Jordan Journal of Economic Sciences, Volume 5, No. 2 2018

Commonality in Volatility: Does it Exist in Amman Stock Exchange?

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ABSTRACT

This study aims to investigate whether individual stock volatility co-moves with the overall market volatility in emerging markets. Our data set consisted of the daily observations of 105 companies listed in Amman Stock Exchange (ASE) over the period 2006-2015. Time series GARCH (1, 1) regressions were estimated for each stock individually. The results indicated a strong evidence of commonality in volatility in ASE. Thus, 76%- 89% of the firms investigated showed a statistically significant positive co-movement of their volatilities with the overall market volatility. However, when sectoral volatility was added to the models, the evidence of co-movement with market volatility became less important in the financial and industrial sectors. The firms in these two sectors showed a stronger co-movement of their volatilities with sectoral volatility if compared to their co-movement with market volatility. Moreover, our results exhibited no size effect in the commonality in volatility. No significant differences were found between the portfolios of different sized stocks. Our findings are vital to investors, portfolio managers, researchers and all parties who are interested in stock exchanges. To the best of authors' knowledge, this study is the first in Jordan that tackles commonality in volatility.

Keywords: Commonality, Volatility, Market, Size effect, Sectorial commonality, Amman stock exchange.

INTRODUCTION

Stock price volatility is one of the well-researched phenomena in financial markets worldwide. It is a key element of the investment decisions and portfolio creations. Thus, both investors and portfolio managers consider volatility a main indicator of investment risk. Volatility is vital in pricing derivatives as well because knowing the price volatility of the underlying asset at which the derivative contract is made plays a key role in pricing that contract. Mainly, volatility is important for determining the rate of return and cost of capital and assessing investment and leverage decisions in addition to its essential part in risk management, hedging strategies and asset pricing.

Volatility is inherently unobservable and thus measuring it is crucial in financial research. Traditional GARCH models are the most well-known models that forecast return and volatility based on lagged returns and innovations. The ARCH class models do not make use of sample standard deviation but formulate conditional variance of returns via maximum likelihood procedure (Engle, 1982). Other measures of volatility include historical volatility models which are based on the sample standard deviation of returns. These models include random walk, historical averages of squared return, time series models based on historical volatility using moving averages, exponential weights and autoregressive models

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Received on 5/4/2017 and Accepted for Publication on 10//2017.

(see for example Brown, 1990; Engle, 1993; Aydemir, 1998; Tylor, 2004). Some researchers utilized option implied standard deviation based on the black-scholes (1973) model while others depended on stochastic volatility models forecasts (for more detailed discussion see Ghysels, *et al*, 1996). More sophisticated volatility forecasting models are based on neural networks (see for example Hu and Tsoukalas, 1999) and genetic programming such as that used in Zumbach *et al*.(2002).

Researchers have proposed a set of different explanations of volatility in financial markets. Pryymachinco (2003) has divided these explanations into two categories, those attempting to relate the stock price volatility to the changes in the fundamentals such as those changes in the macroeconomic factors or changes in investment profits (Chen, *et al*., 1986; Harvey, 1995; Yom, 2000) and those based on the non-fundamental factors such as bubbles and fads, irrationality of agents and information asymmetry (West, 1988; Timmerman, 1993; Sarno and Taylor, 1999). The latter seems to be more vital in the emerging stock exchanges. Nelson (1996) listed several factors associated with market volatility changes. These factors include positive serial correlation in volatility, which means that large changes tend to be followed by large changes of either sign, whereas small changes tend to be followed by small changes, a phenomenon called volatility clustering. Trading and non-trading days also affect volatility. Thus, volatility is found to be higher on Mondays comparing to other days of the week. Moreover, volatility tends to be higher during recession and financial crises. Daly (2011) argued that trading volume, contrarian trade, and the introduction of futures and options influence volatility over the short-term, while corporate leverage and nominal interest rates have long term effects.

Recent research found that correlation among volatility is stronger than that among returns and both tend to increase during bear markets and financial crises. Bekaert *et al.* (2012) found co-movements in average idiosyncratic volatility across countries. Their sample included 23 developed equity markets. Barigozzi *et al.* (2014) showed a common secular trend in realized volatilities. Engle and Figlewski (2015) documented a common factor in option-implied volatilities of 28 stocks of the Dow Jones Industrial Average. Veredas and Luciani (2015) examined the factor structure in realized volatilities and introduced an approximate dynamic factor model for modeling and forecasting large panels of realized volatilities. Their model captures co-movements and clustering. However, the commonality in volatility was unexplored until Sharma *et al*. (2014) whose introduced significant evidence of co-movement between individual stock volatility and market volatility in NYSE. Their study provided the first evidence of commonality in volatility in the developed markets. Sharma *et al*. (2014) used the volatility spillover theory and the contagion theory to explain the possible relationship between firm volatility and market volatility. Specifically, they argued that volatility spillover takes place when volatility originates from the market and spills over to the firm. This happens because financial markets are characterized by information processing, advances in computer technology and liberalized capital movements (Kim and Rogers, 1995; Wongswan, 2006). In addition, Sharma *et al*. (2014) utilized what they called "market-to-firm contagion" to explain the possible commonality in volatility phenomenon. They argued that if the market and the firms comprising it are moderately correlated during periods of stability, then a shock to the market has ripple effects and leads to a significant increase in firm level co-movement, which in turn would constitute contagion. Motivated by their findings and to the best of authors' knowledge, this study is the first in Jordan that tackles the same issue. We investigate the effect of market volatility on individual stock volatility in Amman Stock Exchange (ASE) over the period 2006-2015. Moreover, we examine the co-movement between individual stock and sectoral volatility and inspect whether the commonality is related to firm size. Examining this topic in emerging markets seems to be more vital than investigating it in developed markets. Emerging markets are characterized by high volatility, volatility clustering, information asymmetry, investors' irrationality, smaller market capitalization and less number of firms than developed markets. The motivation underlying this study is well-known. Joint movements in volatility influence the distribution of portfolio returns, and thus play an important role in risk management, portfolio selection, and derivative pricing. Co-movements in volatility could also help to expand our understanding of financial markets and to shed light on issues such as contagion and the transmission of shocks through the financial system. Moreover, it helps understanding the mechanism in which financial crises happen. The remaining of this study is organized as follows: Section 2 reviews the literature, section 3 describes data and methodology, section 4 explains the results of analysis and section 5 concludes this study.

