a large proportion of the total trading volume. In other words, most listed shares are thinly traded on the secondary market.

The fact that in 2001 only 10 companies accounted for about 66% of the total markets trading volume and the market value of these companies shares accounted for about 72% of the capitalization of all listed companies, we can state that the ASE is highly concentrated in terms of market value of companies and trading volume.

Regardless of the differences in their mechanisms, all securities markets have one thing in common and that is to bring buyers and sellers together. In ASE any investor who wants to buy or sell a security must do so through the agency of a stock-

Table 2
Trading Activity on the Secondary Market

Year	Turnover Ratio	Trading Volume in 10 Most Active Shares as a % of Total Trading
1978	2.8	75
1980	7.4	66
1982	14.4	57
1984	7.9	56
1986	11.9	56
1988	32.3	52
1990	31.5	30
1992	87.1	48
1994	26.1	54
1996	15.4	53
1998	15.9	77
1999	17.9	61
2000	11.3	65
2001	19.9	66

Source: Various ASE Annual Reports

broker. The trading mechanism is continuous and strict price and time priority rules are followed. For example, for any two or more buy (sell) orders on the trading board, the order with the higher (lower) price has priority in execution. Similarly, if two orders or more orders of the same type have similar prices, the one noted on the board first has the priority in execution. Daily price limits (5%) are imposed on all listed shares. These limits are applied as a mechanism to stabilize the movement of prices i.e., to prevent shares from excessive volatility, and to protect investors by limiting potential daily losses to a maximum. The ASE launched the electronic trading system on 15 June 2000. However, it must be noted that the market-making mechanism has not changed. In other words, the "old" manual system has simply been replaced by an electronic one.

As it stands, the trading mechanism in ASE suffers from one major weakness; lack of immediacy. If, for example, there is an imbalance between buy and sell orders during a trading day, successive buy (sell) orders may well get noted on the trading board without counter sell (buy) orders arriving at the market. Furthermore, any imbalance between buy and sell orders would cause the price of a stock to change suddenly (and by a large percentage) from one transaction to the next. This is due to the absence of dealer who stands ready and willing to buy a stock at the bid and sell a stock at the ask. Indeed Cohen *et al*., (1983) analyzed the impact of the specialist on the standard deviation of daily price changes. In their simulation study, they showed that the presence of specialists reduces the standard deviation of daily transaction prices from an average of 1.44% to about 0.89%. This may imply that, the behavior of price changes on ASE would be more continuous if there were specialists operating in the market. Moreover, investors would be assured of getting their orders executed immediately when they submit market orders. This is perhaps why the trading volume in the shares of only 10 companies (out of a total of 120 listed companies) accounts for more than 50% of the trading volume in the shares of all listed companies.

Literature Review

Several authors have discussed theoretically the impact of price limits and circuit breakers on stock market volatility[4]. Harries (1998) discusses the

4 See Kyle (1988), Harris (1989, 1998) and Moser (1990) for surveys of the theoretical literature.

impact of price limits and circuit breaks in particular, and several theoretical models of their impacts. Theoretically (from Harries (1998)), it is not clear whether the imposition of price limits will bring about the desired effect of reducing stock market volatility. One theoretical argument behind the imposition of price limits is that when new information arrives, investors tend to "overreact"[5] and share prices could reach the limit. Thus, in the short-run the market price may react to new information erratically, and the activation of price limits provides the market with additional time to evaluate the information and to reformulate new investment strategies. During the "reassessment" period, the market "cools down". Thus, volatility subsides once the limits are hit. In other words, this argument suggests that volatility which related to uncertainly about underlying stocks value should decline during post-limit days. Furthermore, if the trading process (i.e., order imbalance originate among uniformed traders) causes the volatility, a price limits that stops their trading may be reduced the volatility. This may come from protection them from trading losses that they will likely incur in poorly functional markets. Price limits (and trading halts) may also decrease this volatility if this rule allows traders greater time to response to intraday margin calls and/or to remove stop-loss orders. When traders are unable to satisfy their margin calls, brokers will trade to stop their losses. Since stop-loss orders further imbalance an uninformed order flow, a halt that reduces their number may reduce volatility. Kodres and O'Bren (1994) also provide theoretical model shows that circuit breakers can decrease volatility by encouraging traders to offer more liquidity to markets.

Opponents against price fluctuation limits argue that they serve no purpose other than to slow down or delay the price change. They say that even though it can stop the rice of a share from free falling on the trading day when a shock hits, the price will continue to move in the direction towards equilibrium as new trading limits are established in subsequent trading days. According to this point of view, price limits only prolong the number of trading days for the market to adopt a disturbance. Fama (1989)

5 The overreaction in financial markets was first noted by Keynes (1936) "day-to-day fluctuations of existing investments, which are obviously of an ephemeral and non-significant character, tend to have an altogether excessive and even an absurd influence on the market"(pp. 153-154). Investors overreactions to each others trades has also been noted by French and Roll (1986) as an explanation of the greater volatility of stock returns during times when the stock exchanges are open.

and more recently Kim (2001) in thier criticized the introduction of the circuit breakers as a market rule to reduce noise or unnecessary volatility argued that that this system results in the reduction of the supply and liquidity when the demand increases. Rather, it could increase the volatility by inciting trading in anticipation of halts. They insisted that this system can only delay the adjustment of price to changes in fundamental values. This argument is highly consistent with the study of Roll (1988), which showed empirically that the market decline of each country during the crash of 1987 is similar irrespective of the price limits. The result of Rolls study indicates that the price limits can influence price adjustment speed, but do not have any effect on the size of the price adjustment.

Furthermore, Subrahmanyam (1994) provides an argument suggests that price limits (and trading halts) may increase volatility. According to this argument, if traders fear that a halt will occur before they can submit their order, they may submit them earlier than otherwise to increase the probability that they execute. Thus, when trading halts are likely to occur, rational traders will increase market volatility by altering their trading strategy to account for the probability of a trading halt.

In summary, the results of theoretical studies of the effect of price limits are mixed. Price limits slow price changes associated with fundamental information. The impact that delayed price changes have on volatility is not clear. Volatility is reduced if the restrictions apply to traders who contribute to volatility. Otherwise, preventing trading by agents whose participation conveys information may increase volatility. The net effect of these types of trading interruptions on volatility is indeterminate.

While there have been many empirical studies that examined the behavior of stock markets volatility, papers that examine the impact of price limits have been relatively limited. For example, Ma *et al.*, (1989) compared the returns volatilities between pre-limit and post-limit periods and showed that the imposition of price limits is effective in the Treasury bonds future market in that they reduce their volatility. Moser (1990) examined the effect of triggered of price limits during the "Mini Crash" of October 13, 1989. He shows that the failure to coordinate the circuit breakers caused volumes to increase substantially at the NYSE. He argues that this may have exacerbated the problem. Santoni and Liu (1993) test for changes in volatility surrounding the adoption of the circuit breakers using an ARCH model. Using data through May 1991, they find no significant effect.