2. Literature Review

Sharma *et al*. (2014) are the first researchers to explore commonality in volatility in financial markets. Using time series GARCH (1, 1) model and a sample of 560 firms listed in NYSE over the period 1998-2008. They found that market volatility has a statistically significant effect on firm volatility for at least 50% of firms investigated and for 12 out of 14 sectors. Moreover, their results showed a significant size effect; thus, commonality is apparent for large firms and weak in small firms. Sharma *et al*. (2014) also found that market volatility predicts firm volatility for firms belonging to 5 out of 14 sectors. Recently, Herskovic *et al*. (2016) found a common factor in idiosyncratic volatility that is priced in the cross section of US stock returns. Wlodarczyk and Otola (2016) investigated whether the strength of firm-market volatility relationship has changed after subprime crisis on the Polish Capital Market. Their sample consisted of selected companies listed on the Warsaw Stock Exchange (WSE) from the construction and IT sectors during 2004–2011. For each company, ARFIMAX-FIGARCH model with additional exogenous variables, which represented market volatility, were estimated in the stable and the turbulent period. Their results showed no significant increase in the fraction of firms from a given sector of Polish Capital Market whose volatility is strongly and positively related to market volatility in the pre-crisis period compared with the post-crisis period.

In the Jordanian context, Rousan and AL-Khouri (2005) modeled the market volatility in ASE. The study investigated the behavior of stock prices and return volatility using daily data of the general index over the period 1992-2004. The results demonstrated that returns exhibit a significant level of serial correlation which is related to conditional heteroskedasticity due to time varying volatility. 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. Al-Rjoub (2011) examined the impact of different crises, namely, the Mexico's Tequila crises of 1994, the Asian /Russian crises in 1997-1998, the attack of 9/11 on the United States in 2001, the war on Iraq in 2004, the financial crisis in November 2005 and the global financial crisis of 2008-2009, on the behavior of stock returns and volatility during these crises. He found that imported crises cause volatility to decrease or increase based on the general public expectations. The local stock market crash during 2005 and the global financial crises of 2008 had no impact on volatility. Stock returns were found to be reliably negative during the above financial crises except during the war on Iraq in 2004. In another study, Al-Rjoub and Azzam (2012) examined the behavior of stock returns and volatility in ASE during global, regional and local events, mainly during the 2008-2009 crisis. Their data covered the period 1992-2009. They defined stock market crash as a 20 percent decline in the stock market and also used a 35 percent or more fall in emerging stock market from its historical maximum as a definition of stock market crash. Their results showed that crises in general have negative impact on stock returns for all sectors, with the banking sector being the most affected. The effect of the 2008-2009 crash is the most severe, with the largest drop in stock prices and high volatilities. Al-Rjoub and Azzam (2012) provided evidence of high persistence in volatility and strong reverse relationship between stock return and its volatility before and after the crises.

Overall, volatility is an important phenomenon in finance and it is more vital in emerging markets if compared to developed stock exchanges as the former are characterized by higher average sample returns. That is, their returns are more predictable and their stock prices are highly volatile. To the best of authors' knowledge, this is the first study that investigates commonality in volatility in ASE.

3. Data and Methodology

Our data set consisted of the daily observations of 105 firms listed in ASE over the period 2006-2015. The firms were selected according to the following criteria:

i. Firms should be established before 2011.
ii. Firms should not have been involved in attainments, mergers, splits or any structural changes during the study period.
iii. Firms that are thinly traded were excluded in order to avoid range-based volatility estimator for the opening jumps in the Geometric Brownian Motion. Thus, the Geometric Brownian Motion is a continuous-time stochastic process in which the logarithm of the randomly varying quantity follows a Brownian motion (also called a Wiener process) with drift (Ross, 2014).

We used three volatility proxies and thus we estimated three models each using a specific proxy each time. The first measure of volatility (VOL1) that was utilized was proposed by Parkinson (1980), who constructed this volatility proxy assuming a geometric Brownian motion with no drift in the stock prices. It is given in the following formula:

$$VOL1 = 0.361[\ln(HP/LP)]^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where: *HP* denotes the highest price during the day, *LP* denotes the lowest price during the day.

The second volatility measure (VOL2) that we used was introduced by German and Klass (1980) and is given in the following equation:

$$VOL2 = 0.5[\ln(HP) - \ln(LP)]^2 - [2\ln 2 - 1][\ln(CP) - \ln(OP)]^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where: *CP* is the closing price, *OP* is the opening price.

The third volatility measure (VOL3) that we utilized was proposed by Rogers and Satchel (1991) and Rogers *et al.* (1994) and it is given in the following equation:

$$VOL3 = [\ln(HP) - \ln(OP)][\ln(HP) - \ln(CP)] + [\ln(LP) - \ln(OP)][\ln(LP) - \ln(CP)] \ldots\ldots\ldots \quad \ldots(3)$$

To investigate the commonality in volatility, the following time series GARCH (1,1) model was estimated (Sharma, *et al*., 2014):

$$VOL_t = \beta_0 + \beta_1 VOL_{mkt,t} + \beta_2 VOL_{mkt,t-1} + \beta_3 VOL_{mkt,t+1} + \beta_4 R_{mkt,t} + \beta_5 R^2_{mkt,t} + e_t \quad \ldots\ldots\ldots\ldots(4)$$

Where VOL_t represents the individual stock volatility on day t. $VOL_{mkt,t}$ represents the overall market volatility computed by averaging the individual volatilities of all stocks except the underlying stock for which the model is estimated. $VOL_{mkt,t-1}$ and $VOL_{mkt,t+1}$ are the lag and lead values of market volatility, respectively. $R_{mkt,t}$ denotes market return on day *t*. $R_{mkt}{}^2{}_{,t}$ denotes squared market return on day *t*. The last two variables were added as control variables to the model. This model was estimated three times for each individual stock using a certain volatility measure each time.

To investigate sectoral commonality in volatility, we estimated the following time series GARCH (1,1) model (Sharma, *et al*., 2014):

$$VOL_t = \alpha_0 + \alpha_1 VOL_{\sec,t} + \alpha_2 VOL_{\sec,t-1} + \alpha_3 VOL_{\sec,t+1} + \alpha_4 VOL_{mkt,t} + \alpha_5 VOL_{mkt,t-1} + \alpha_6 VOL_{mkt,t+1} + \alpha_7 R_{mkt,t} + \alpha_8 R^2_{mkt,t} + e_t \quad (5)$$

Where: $VOL_{\sec,t}$ is the sectoral volatility which is estimated by averaging individual volatilities for all stocks in that sector except the underlying stock for which the model is estimated. The firms in ASE were classified into three main sectors, the financial sector, the services sector and the industrial sector. $VOL_{\sec,t-1}$ and $VOL_{\sec,t+1}$ are the lag and lead values of sectoral volatility, respectively. Once again, this model was estimated three times for each stock using a specific volatility measure each time.

The size effect of commonality was investigated by dividing the sample stocks into ten portfolios according to their size, which was measured by market capitalization. The 105 sample stocks were sorted according to their market capitalization each year, the smallest company in the sample was the Specialized Jordanian Investment with an average market capitalization of JD 2,681, 250 and the largest company was the Arab Bank with an average market capitalization of JD 4,127,820,000 over the study period. Thereafter, sample stocks were divided into ten portfolios each consisting of 10 or 11 stocks.

Portfolio 1 represents the portfolio of smallest stocks while Portfolio 10 represents the portfolio of largest stocks. The portfolios were rebalanced annually. Afterward, we estimated equation (4) for the ten portfolios. The market capitalization of portfolio 1 over the study period is on average JD 29,887,101 while the market capitalization of portfolio 10 over the study period is on average JD 16,663,237,023.

The LM test was used to test for ARCH effects and the results showed statistically significant ARCH effects in the sample stocks, (results are available upon request). The Augmented Dicky Fuller test was applied to check the stationarity of time series.

4. Results of Analysis

Table 1 reports the descriptive statistics of the three daily volatility proxies. The results are comparable. The mean values are 0.0003, 0.0009 and 0.0003 of VOL1, VOL2 and VOL3, respectively. The minimum values are zeros of the three measures while the maximum values range from 2.28% to 5%. Figure 1 displays the behavior of the three daily volatility proxies over the study period. It shows that returns are highly volatile in ASE. Stock prices show high levels of volatility and volatility clustering. Moreover, volatility seems to persist for relatively long periods of time over the study period.

Table 1: Descriptive statistics of volatility measures of ASE over the period 2006-2015

	VOL1	VOL2	VOL3
Mean	0.0003	0.0009	0.0003
Median	0.0001	0.0003	0.0000
Maximum	0.0228	0.0499	0.0332
Minimum	0.0000	0.0000	0.0000
Std. Dev.	0.0006	0.0019	0.0009

Mean, median, maximum, minimum and standard deviation values of volatility proxies in ASE over the period 2006-2015 were reported. "VOL 1" denotes the volatility proxy introduced by Parkinson (1980), "VOL 2" denotes the volatility proxy introduced by German and Klass (1980) and "VOL 3" denotes the volatility proxy introduced by Rogers and Satchel (1991) and Rogers *et al.* (1994).