Lee *et al.*, (1994) examined the effect on subsequent trading volume and volatility of trading halts for individual securities on the NYSE. Individual trading halts occur because of order imbalance, pending news and news dissemination. In their study, they match trading halts with "pseudo halts"-periods where the same stock had similar pricing characteristics with no trading halt. They find that volumes were significantly higher for three days after trading halts relative to pseudo halts. They also find that volatility is significantly higher for one day after the halt was imposed. In recent study, Christie *et al.*, (2002) examined the effect of news-related trading halts on the NASDAQ on prices, transaction costs and trading volume. They find that the uncertainty associated with the trading halt is not resolved when trading resumes. When halts reopen with a five-minute quotation period prior to trading, trading resumes with a larger median inside spread and with much higher volatility.

In emerging markets however there is relative paucity of empirical literature on the effects of price limits on stock market volatility. For example, Chung (1991), Chen (1993) looked at the Korean, Taiwanese stock markets respectively and found evidence did not support that price limits reduce the volatility in these markets. Phylaktis *et al.*, (1999) examined the effect of the price limits on stock market volatility in the Athens Stock Exchange. They compared the volatility before and after price limits imposed. They find that the imposition of price limits did not have the desired effect on volatility. More recently, Bildik and Elekdag (2002) used the same methodology of Phylaktis *et al.*, and found that volatility decreased in the Istanbul Stock Exchange after the increase in price limits. Finally, Ngassam (2002) examined the effect of price limits on stock price volatility using data from Johannesburg stock exchange. They compared the return volatilities between high price limit portfolio and low price limit portfolio constructed on the basis of ranked price limit rates. His results showed that price limits serve to reduce stock price volatility in Johannesburg stock exchange.

Methodological Framework

As emphasized by Pagan (1996), many financial time series data have a number of common characteristics. First, asset prices are generally nonstationary and often have a unit root, whereas returns are usually stationary. Second, returns series usually show little autocorrelation, while serial independence between the squared values of the series is often rejected (nonlinear relationships between subsequent observations). Volatility of returns appears to be clustered. Returns go through periods of high and low variance. This fact points towards time-varying conditional variance. Finally, beginning with the seminal works of Mandelbort (1963) and Fama (1965), the empirical evidence indicates that the probability distribution of stock (and other) returns cannot be approximated by the identical Gaussian distribution. The series were characterized by leptokurtosis.

The above characteristics have been modeled successfully in the financial econometrics literature by the use of generalized autoregressive conditionally heteroskedastic (GARCH) model developed by Bollerslev (1986). This model has been applied successfully to financial data and has become the most popular tools to study financial market volatility. Pagan and Schwert (1990) show that the GARCH model performs quite well in comparison with many alternative models for modeling conditional volatility of stock returns. Most recently, Engle and Patton (2001) and Schwert (2002) used a GARCH (1,1) to model conditional variance for the Nasdaq.

The specification of conditional variance in a model is given in Equation (1) below:

$$\varepsilon_t = h_t^{1/2} u_t \qquad (1)$$

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

with u_t being IID, $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ and $\sum_{i=1}^{p} \alpha_i + \sum_{j}^{q} \beta_j < 1$.

In practice, numerous studies have demonstrated specification is most appropriate (see Engle and Patton, 2001; Alexader, 2001; Li *et al.*, 2002; and Engle, 2003). In this model, the conditional variance is a function of three terms: First, the mean, ω. Second, news about volatility from the previous period, measured by the lag of the squared residual from the mean equation, ε_{t-1}^{2} (the ARCH term). Third, last period's conditional variance, $h_{t\text{-}1}$ the (GARCH term). The coefficients of the model are easily interpreted. The estimate of α shows the impact of current news on the conditional variance process and the estimate of β the persistence of volatility to a shock or, alternatively, the impact of "old" news on volatility. Engle and Bolleslev (1986) show that the persistence of shocks to volatility depends on the sum of $\alpha + \beta$. Values of the sum lower than unity imply a tendency for the volatility response to decay over time, at a slower rate the closer the sum is to unity. In contrast, values of the sum equal to (or greater) than unity imply indefinite (or increasing) volatility persistence to shocks over time.

It is interesting to note here that despite the success of GARCH models in capture the features of conditional volatility, they have some undesirable characteristics. Firstly, the theoretical observation that if a GARCH model is correctly specified for one frequency of data, then it will be misspecified for data with different time scales; makes researchers uneasy (see for example, Bollerslev, *et al*., 1992; and Engle and Patton, 2001). Secondary, GARCH models often do not fully capture the thick tails property of high frequency financial time series. This has led to the use of non normal distributions to better model this excess kurtosis. Some researchers such as Kaiser (1996) and Beine, *et al*., (2000) use Student-t distribution while others, Nelson (1991) and Kaiser (1996) suggest the Generalized Error Distribution (see for example Peters, 2001). Finally, GARCH models impose the assumption that the conditional volatility is affected symmetrically by positive and negative innovations. For equity returns it is particularly unlikely that positive and negative shocks have the same impact on the volatility. This asymmetry is ascribed to a leverage effect. To solve this problem, many nonlinear extensions of the GARCH model have been proposed. Among the most widely spread are Exponential GARCH (EGARCH) of Nelson (1991), the so called GJR of Glosten, *et al*., (1993) and the asymmetric Power ARCH (APARCH) of Ding, *et al*., (1993)[6].

The model that we are using in our research as an alternative to specification (1) to investigate for the effect of price limits effect is Nelsons (1991) Exponential GARCH (EGARCH) model. As the GJR models, it also explicitly incorporates the asymmetric nature of volatility into conditional variance, however not requiring the non-negatively constraints on parameters. This advantage of EGARCH over GJR model is the main reason for our choice. Thus, the core EGARCH model we use to analysis the daily stock returns in the ASE is as follows:

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

$$\beta \log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \qquad (2)$$

where ω, α, β, and δ are parameters. The EGARCH model has two distinct advantages over the GARCH model. First, the logarithmic construction of Equation (2) ensures that the conditional variance is strictly positive, thus, the non-negative constraints used in the estimation of the GARCH are not necessary.

6 For more detailed information about these models see for example Campbell *et al*., (1997); Alexader (2001); and Li *et al*., (2002).

Second, since the parameter δ typically enters Equation (2) with a negative sign, bad news, $\varepsilon_t < 0$, generates more volatility than good news.