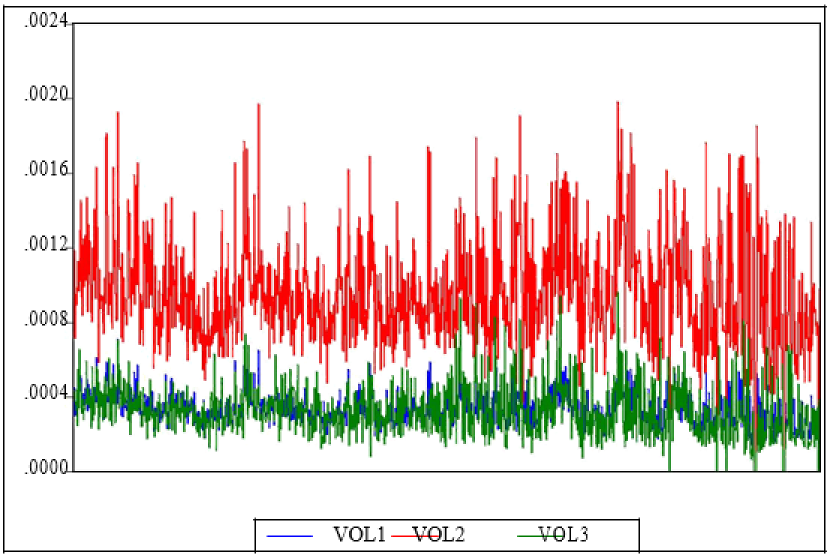

Figure 1: Volatility measures in ASE over the period (2006-2015)

Table 2 reports the estimation results of the commonality in volatility for each of the three models. It is clear that each model is related to a certain volatility measure. The results indicated a clear evidence of commonality in volatility in the three estimated models. The percentage of firms that have positive and statistically significant coefficients of co-movement between individual stock volatility and market volatility ranged from 67% in model 3 to 89% in model 2. The lead and lag effects were less important than the co-movement at the concurrent level. Only few firms exhibited a statistically negative co-movement between their volatilities and market volatility. Their percentage ranged from zero in model 2 to 4.5% in model 3. The coefficient of co-movement averaged 0.6013 in model 1, 0.6004 in model 2 and 0.5795 in model 3 for all sample stocks. The adjusted R squared ranged from 11% to 14% for the three GARCH models.

Our results are consistent with those of Sharma *et al.* (2014), who discovered evidence of commonality in volatility in NYSE over the period 1998-2008. Thus, we provide evidence that this phenomenon exists not only in developed markets but also in emerging markets. Moreover, the percentages of firms that have positive and statistically significant coefficient of co-movement between individual stock volatility and market volatility are higher in ASE compared to those in NYSE. In other words, the evidence of commonality in volatility seems to be stronger in emerging markets compared to developed markets. This could be explained by the nature of these markets which are characterized by smaller market capitalization, fewer numbers of investors, asymmetric information, lower levels of efficiency, higher levels of volatility and volatility clustering. Figures 2 and 3 show the volatilities of some companies that co-move with the market volatility and the volatilities of some companies that do not co-move with the market volatility, respectively.

Table 2. Commonality in volatility in ASE over the period 2006-2015

Daily values of volatility measure for each stock was regressed on the concurrent, lead and lag values of market volatility measured as an average of the volatilities of all sample stocks except the underlying stock. Time series GARCH (1, 1) regressions were estimated. Volatility was measured by three proxies, model 1 uses the volatility proxy introduced by Parkinson (1980), model 2 uses the volatility proxy introduced by German and Klass (1980) and model 3 uses the volatility proxy introduced by Rogers and Satchel (1991) and Rogers *et al.* (1994). Market return and squared return were added as control variables to the model. Cross-sectional averages of time series slope coefficients were reported. "Concurrent", "Lag" and "Lead" refer, respectively, to the same, previous, and next trading day observations of market volatility. "% + Sig" denotes the percentage of stocks with significant positive slope coefficients of market volatility. "% - Sig" denotes the percentage of stocks with significant negative slope coefficients of market volatility. "Adjusted R^2" denotes the cross-sectional average of the adjusted R^2 of the sample stocks.

	Model 1	Model 2	Model 3
Concurrent	0.6013	0.6004	0.5795
% + Sig	0.7727	0.8939	0.6667
% - Sig	0.0152	0.0000	0.0455
Lag	0.0335	0.0134	0.0323
% + Sig	0.1667	0.1970	0.1515
% - Sig	0.0758	0.0606	0.1212
Lead	0.0639	0.0490	0.0575
% + Sig	0.2424	0.2273	0.3333
% - Sig	0.0606	0.0758	0.0606
Adjusted R^2	0.12	0.14	0.11