As we have mentioned above, one theoretical argument behind the imposition of price limits is that when new information arrives, investors tend to "overreact" and share prices could reach the limit. Thus, price limits give additional chance to market to evaluate the information and to reposition their strategies and thereby this cool-off period decreases the volatility. In other words, this argument suggests that volatility which related to uncertainly about underlying stocks value should decline during post-limit days. In order to test the effect of price limits on stock market volatility, we test this hypothesis which implies that volatility declines one day following limit day provides favorable evidence for price limits. On the other words, we aims to determine whether hitting a price limit on a given day has an impact on the volatility of stock prices during the subsequent trading day. To test for this, we extend Equation (2) to include dummy variable (lagged one day; D_{t-1}) that takes the value of one if the observed price hits the upper or lower limit on a trading day and zero otherwise. Thus, the conditional volatility represented by Equation (2) is modified to takes the form:

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

$$\beta \log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma D_{t-1} \qquad (3)$$

where D_{t-1} is the dummy variable associated with the price limits.

Based on the theoretical argument mentioned above (price limits reduce stock volatility in the post-limit day), we expect the value of γ to be negative. To find the occurrences of prices that reach their limits, we identify the days where the closing price matches its previous days closing price plus its price limit (5%). In other words, we assume upward or downward limits are reached for a specific stock when $P_t = p_{t-1} + LIMIT_t$, where P_t represents Day *t*'s closing price, P_{t-1} represents the previous day's closing price, and $LIMIT_t$ is the maximum allowable upward and downward price movement for each day *t*.

However, previous works indicate that trading activity, represented by volume or the daily value of transaction, may be an important determinant of conditional volatility in stock returns[7]. Trading activity proxies for

7 Various studies reported that volume leads stock prices changes and found significant relationships between volume and stock volatility and that trading volume is a source of risk due to flow of information (See for example, Lamoureux and Lastrapes, 1990a; Kim and Kon, 1994; Gallo and Pacini, 2000; and Omran and McKenzie, 2000).

the amount of information flow into the market, which has been given as one of the explanations for the prominence of GARCH models. The relationship between the volatility of returns and trading volumes is theoretically based on the implication of the Mixture of Distributions Hypothesis (MDH). According to the MDH, a serially correlated mixing variable measuring the rate at which information arrives to the market explains the GARCH effect in the returns. On other words, this hypothesis suggests that the variance of daily price increments is heteoskedastic especially when related to the rate of daily information arrival. Thus, our final variance equation is modified further and takes the form:

$$\log(h_t) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right]$$
$$\beta \log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma D_{t-1} + \nu V_t \quad (4)$$

where V_{t-1} represents trading volume[8].

To complete the GARCH model, a mean equation must be specified. Thus, we propose the following specification for the mean equation:

$$LogP_t = \mu + logP_{t-1} + \varepsilon_t \quad t = 1,...,\mathrm{T} \quad (5)$$

where, P_t and P_{t-1} are the stock prices at time t and t-1 respectively, and ε_t is a random error (independent and normal distribution, $\varepsilon_t \sim IND(0,\sigma^2)$). If Equation (5) is rearranged so that the lagged logarithmic stock price is moved to the left-hand side of the equal sign, we get a function that states that relative stock returns will be a linear function of a constant and news (residuals)- the mean equation.

Estimating of the EGARCH model on smaller, less liquid markets such as the ASE is more involved, due to the problem of non-synchronous trading. Though this can safely be ignored for actively traded stocks, the fact that many ASE stocks have extended periods of non-trading means this aspect must be considered when performing the EGARCH analysis[9]. Infrequently traded shares can affect the results of empirical studies on volatility using EGARCH model by introducing bias into the analysis[10]. The source of bias is the fact that prices recorded at the end of a time period may represent the outcome of transaction with occurred in an earlier period, leading to autocorrelation being evident in a time series which would otherwise exhibit independence. Thus, non-synchronous trading may induces positive

8 The lag of volume is used to avoid simultaneity issues, see Harvey (1989) for further details.

9 The GARCH framework to date has been implicitly based on the assumption of continuous trading, an assumption that may not satisfied for many ASE stocks.

10 For more detailed information see for example Campbell *et al*., (1997).

first-order serial correlation in the return series. To control for this problem, it is common to adjust the return equation by including a moving average term (see French *et al*., 1987; and Lange, 1999). Therefore, in the empirical test, we will add a moving average term, MA(1), on the right-hand side of the mean equation to cope with any serial correlation which may be caused by non-synchronous trading in the stocks.

The main assumption under the GARCH models mentioned above is that the conditional distribution of returns is normal, i.e. standardized residuals of these models should be normal. However, in practice, despite the flexible functional forms specified above, there is often excess kurtosis in the standardized residuals of GARCH models. To deal with this problem, Bollerslev and Wooldrige (1992) studied quasi-maximum likelihood (QML) estimation of GARCH models. They argued that under a correct specification of the first and second moment, consistent estimates of the parameters of the model could be obtained by maximizing a likelihood function constructed under the assumption of conditional normality. Consistent parameter estimates can then be obtained using a robust covariance matrix estimator. Therefore, in this study we compute the QML covariance and standard errors using the methods described by Bollerslev and Wooldrige (1992) and Glosten *et al*., (1993). Moreover, in searching for the best specification that provides adequate explanation conditional volatility in the ASE, some diagnostic tests are performed. Among models satisfy standard statistical assumptions (i.e. independence and homoskedasticity), model selection is based on the Schwartz Information Criterion (SIC)[11].

To determine EGARCH specification provides an adequate explanation of returns and volatility in the Jordanian market, some diagnostic tests are performed. First, we examine whether the standardized residuals of the estimated models display excess skewness and kurtosis. If properly specified, the EGARCH model should be able to significantly reduce the excess skewness and kurtosis present in normal returns. Second, we examine whether the squared standardized residuals of the models are independent and identically distributed. Third, we examine whether the standardized residuals of the estimated models display ARCH effects (ARCH-LM test). Properly specified models should be able to significantly remove the ARCH effects. Fourth, we test whether the standardized residuals of the estimated models display non-linearity relationships (Ramsey (1969) RESET test).

11 For more detailed information about specification and estimation of GARCH models see for example Campbell *et al*., (1997); Engle (2000); and Alexander (2001).

Statistical Properties of the Series

In this study, we consider daily closing prices for 17 individual stocks from January 1998 through December 2002. These stocks were collected based on their liquidity and trading volume so that such assets represent a determinant percentage (about 75 percent) of the trading volume in the ASE. Daily data for all stocks trading in the ASE is obtained from ASE data base.