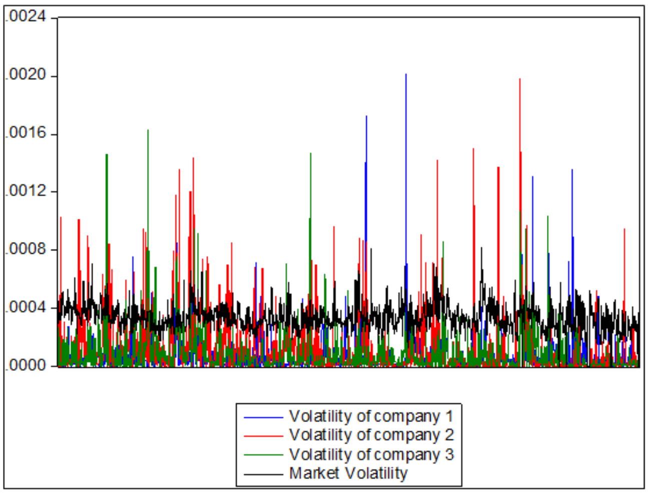

Figure 2: Volatilities of some companies that show market commonality in ASE over the period 2006-2015

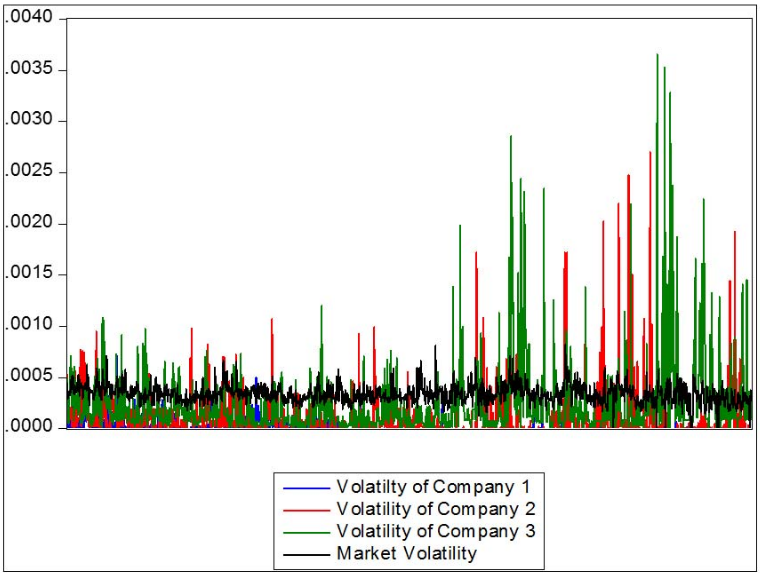

Figure 3: Volatilities of some companies that do not show market commonality in ASE over the period 2006-2015

Table 2 reports the results of commonality in volatility according to different sectors. The evidence is apparent in the three sectors of ASE. The percentage of firms that have a positive and statistically significant coefficient of co-movement between their specific volatilities and market volatility ranged from 81.8% to 93.9% in the services sector, from 57.1% to 85.7% in the industrial sector and from 41. 6% to 66.7% in the financial sector.

Table 3. Commonality in volatility according to sectors

Daily values of volatility measure for each stock were regressed on the concurrent, lead and lag values of market volatility (measured as an average of the volatilities of all sample stocks except the underlying stock). Time series GARCH (1, 1) regressions were estimated. Volatility was measured by three proxies, "Model 1" uses the volatility proxy introduced by Parkinson (1980), "Model 2" uses the volatility proxy introduced by German and Klass (1980) and "Model 3" uses the volatility proxy introduced by Rogers and Satchel (1991) and Rogers *et al.* (1994). Market return and squared return were added as control variables to the model. "% + Sig" denotes the percentage of stocks in a certain sector with significant positive slope coefficients of concurrent market volatility. "% - Sig" denotes the percentage of stocks in a certain sector with significant negative slope coefficients of concurrent market volatility. "Financial" denotes the results of the stocks in the financial sector. "Services" denotes the results of the stocks in the service sector. "Industrial" denotes the results of the stocks in the industrial sector.

	Model 1	Model 2	Model 3
Financial			
% + Sig	0.6667	0.8333	0.4167
% - Sig	0.0000	0.0000	0.1667
Services			
% + Sig	0.9394	0.9394	0.8182
% - Sig	0.0000	0.0000	0.0303
Industrial			
% + Sig	0.5714	0.8571	0.5714
% - Sig	0.0476	0.0000	0.0000

Table 3 reports the estimation results of regressing the individual stock volatility on the concurrent, lag and lead values of both market and sectoral volatility. The results indicated a stronger evidence of sectoral commonality in volatility than that of market commonality. Indeed, after controlling for the market volatility, a strong evidence of co-movement with sectoral volatility was found. The evidence of co-movement with market volatility becomes less important when the sectoral volatility is added to the models. The percentages of firms whose specific volatilities co-move with market volatility have decreased. On the other hand, the percentage of firms that have positive and statistically significant coefficient of co-movement between specific volatility and sectoral volatility ranged from 91.7% to 100% in the financial sector, from 90.5% to 100% in the industrial sector and from 18.2% to 33.3% in the services sector. The coefficients of co-movement with sectoral volatility were also larger than those with market volatility. The coefficient of sectoral volatility ranged from 0.3876 to 0.6782 in the financial sector, from 0.4670 to 0.5614 in the services sector and from 0.7219 to 0.7829 in the industrial sector. The evidence of sectoral commonality was more apparent in the financial and industrial sectors. The firms in the service sector showed comparable evidence of commonality at both the sectoral and market levels. These results are consistent with the spillover theory, which indicates that volatility spills over from the sector and the market levels to the firm level.