According to Fama (1965), stock prices in an efficient market should fluctuate randomly through time response to the unanticipated component of news. This requires that the distribution of the changes in stock price must be stationary over time, i.e., log P_t should be I (1) ($\Rightarrow \Delta$ log $P_t \sim I(0)$). Therefore, the study begins by testing whether the behavior of stock prices is characterized by a martingale: i.e. the logarithm of prices contains a single unit root[12]. To test for this, the Augmented Dickey Fuller (ADF) test is performed. The lag is chosen as the highest one for which this autocorrelation is significant (provided this is less than $\sqrt{N}$). The results are reported in Table (3). The results show the t-statistics values of

Table 3
Tests for a Unit Root

Stock	ADF Stat. (log (P_t))	ADF Stat. (Δ log (P_t)
1	-1.019	-14.217
2	-2.134	-13.264
3	-0.982	-15.385
4	-1.893	-11.042
5	-1.296	-14.092
6	-2.273	-15.327
7	-1.017	-13.102
8	-1.739	-13.829
9	-2.012	-14.982
10	-1.083	-13.746
11	-0.947	-16.028
12	-2.592	-14.163
13	-1.402	-12.748
14	-0.835	-15.019
15	-1.737	-11.943
16	-0.460	-10.682
17	-1.857	-14.937

Critical values of augmented Dickey-Fuller tests: -3.41 and 3.96 at the 5% and 1% significant levels respectively.

12 For more detailed information see for example Campbell *et al*., (1997) and Groenewold (1997).

the ADF test of the rejection of a unit root, indicating that stock prices display a degree of time dependence. These results also support the martingale model for stock prices.

Table (4) presents summary statistics about the continuously compounded returns series. These returns are calculated according to $r_t = Lm\ (P_t) - Ln\ (P_{t-1})$ where P_t and P_{t-1} are prices of the stock at time t and t-1 respectively. The first statistic is the sample mean return of each stock. In eleventh out of 17 stocks the returns reveal negative means and this suggests a downward trend in the ASE during the period of study. The striking features of the stock market returns (displayed in Table (4)) are their low unconditional volatility (measured standard deviation) and departure from normality. The results in the table provide considerable evidence of departures of daily returns from normality. Under the null hypothesis of normality, the skewness statistic has a normal distribution with zero mean. The null hypothesis is rejected in all but one case. Furthermore, the coefficients of skewness for most stocks indicate that the return series typically have asymmetric distributions skewed to the right. The same is also true of the results reported for excess kurtosis. The statistic is normal with zero mean under the null hypothesis. The null hypothesis is rejected in all cases. These two forms of departures from normality are reflected in the results of the goodness-of-fit test for non-normality reported in the next column. In all cases, the test statistic of normality (Jarque-Bera (1987) test) has a χ^2 distribution with 57 degrees of freedom that has a 1% critical value of 88.379. The null hypothesis is clearly rejected in all but one case.

The statistics for the Box-Pierce test statistic for first autocorrelation coefficient of the stock returns obtained from through are mainly negative and only in 10 out of 17 stocks are significant, further suggesting the presence of asymmetric (leverage effect) in volatility[13]. The Box-Pierce test statistic for ten-order serial correlation for the levels shows a significant serial correlation left in the returns for most stocks. Moreover, the Box-Pierce test statistic for serial correlation in the squares strongly suggests the presence of time-varying volatility, suggesting that volatility clustering is present. Furthermore, the ARCH-LM test statistics report

13 If the first-order autocorrelation coefficient between lagged return and current squared returns (Box-Pierce test) is negative and significantly different from zero, then there is an asymmetry in volatility clustering with will not be capture by a symmetric GARCH model (Alexander, 2001).

Table 4
Basic Statistical of Data

Stock	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Normality	ρ_1	ϱ (10)	ϱ^2(2)	ARCH(4)-LM	RESET	Up limit	Down limit	Total hit %
1	-0.0010	0.0382	-0.07163	0.0273	-23.310	612.504	12066384*	0.017	7.689	184.25*	0.003	1.528	9	6	1.02
2	-0.0014	0.0511	-0.0676	0.0290	-16.268	380.490	4635713*	-0.021	8.003	195.14*	6.001**	8.372**	17	18	3.13
3	-0.0017	0.0541	-0.0524	0.0262	-11.691	221.697	1562118*	-0.039	10.768	205.33*	0.001	5.062	19	22	4.01
4	0.0002	0.0588	-0.1806	0.0111	-5.092	105.087	339888.2*	-0.468*	375.430*	121.58*	32.166*	75.5338	12	14	2.21
5	0.0000	0.0541	-0.0541	0.0134	-0.043	8.626	1022.403*	0.011	4.4223	201.02*	0.757	1.190	27	31	5.07
6	-0.0002	0.0516	-0.3075	0.0173	-8.286	142.634	638485.6*	-0.013*	12.249	190.55*	15.047*	18.993*	38	27	6.18
7	-0.0009	0.0491	-0.0693	0.0273	-21.391	540.107	9374764*	0.028	15.785**	226.61*	0.003	3.459	22	13	3.15
8	-0.0010	0.0481	-0.0644	0.0253	-21.128	537.359	9278212*	-0.290*	5.638	241.138	0.007	6.179	9	7	1.71
9	-0.0001	0.2495	-0.0527	0.0174	3.957	58.179	100343.2*	-0.228*	94.918*	115.09*	12.144*	10.438**	19	16	3.14
10	0.0014	0.0526	-0.0556	0.0204	0.071	4.210	17.940	-0.154*	53.003*	143.15*	117.294*	20.122*	56	41	9.16
11	-0.0009	0.0500	-0.0524	0.0152	-0.194	6.903	496.90*	-0.018*	21.403**	150.75*	48.489*	42.361*	16	10	3.01
12	0.0000	0.0491	-0.0513	0.0076	-0.610	18.977	8291.42*	-0.071	3.575	200.15*	84.913*	39.616*	9	5	0.94
13	-0.0018	0.0522	-0.0691	0.0283	-18.658	454.489	6627380*	-0.021*	2.071	201.09*	22.009*	14.920	19	31	4.17
14	0.0012	0.0493	-0.0720	0.0288	-20.130	504.066	8159735*	0.022	27.885*	183.45*	0.004	2.119	13	8	2.09
15	-0.0007	0.0800	-0.0541	0.0174	0.256	5.447	201.826*	-0.153*	113.120*	165.78*	51.754*	9.971**	38	22	5.18
16	-0.0008	0.0221	-0.0529	0.0065	-7.398	57.902	104406.5*	-0.552*	462.760*	127.04*	118.357*	43.753*	0	6	0.72
17	0.0001	0.0524	-0.0856	0.0137	-2.9654	48.0925	66795.63*	-0.129*	18.079*	147.46*	12.631*	21.272*	14	7	2.06

Notes: *, ** significant at 1% and 5% respectively. Normality represents the Jarque-Bera (1987) normality test, which follows a chi-squared distribution, with two degrees of freedom. ρ_1 is the first autocorrelation coefficient. Q(2) and $Q^2(12)$ are Ljung-Box tests for serial correlation in the returns and squared returns data respectively. ARCH (4)-LM is a test for conditional heterocedasticity in returns for four orders. The OLS-regression is $\gamma^2 = \alpha_0 + \alpha_1 * \gamma^2_{t-1} + ... + \alpha_4 * \gamma^2_{t-4}$. $T * R^2$ is used and is χ^2 distribute with 6 degrees of freedom. T is the number of observations, y is returns and R^2 is the explained over total variation. $\alpha_0, \alpha_1 ... \alpha_4$ are parameters. RESET (12,4) is a test for non-linear dependence linearity in conditional mean of return: 12 is number of lags and 4 is the number of moments that is chosen in implementation of the test statistic. $T * R^2$ distributed with 12 degrees of freedom.

highly significant changing volatility in most stocks. These results confirm the presence of time-varying volatility in. the null hypothesis of no higher order non-linear dependence in return series was not satisfied for the most stocks using Ramseys (1969) RESET test. The fourteenth and fifteenth columns show the number of times each stock hitting the upper and lower price limits, respectively. The total number of times that stocks hitting these limits ranges from zero to 35. The last column reports the percentage of days in the sample that the given stock reached the price limit. These percentages range only from 0.79% to 9.16%.

The Empirical Results

In the previous section, we have established the existence of significant variations from the normal distribution, ARCH effects, non-linearity and asymmetric volatility. These suggest that the EGARCH model is the most appropriate to capture the observed characteristics in the daily returns data discovered above.

Table (5) reports the estimation results of the EGARCH with the mean equation for each stock. The appropriate EGARCH model is selected using Schwartz Information Criterion (SIC). We find that on the whole, a EGARCH (1,1) model is the most parsimonious representation of the variance of all stocks considered. The mean equation includes an MA(1) term in order to remove any serial correlation in the returns which may be caused by non-synchronous trading in the stocks.

Table (6) provides diagnosis statistics for the estimated model for each stock, showing that the considerable specification successfully captures the behavior pattern of stock returns under investigation. In all cases no evidence of additional ARCH structure is detected, and interestingly, the null hypothesis of linearity in the mean for EGARCH is accepted (RESET test) in all cases. Also, the Q(10) for standardized residuals and the squared standardized residuals $Q^2(10)$ lead to accept the null hypothesis of no correlation in all cases. While, the numbers for kurtosis and skewness for the standardized residuals have lower values than the raw data, the Jarque-Bara test indicates that the residuals are remained not conditionally normally distribution. It is interesting to note here that when the assumption of conditional normality does not hold, the ARCH parameter estimates will still be consistent, but the estimate of the covariance matrix will not be consistent. Indeed, in this paper we have used the method of heteroskedasticity consistent covariance suggested by Bollerslev and Wooldridge

Table 5
EGARCH (1,1) Estimates of Daily Stock Returns

$$P_t = \mu + \rho\varepsilon_{t-1} + \varepsilon_t \qquad \text{(mean equation)}$$

$$g(h_t) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right]\beta\log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma D_{t-1} + \nu V_t \qquad \text{(variance equation)}$$

Stock	μ	ρ	ω	α	β	δ	γ	$\nu^{*}10^{4}$
1	0.004 (1.937)**	0.1525 (4.084)*	-2.503 (-1.973)**	0.094 (2.146)**	0.991 (4.149)*	0.072- (-3.294)*	0.052 (1.654)	0.622 (2.450)**
2	0.0005 (0.710)	0.192 (4.110)*	-8.882 (-0.670)	0.0634 (3.639)*	0.707 (4.779)*	-0.018 (-5.008)*	0.062 (0.541)	0.248 (0.557)
3	-0.001 (-1.817)	0.081 (3.138)*	-8.141 (-3.355)*	0.0712 (5.598)*	0.898 (3.618)*	-0.027 (-2.748)*	0.054 (1.035)	0.906 (1.178)
4	-0.007 (-0.220)	0.284 (3.473)*	-3.993 (-1.250)	0.197 (5.329)*	0.847 (2.341)**	-0.079 (-2.407)**	0.070 (1.214)	0.372 (4.655)*
5	0.006- (-2.210)**	0.006 (0.750)	-7.764 (-2.555)**	0.065 (4.605)*	0.724 (3.292)*	0.036- (-4.727)*	0.047 (0.670)	0.191 (4.676)*
6	-0.001 (-1.763)	0.017 (1.944)**	-3.964 (-1.114)	0.107 (2.231)**	0.959 (2.397)**	-0.026 (-3.431)*	-0.098 (-0.881)	0.645 (0.997)
7	0.0004 (0.717)	0.392 (4.880)*	-1.962 (-1.055)	0.171 (2.837)*	0.920 (2.133)**	0.053 (-2.436)**	1.088 (1.961)**	0.196 (5.331)*
8	-0.003 (-1.316)	0.124 (2.382)**	-3.638 (-1.073)	0.167 (2.167)**	0.623 (4.886)*	-0.062 (-6.725)*	0.294 (2.020)**	0.359 (2.576)**
9	-0.008 (-1.706)	0.142 (3.508)*	-3.533 (-3.760)*	0.248 (2.988)*	0.572 (3.438)*	-0.064 (-2.518)**	0.057 (0.869)	0.121 (6.284)*
10	-0.001 (2.561)*	0.094 (2.427)**	-3.263 (-3.639)*	0.149 (1.978)**	0.798 (2.685)*	-0.047 (-6.725)*	0.068 (3.767)*	0.846 (2.975)*
11	-0.008 (-1.996)	0.050 (1.359)	-8.502 (-0.462)	0.156 (2.407)**	0.334 (2.136)**	0.071- (-6.986)*	0.096 (3.770)*	0.683 (1.249)
12	0.0001 (0.591)	0.055 (0.743)	-2.086 (-1.841)	0.033 (3.155)*	0.421 (1.907)**	0.036- (-2.214)**	-0.023 (-0.920)	-0.826 (-1.048)
13	-0.009 (-0.923)	0.006 (0.902)	-2.086 (-1.841)	-0.031 (-0.153)	0.004 (0.492)	0.080- (-0.096)	0.095 (2.257)**	0.683 (3.947)*
14	0.008 (0.660)	0.004 (0.967)	-2.069 (-2.840)*	0.204 (0.316)	0.872 (3.107)*	0.075- (-5.245)*	0.019 (0.998)	0.633 (0.941)-
15	-0.001 (-1.780)	0.092 (2.311)**	-2.375 (-7.577)*	0.025 (2.415)**	0.298 (2.469)**	0.053- (-2.514)**	-0.061 (-0.164)	0.428 (4.663)*
16	-0.003 (-1.915)**	0.319 (2.055)**	-10.257) (-0.977)	0.060 (4.710)*	0.671 (5.207)*	-0.070 (-3.751)*	0.049 (0.184)	0.407 (0.587)
17	0.003 (0.096)	0.148 (3.226)*	-2.796 (-4.108)*	0.033 (1.101)	0.167 (0.417)	0.067- (-6.621)*	0.071 (0.882)	0.521 (7.511)*

Notes: t-statistics iside parenthesis computed from the quasi-maximum likelihood (QLM) heteroskedasticity consistent covariance described by the Bollerslev and Woolridge (1992). The model is estimated using G@RCH 2.0 package of Laurent and Peters (2001).This package is written in Ox programming language. G@RCH 2.0 can be downloaded free of charch for academic purposes at http://www.egss.ulg.ac.be/garch/. "*", "**" denote statistical significant at 1%, %5 respectively.