Table 4. Sectoral commonality in volatility in ASE over the period 2006-2015

Daily values of volatility measure for each stock were regressed on the concurrent, lead and lag values of market volatility (measured as an average of the volatilities of all sample stocks except the underlying stock) and on the concurrent, lead and lag values of sectoral volatility (measured as an average of the volatilities of all sample stocks in that sector except the underlying stock). Time series GARCH (1, 1) regressions were estimated. Volatility was measured by three proxies, "Model 1" uses the volatility proxy introduced by Parkinson (1980), "Model 2" uses the volatility proxy introduced by German and Klass (1980) and "Model 3" uses the volatility proxy introduced by Rogers and Satchel (1991) and Rogers et al. (1994). Market return and squared return were added as control variables to the model. Cross-sectional averages of time series slope coefficients were reported. "Concurrent", "Lag" and "Lead" refer, respectively, to the same, previous, and next trading day observations of market or sectoral volatility. "% + Sig" denotes the percentage of stocks with significant positive slope coefficients. "% - Sig" denotes the percentage of stocks with significant negative slope coefficients. "MKT" denotes the market volatility while "Sector" denotes sectoral volatility. "Adjusted R^2" denotes the cross-sectional average of the adjusted R^2 values.

	Model 1		Model 2		Model 3	
	MKT	Sector	MKT	Sector	MKT	Sector
Financial						
Concurrent	0.0314	0.6172	0.0256	0.6782	0.0099	0.3876
% + Sig	0.4167	0.9167	0.2500	1.0000	0.2500	0.9167
% - Sig	0.1667	0.0000	0.0000	0.0000	0.2500	0.0000
Lag	-0.0125	0.0242	-0.0201	0.0113	-0.0006	-0.0568
% + Sig	0.1667	0.0000	0.2500	0.1667	0.2500	0.1667
% - Sig	0.2500	0.0833	0.4167	0.0833	0.2500	0.4167
Lead	-0.0103	0.2238	-0.0100	0.2285	0.0063	0.3355
% + Sig	0.2500	0.7500	0.2500	0.5000	0.1667	0.9167
% - Sig	0.1667	0.0833	0.0833	0.2500	0.2500	0.0000
Adjusted R^2	0.13		0.16		0.12	

Services						
Concurrent	0.2499	0.5044	0.2381	0.4670	0.1736	0.5614
% + Sig	0.3939	0.2121	0.3030	0.3333	0.2727	0.1818
% - Sig	0.0303	0.0606	0.0606	0.1212	0.0606	0.0606
Lag	0.1017	-0.0302	0.1421	-0.0821	0.0840	-0.0125
% + Sig	0.1515	0.0606	0.0909	0.0909	0.3030	0.0303
% - Sig	0.0606	0.2121	0.0606	0.1515	0.0303	0.1818
Lead	0.0687	0.0093	0.0136	0.0291	0.1199	-0.0326
% + Sig	0.1818	0.0303	0.1212	0.1212	0.2424	0.0909
% - Sig	0.0909	0.1515	0.0606	0.1212	0.0303	0.1818
Adjusted R^2	0.17		0.18		0.16	
Industrial						
Concurrent	0.0288	0.7219	0.0190	0.7829	0.0248	0.7727
% + Sig	0.0952	1.0000	0.1905	0.9048	0.2381	0.9048
% - Sig	0.0476	0.0000	0.0000	0.0000	0.0952	0.0000
Lag	0.0482	-0.0337	0.0007	-0.0297	0.0294	-0.0545
% + Sig	0.1429	0.1905	0.0476	0.1429	0.1429	0.0476
% - Sig	0.0476	0.1429	0.0952	0.0952	0.0476	0.1429
Lead	0.0589	0.0176	0.0508	0.0734	-0.0028	0.0478
% + Sig	0.1429	0.2381	0.1905	0.2857	0.1429	0.2381
% - Sig	0.0476	0.1429	0.0000	0.0000	0.0952	0.0952
Adjusted R^2	0.12		0.13		0.13	

The studies in developed markets showed size effect in the commonality in volatility. Sharma *et al.* (2014) found that the evidence of commonality is weak for small sized firms. Thus, the large firms were found to exhibit more apparent evidence of commonality than small firms. The results of size effect in Table 5 contrasted with those of previous studies. We divided the sample firms into ten portfolios according to their size. Portfolio 1 consisted of the smallest stocks while Portfolio 10 represented the largest stocks. The results exhibited no evidence of size effect. In fact, no obvious differences were found between the estimation results of the three models of commonality in volatility of Portfolios 1 and 10. The results of the two portfolios were comparable. These results demonstrated that the commonality in volatility in ASE is not a size-related phenomenon; it exists regardless of the size of the firm.