(1992) to cope with that problem and to get consistent t-values for the parameters.

Starting with the mean equation results, Table (5) observe that the MA(1) term is highly significant in the most stocks. This indicates that the stock returns exhibit serial correlation. In other words even after we take into consideration the impact of non-synchronous trading, the stocks reflect inefficiency during the period of the study.

The results show strong evidence that the daily stock returns can be characterized by the EGARCH mod-

Table 6
Diagnostics Tests on EGARCH (1,1) Residuals

Stock	Skewness	Kurtosis	Normality	ϱ (2)	ϱ^2 (10)	ARCH(4)-LM	RESET
1	-1.330	6.610	1767.2*	13.345	0.006	0.009	0.007
2	-0.855	5.625	437.77*	12.648	0.406	0.291	0.361
3	-1.658	10.951	3028.9*	15.313	0.052	0.0118	0.010
4	-1.219	9.462	2407.2*	4.650	2.083	0.003	0.061
5	-0.078	3.099	15.09	10.077	10.340	7.732	2.364
6	-2.317	6.554	1682.5*	24.794*	0.301	0.006	0.036
7	-4.274	7.063	11503.6*	3.007	0.049	0.129	0.149
8	-4.264	7.041	12721.3*	19.875**	0.785	0.698	1.049
9	2.400	6.556	4656.9*	10.410	0.982	0.735	2.014
10	-0.342	5.916	363.98*	8.436	13.581	0.716	3.079
11	-0.484	7.100	719.85*	7.256	13.665	3.206	4.0481
12	0.615	7.903	906.4	4.378	14.203	3.522	4.098
13	-0.971	5.060	1764.0*	11.149	0.205	0.026	0.051
14	-1.513	13.740	5636.13*	3.844	0.215	0.191	0.721
15	-0.038	5.063	282.25*	13.271	0.689	3.389	4.180
16	-1.096	4.113	7931.22*	5.654	0.498	1.161	1.801
17	-0.308	3.871	443.36*	7.632	0.508	0.149	0.724

Notes: *, ** significant at 1% and 5% respectively. Normality represents the Jarque-Bera (1980) normality test, which follows a chi-squared distribution, with two degrees of freedom. Q(2) and Q^2(12) are Ljung-Box tests for serial correlation in the returns and squared returns data respectively. ARCH (4)-LM is a test for conditional heterocedasticity in residuals for four orders. The OLS-regression $\gamma^2 = \alpha_0 + \alpha_1 * \gamma^2_{t-1} + ... + \alpha_4 * \gamma^2_{t-4}$. $T * R^2$ is used and is χ^2distribute with 6 degrees of freedom. is the number of observations, y is residuals and R^2 is the explained over total variation. $\alpha_0, \alpha_1 ... \alpha_4$ are parameters. RESET (12,4) is a test for non-linear dependence linearity in conditional mean of residuals: 12 is number of lags and 4 is the number of moments that is chosen in implementation of the test statistic. $T * R^2$ distributed with 12 degrees of freedom.

el. The coefficient of the lagged squared returns, α, is positive for all stocks and statistically significant for most stocks. These results confirm the tendency for shocks to persist, with large (small) price changes typically followed by similar ones. In other words, periods of relatively high (or low) volatility are found to be time-dependent, consistent with the indication of Table (5). The coefficient of the lagged conditional variance, β, is significantly positive and less than one for most returns examined. The low magnitude of β coefficients indicate a relatively short-memory in the volatility shocks. In fact, the measure of volatility persistence given by the sum of the $\alpha + \beta$ coefficients is considerably less than unity, implying that the effect of shocks to volatility tends to decay within a few time lags (i.e., the duration of a shock is typically only a few days)[14]. The results also show distinct significant leverage effect in most stocks (a significant negative value for the δ parameter)-bad news has a greater impact on conditional variance than good news. Furthermore, the results show that in 10 out of 17 cases the coefficients on the trading volume are positive statistically significant, indicating that the trading volume has significant effect on volatility persistence. This agrees with the theoretical and empirical works outline in Section III: a higher volume is a proxy for increased news arrivals, which suggests increases in trading volatility.

The surprising result of this paper is the effect of price limits on volatility. As evident in Table (5), the dummy variable coefficients γ are negative for 3 stocks out of 17 stocks and none of them are significant. The results also show that the coefficient of price limits is positive in 14 stocks, and in 5 stocks only are statistically significant implies that the price limits have a positive effect on the volatility of these stocks. One explanation of this unexpected result can be found in the big hand theory of Keyness (1936). In a thin stock market, such as the one in Jordan, price limits could be used by big hands to signal to its daily limit for a few sessions and that could attract many uninformed traders as it gives them the illusion that the price could keep on hitting its limits, and that could increase volatility[15]. This result is also consistent with Fama (1989) who argued that price limits could increase the price volatility inciting trading in anticipation of halts.

14 See Lamoureux and Lastrapes (1990b).

15 The big hand theory argued that price limits merely provide a tool for big hands to signal their manipulation to attract followers.

The fact that all coefficients are very low in magnitude, only 5 have significant positive coefficients and none of stocks has negative significant coefficient, the overall results indicate that the price limits have no impact on stock market volatility[16]. Thus, our results support the argument that price limits may only prolong the number of trading days it would take for the market to adapt towards equilibrium. Therefore, according to this argument, price limits have no effect on volatility, particularly to reduce it, it only cause longer and more significant serial correlation in stock returns. On other worlds, the price limits that restrict the trading of informed traders[17] may make the market less efficient.

Nerveless, price limits may still benefit the market by compensate it for other weakness in the trading process. For example, when brokers cannot collect margins continuously in real time, price limits give them time to collect margins. When orders flow exceeds the processing capacity of a market, price limits protect traders from trading in an informationally disorganized market (see Harris, 1998).

Summary and Conclusions

In this paper we have examined the effect of price limits on the volatility of a cross section of individual shares listed in the ASE using the GARCH models. Based on our cross-section of stocks, the results of this paper suggest that the price limits regulation in the ASE have not had the desired effect on stock market volatility, which was to reduce it. Thus, our results support the Famas (1989) argument that this system may only delay the adjustment of price to changes in fundamental values and therefore causes stock prices to behave in less efficient manner. On other words, according to this argument, price limits may only prolong the number of trading days it would take for the market to adapt equilibrium and have no effect on volatility. Thus, the price limits may contribute to irrational (inefficient) stock price movements. This finding also suggests that, in any event that causes sharp price swings in stocks, Jordanian investors need to fully evaluate and consider the risks (volatility) even if the trading in these stocks is halted because the limits are reached.

These unexpected results may imply that the reconsideration of the current form of circuit breaker could

16 This conclusion is highly consistent with Phylaktis *et al.*, (1999) findings for Athens Stock Exchange.

17 Informed traders-also known as speculators-trade to profit from their superior ability too forecast future prices based on their access to fundamental information.

be important to develop the ASE. This revision could consider either reducing the existing distortions by making the price limits more binding (i.e., by narrowing the current range of permissible price changes), or introducing an alternative type of circuit breaker, such as the trading halts adopted for index declines in several mature markets. These may well help in making the market more efficient.

While we found strong support in against of the effect of price limits on stock price volatility, the empirical analysis in this paper may subject to spurious results since the effect of price limits on stock price volatility examines without control for other variables such as macro economic and financial volatility. Thus, one interest potential area for future research is to control for these factors in investigation the effect of price limits on volatility. Furthermore, the above analysis suffers from a shortcoming in the use of daily closing data to measure market volatility, which is changing constantly throughout a trading day. In particular, large and more frequent intraday variations are likely to occur in times of market turbulence. Thus, for an indicator to fully reflect volatility condition, statistics capturing changes during the day are needed. However, unavailability of the data on intraday stock prices over the period under investigation constraint us to use closing price.

References

Alexander, C. 2001. *Market Models: A Guide to Financial Data Analysis*. John Wiley & Sons, UK.

Bekaert, G., and Wu, G. 2000. Asymmetric Volatility and Risk in Equity Markets. *Review of Financial Studies*, 13: 1-42.

Bildik, R. and Elekdag, S. 2002. Effects of Price Limits on Volatility: Evidence from the Istanbul Stock Exchange. Working Paper, Istanbul Stock Exchange, memio.

Bollersev, T. 1986. Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics*, 33: 307-327.

Bollerslev, T. and Wooldrige, J. 1992. Quasi-Maximum Likelihood Estimation inference in Dynamic Models with Time-Varying Covariances. *Econometric Theory*, 11: 143-72.

Campbell, J.Y., Lettau, M., Malkiel, B.G. and Xu, Y. 2001. Have Individual Stocks Become more Volatile? An Empirical Exploration of Idiosyncratic Risk. *Journal of Finance*, 56: 1-43.

Campbell, J.Y., Lo, A.W. and MacKinlay, A.C. 1997. *The Econometrics of Financial Markets*. Princeton University Press, New Jersey.

Chen, Y.-M. 1993. Price Limits and Stock Market Volatility in Taiwan. *Pacific Basin Finance Journal*, 1: 139-153.

Christie, W.G., Crown, S.A. and Harris, J.H. 2002. Nasdaq Trading Halts: The Impact of Market Mechanisms on Prices, Trading Activity, and Execution Costs. *Journal of Finance*, 57: 1443-78.

Chung, J.-R. 1991. Price Limit system and volatility of Korean Stock Market. In Rhee, S. G. and Chang, R. P. (Eds), *Pacific Basic Capital Market Research*, Amsterdam: North-Holland.

Cohen, K., Mair, R. Schwartz, S. and Whitcomb, D. 1983. A Simulation Model of Stock Exchange Trading. *Simulation*, November: 181-191.

De Long, J., Shleifer, A., Summers, L., and Waldmann, R. 1989. The Size and Incidence of the Losses from Noise Trading". *Journal of Finance*, 44: 681-696.

Ding, Z., Granger, C. W. J. Engle, R. F. 1993. A Long Memory Property of Stock Market Returns and a New Model. *Journal of empirical Finance*, 1: 83-106.

Engle, R. 2000. *ARCH Selected Readings*. Oxford University Press, New York.

Engle, R. and Bollerslev, T. 1986. Modelling the Persistence of Conditional Variances. *Econometric Reviews*, 5: 1-50.

Engle, R. F. and Patton, A. J. 2001. What Good is a Volatility Model? *Quantitative Finance*, 1: 237-45.

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

Fama, E. 1989. Perspectives on October 1987, or What did we Learn from the Crash. In Kamphuis, R. W., Kormendi, R. C. and Watson, J. W. H. (Eds), *Black Money and the Future of Financial Markets*. Homewood, IL: Irwin.

Fornari, F. and Mele, A. 1996. Modeling the Changing Asymmetry of Conditional Variances. *Economic Letters*, 50: 197-203.

French, K. R. and Roll, R. 1986. Stock Return Variance: The Arrival of Information and the Reaction of Traders. *Journal of Financial Economics*, 19, 3-29.

French, K., Schwert, G. and Stambaugh, R. 1987. Expected Stock Returns and Volatility. *Journal of Financial Economics*, 19: 3-30.

Gallo, G. M. and Pacini, B. 2000. The Effect of Trading Activity on Market Volatility. *The European Journal of Finance*, 6: 163-175.

Glen, A., Lee, K. and Singh, A. 2000. Competition, Corporate Governance and Financing of Corporate Growth in Emerging Markets. Working Paper, Cambridge University, mimeo.

Glosten, L., Jaganathan, R. and Runkle, D. 1993. On the Relation Between the Expected Value and Volatility of the Normal Excess Return on Stocks. *Journal of Finance*, 48: 1779-1801.

Gonzales-Rivera, G. 1996. Smooth Transition GARCH Models. *Working*

Paper, University of California, mimeo.

Garner, A. 1988. Has the Stock Market Crash Reduce the Consumer Spending? Working Paper, Federal Reserve Broad, Washington; D.C.

Harris, L. 1989. The Dangers of Regulatory Over-reaction to the October 1987 Stock Market Crash. *Cornell Law Review*, 74: 927-42.

Harris, L. 1998. Circuit Breakers and Program Trading Limits: What Have we Learned? In Litan, R. and Santomero, A. M. (Eds), *Brookings-Wharton papers on Financial Services*. Brookings Institution press.

Harvey, C. 1989. Time-Varying Conditional Covariances in Tests of Asset Pricing Models. *Journal of Financial Economics*. 24: 289-317.

Jarque, C. and Bera, A. 1987. A Test for Normality of Observations and Regression Residuals. *International Statistical Review*, 55: 163-72.

Keynes, J. M. 1936. *The General Theory of Employment, Interest and Money*. London: The Royal Economic Society.

Kim, D. and Kon, S. 1994. Alternative Models for the Conditional Heteroskedasticity of stock Returns. *Journal of Business*, 67: 563-588.

Kim, J., and Singal, V. 2000. Stock Market of Openings: Experience of Emerging Economies. *Journal of Business*, 73: 25-66.