Table 5. Size effect of commonality in volatility in ASE over the period 2006-2015

Daily values of volatility measure for each portfolio were regressed on the concurrent, lead and lag values of market volatility measured as an average of the volatilities of all sample stocks except the underlying stocks in the portfolio. Time series GARCH (1, 1) regressions were estimated. Sample stocks were divided into ten portfolios according to their size. "Port1" denotes Portfolio 1 which consisted of the smallest sample stocks while "Port10" denotes Portfolio 10 which represented the largest sample stocks. Volatility was measured by three proxies, model 1 uses the volatility proxy introduced by Parkinson (1980), model 2 uses the volatility proxy introduced by German and Klass (1980) and model 3 uses the volatility proxy introduced by Rogers and Satchel (1991) and Rogers et al. (1994). Market return and squared return were added as control variables to the model. "Concurrent", "Lag" and "Lead" refer, respectively, to the same, previous, and next trading day observations of market volatility. "MKT" denotes market return while MKT^2 denotes squared market return. "C" denotes intercept.

	Port1				Port10		
	Model1				Model1		
Variable	Coefficient	z-Stat	Prob.	Variable	Coefficient	z-Stat	Prob.
C	0.0001	7.7384	0.0000	C	0.0000	0.7195	0.4718
Concurrent	0.1350	3.3722	0.0002	Concurrent	0.1890	3.7701	0.0002
Lag	-0.1033	-1.2519	0.2106	Lag	0.0012	0.0249	0.9801
Lead	-0.0479	-0.5947	0.5521	Lead	-0.0489	-1.1091	0.2674
MKT	-0.0017	-1.1893	0.2343	MKT	0.0011	1.8849	0.0594
MKT^2	0.0336	0.3102	0.7564	MKT^2	0.7303	15.3549	0.0000
	Model2				Model2		
Variable	Coefficient	z-Stat	Prob.	Variable	Coefficient	z-Stat	Prob.
C	-0.0004	-5.7856	0.0000	C	-0.0001	-2.5626	0.0104
Concurrent	0.2797	6.6460	0.0000	Concurrent	0.1729	4.7878	0.0000
Lag	0.1392	3.1051	0.0019	Lag	0.0939	2.5249	0.0116
Lead	0.5820	10.2497	0.0000	Lead	0.0091	0.2635	0.7921
MKT	-0.0080	-3.0321	0.0024	MKT	0.0021	1.6786	0.0932
MKT^2	0.4488	1.6567	0.0976	MKT^2	2.3268	20.5267	0.0000
	Model3				Model3		
Variable	Coefficient	z-Stat	Prob.	Variable	Coefficient	z-Stat	Prob.
C	0.0002	6.1522	0.0000	C	0.0001	15.4201	0.0000
Concurrent	0.1265	2.2234	0.0262	Concurrent	-0.0509	-5.2250	0.0000
Lag	-0.1123	-1.6969	0.0897	Lag	-0.0399	-2.0939	0.0363
Lead	-0.1167	-1.7134	0.0866	Lead	-0.0270	-2.0112	0.0443
MKT	-0.0003	-0.1772	0.8594	MKT	-0.0011	-2.5947	0.0095
MKT^2	0.1754	1.3526	0.1762	MKT^2	0.3217	10.9480	0.0000

The commonality of volatility analysis is repeated on three sub-periods before the global financial crises (2006-2007), during the global financial crises (2008-2009) and after it (2010-2015). Table 5 shows the results of analysis.

The evidence of commonality in volatility exists in the three sub-periods; however, it increased in the global financial crises period. The percentage of firms whose volatilities positively co-move with the overall market volatility has increased to 82%-90% during the global financial crises. These results are consistent with the contagion theory, which indicates that a shock to the market increases the volatility effects and leads to a significant increase in firm-market co-movement.

Table 6. Commonality in volatility in ASE over sub periods

Daily values of volatility measure for each stock were regressed on the concurrent, lead and lag values of market volatility (measured as an average of the volatilities of all sample stocks except the underlying stock). Time series GARCH (1, 1) regressions were estimated. Volatility was measured by three proxies, "Model 1" uses the volatility proxy introduced by Parkinson (1980), "Model 2" uses the volatility proxy introduced by German and Klass (1980) and "Model 3" uses the volatility proxy introduced by Rogers and Satchel (1991) and Rogers et al. (1994). Market return and squared return were added as control variables to the model. Cross-sectional averages of time series slope coefficients of concurrent market volatility were reported. "% + Sig" denotes the percentage of sample stocks with significant positive slope coefficients of concurrent market volatility. "% - Sig" denotes the percentage of sample stocks with significant negative slope coefficients of concurrent market volatility.

Concurrent	Model1	Model2	Model3
(2006-2007)	0.5631	0.5491	0.5651
% + Sig	0.6391	0.6732	0.6851
% - Sig	0.0467	0.03681	0.0119
(2008-2009)	0.7854	0.7916	0.7431
% + Sig	0.8391	0.8951	0.8172
% - Sig	0.1082	0.0762	0.1130
(2010-2015)	0.6439	0.6693	0.6508
% + Sig	0.6854	0.7012	0.6902
% - Sig	0.0335	0.0134	0.0323

5. Conclusion

The financial literature offers much research on stock market volatility over time and linkages that exist among world markets. However, Sharma *et al.* (2014) have pioneered the investigation of commonality in volatility in stock exchanges. They introduced the first evidence of this phenomenon worldwide. Few comparable research studies were done on the emerging markets despite the fact that these markets are characterized by high volatility and volatility clustering. This study has provided evidence of market and sectoral commonality in volatility in ASE using daily data over the period 2006-2015. The evidence introduced in this study is stronger than that provided by Sharma *et al.* (2014) for NYSE. Moreover, the study found that the co-movement of firms' volatilities with sectoral volatility is larger than that with the overall market volatility for two out of three sectors in ASE. The commonality does not differ between portfolios of different sized stocks. Our findings are important to practitioners and academicians as well. They give insights that explain stock price changes in bull and bear markets and more importantly in times of financial crises.