Kim, K. A. 2001. Price Limits and Stock Market Volatility. *Economic Letters*, 71: 131-136.

Kim, K. A. and Rhee, S. G. 1997. Price Limit Performance: Evidence from the Tokyo Stock Exchange. *The Journal of Finance*, 52, 885-901.

Kodres, L. and OBrian, D. 1994. The Existence of Pareto-Superior Price Limits. *American Economic Review*, 84: 919-32.

Kyle, A. S. 1988. Trading Halts and Price Limits. *Review of Future Markets*, 7: 426-34.

Lamourex, C.G. and Lastrapes, W.D. 1990a. Heteroskedasticity in Stock Return Data: Volume versus GARCH Effects. *Journal of Finance*, 45: 221-29.

Lamoureux, G.C. and Lastrapes, W.D. 1990b. Persistence in Variance, Structural Change, and the GARCH Model. *Journal of Business Economics Statistics*, 8: 225-234.

Lange, S. 1999. Modeling Asset Market Volatility in a small Market: Accounting for Non-synchronous Trading Effects. *Journal of International Financial Markets, Institutions and Money*, 9: 1-18.

Laurnet, S. and Peters, J.-P. 2001. G@RCH 2.0: an Ox Package for estimating and Forecasting Various ARCH Models. Proceedings 8th Forecasting Financial Markets, London.

Lee, M. C., Ready, M. J. and Seguin, P. J. 1994. Volume, Volatility, and New York Stock Exchange Trading Halts. *Journal of Finance*, 49: 183-214.

Lehmann, B. 1989. Commentray: Volatility, Price Resolution, and the Effectiveness of Price Limits. *Journal of Financial Services Research*, 3: 201-203.

Li, W.K., Ling, S. and McAleer, M. 2002. Recent Theoretical results for Time Series Models with GARCH. In McAleer, M. and Oxley, L. (Eds), *Contributions to Financial Econometrics*. Blackwell Publishing, UK.

Ljung, C. M. and Box, G. E. P. 1978. On Measuring of Lag in Time Series Models. *Biometrics*, 67: 297-303.

Ma, C. K., Rao, R. and Sears, R. S. 1989. Limits Moves and Price Resolution: The Case of the Treasury Bond Future. *Journal of Future Markets*, 9: 321-35.

Mandelbort, B. 1963. The Variation of Certain Speculative Prices. *Journal of Business*, 36, 394-419.

Moser, J. T. 1990. Circuit Breakers. *Economic Perspectives*, 14: 2-13.

Nelson, D. 1991. Conditional Heterocedascity in Asset Returns: A New Approach. *Econometrica*, 59: 347-70.

Ngassam, C. 2002. Effect of Price limits on volatility and Stock Returns in Emerging Markets: Evidence from the Johannesburg Stock Exchange. *Journal of Comparative International Management*, 5: 16-31.

Omran, M. F. and McKenzie, E. 2000. Heteroskedasticity in Stock Returns Data Revisited: Volume versus GARCH Effects. *Applied Financial Economics*, 10: 553-60.

Pagan, A. R 1996. The Econometrics Financial Markets. *Journal of Empirical Finance*, 3: 15-102.

Pagan, A. R. and Schwert, G. W. 1990. Alternative Models for Conditional stock Volatility. *Journal of Econometrics*, 45:267-90.

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.

Poterba, J.M. 2000. Stock Market Wealth and Consumption. *Journal of Economic Perspectives*, 14: 99-118.

Ramsey, J. 1969. Tests for Specification errors in Classical Least-Squares Regression Analysis. *Journal of the Royal Statistical Society B, 31: 350-71.*

Roll, R. 1988. The International Crash of October 1987. *Financial Analysis Journal*, 44: 19-35.

Roll, R. 1989. Price Volatility, International Market Links, and their Implications for Regulatory Policies. *Journal of Financial Services Research*, 3: 211-46.

Santoni, G. J. and Liu, T. 1993. Circuit Breakers and Stock Market Volatility. Journal of Futures Markets, 13: 261-78.

Schwert, G.W. 2002. Stock Volatility in the New Millennium: how Wacky in Nasdaq? *Journal of Monetary Economics*, 49: 3-26.

Sentana, E. 1995. Quadratic ARCH Models. *Review of Economic Studies*, 62: 639-61.

Singh, A. 1992. The Stock Market and Economic Development: Should Developing Countries Encourage Stock Markets? Working Paper No. 49, University of Cambridge.

Singh, A. 1997. Financial Liberalization Stock Markets and Economic Development. *The Economic Journal*, 107: 771-82.

Singh, A. 1999. Should Africa Promote Stock Market Capitalism? *Journal of International Development*, 11: 343-65.

Singh, A., Singh, A. and Weisse, B. 2000. Information Technology, Venture Capital and the Stock Market. Working Paper, University of Cambridge, mimeo.

Starr-McCluer, M. 1998. Stock Market Wealth and Consumer Spending. Working Paper No. 20, Federal Reserve Broad; Washington, D.C.

Subrahmanyam, A. 1994. Circuit Breakers and Market Volatility: A Theoretical Perspective. *Journal of finance*, 49: 237-54.

Zakoian, J.-M. 1994. Threshold Heteroscedastic Models. *Journal of Economic Dynamics and Control*, 18: 931-55.

الملخص

تحديد الأسعار وشدة التغيرفي السوق: دلائل من بورصة عَمّان

أكثم عيسى المغايرة
الجامعة الهاشمية

اختبرت هذه الدراسة أثر نظام تحديد السعر على شدة التذبذب في أسعار الأسهم في بورصة عمّان (البورصة الأردنية) خلال الفترة ما بين عامي 1999 و 2002. وقد اعتمدت الدراسة على عينة مكونة من سبعة عشر سهماً، تم اختيارها بناء على معيار السيولة وحجم التداول. ومن خلال الاعتماد على هذه العينة، أشارت النتائج إلى أن سياسة تحديد السعر المعمول به حاليا ليس له الأثر المتوقع على شدة تذبذب أسعار الأسهم في بورصة عمّان. إن نتائج الدراسة تشير إلى أنه يجب أن تقوم بورصة عمّان بإعادة النظر في هذه السياسة، وذلك إما بتضييق المدى الحالي لمستوى تغير الأسعار المسموح به، وإما بطرح سياسة بديلة مثل سياسة توقيف التبادل (Trading Halt) التي يجرى العمل بها الآن في العديد من الأسواق المتطورة.

Aktham I. Maghyereh (Ph.D. in Finance and Banking, University of Durham, U.K. 2001). Assistant Professor, Department of Finance and Banking Sciences, The Hashemite University-Jordan. His research focuses on Emerging Markets, Corporate Finance Practices, Markets Integration, Market Efficiency, Market Microstructure, Financial Lliberalization and Financial Development, and Applied Econometrics.