REFERENCES

Al-Rjoub, Samer A. (2011). Business Cycles, Financial Crises, and Stock Volatility in Jordan Stock Exchange, ***International Journal of Economic Perspectives***, 5 (1): 83-95.

Al-Rjoub, Samer, and Hussam Azzam. (2012). Financial Crises, Stock Returns and Volatility in an Emerging Stock Market: The Case of Jordan, ***Journal of Economic Studies***, 39 (2): 178-211.

Aydemir, Abdurrahman. (1998). Volatility Modeling in Finance, 1-46, in. J. Knight and S. Satchell (Eds.), ***Forecasting Volatility in The Financial Markets***, Butterworth Heinemann.

Barigozzi, Matteo, Christian Brownlees, Giampiero M. Gallo, and David Veredas. (2014). Disentangling Systematic and Idiosyncratic Dynamics in Panels of Volatility Measures. ***Journal of Econometrics***, 182 (2): 364-384.

Bekaert, Geert, Robert J. Hodrick, and Xiaoyan Zhang. (2012). Aggregate Idiosyncratic Volatility, ***Journal of Financial and Quantitative Analysis***, 47 (6): 1155-1185.

Black, Fischer, and Myron Scholes. (1973). The Pricing of Options and Corporate Liabilities, ***Journal of Political Economy,*** 81: 637-654.

Brown, Stephen. (1990). Estimating Volatility, 516-537, in. S. Figlewski, W. Silb er, and M. Subrahmanyam (Eds.), ***Financial Options: From Theory to Practice,*** Chicago, Irwin.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross. (1986). Economic Forces and the Stock Market: Testing the APT and Alternative Asset Pricing Theories, ***Journal of Business,*** 59: 383-403.

Daly, Kevin James. (2011). An Overview of the Determinants of Financial Volatility: An Explanation of Measuring Techniques, ***Modern Applied Science***, 5(5): 46-63.

Engle, Robert F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation, ***Econometrica***, 50 (4): 987–1008.

Engle, Robert, and Stephen Figlewski. (2015). Modeling the Dynamics of Correlations among Implied Volatilities, ***Review of Finance,*** 19 (3): 991-1018.

Engle, Robert F., and Victor K. Ng. (1993). Measuring and Testing the Impact of News on Volatility, ***Journal of Finance***, 48 (5): 1749-1778.

Garman, Mark B., and Michael J. Klass. (1980). On the Estimation of Security Price Volatilities from Historical Data, ***Journal of Business***, 53: 67-78.

Ghysels, Eric, Andrew C. Harvey, and Eric Renault. (1996). 5 Stochastic Volatility, 119-191, In. G.S. Maddala, C.R. Rao (Eds.). ***Handbook of Statistics: Statistical Methods in Finance***, Amsterdam: Elsevier Science.

Harvey, Campbell R. (1995). Predictable Risk and Return in Emerging Markets, ***The Review of Financial Studies***, 8: 773-816.

Herskovic, Bernard, Bryan Kelly, Hanno Lustig, and Stijn Van Nieuwerburgh. (2016). The Common Factor in Idiosyncratic Volatility: Quantitative Asset Pricing Implications, ***Journal of Financial Economics***, 119 (2): 249-283.

Hu, Michael Y., and Christos Tsoukalas. (1999). Combining Conditional volatility Forecasts Using Neural Networks: An Application to the EMS Exchange Rates, ***Journal of International Financial Markets***, ***Institutions and Money***, 9: 407-422.

Kim, Sang W., and John H. Rogers. (1995). International Stock Price Spillovers and Market Liberalization: Evidence from Korea, Japan and the United States, ***Journal of Empirical Finance***, 2(2): 117-133. Nelson, Daniel B. (1996). Modeling Stock Market Volatility Changes, 3-15, in. P. Rossi (Ed.), ***Modeling Stock Market Volatility***, Academic Press.

Parkinson, Michael. (1980). The Extreme Value Method for Estimating the Rate of Return, ***Journal of Business***, 53:61-65.

Pryymachinco, Iryna. (2003). ***Stock Price Volatility and its Determinants on the Emerging Financial Market of Ukraine***. Master Thesis. National University, Ukraine.

Rogers, L. Christopher G., and Stephen E. Satchell. (1991). Estimating Variance from High, Low and Closing Prices,

Analysis of Applied Probability, 1: 500-512.

Rogers, Leonard CG, Stephen E. Satchell, and Y. Yoon. (1994). Estimating the Volatility of Stock Price: A Comparison of Methods that Use High and Low Prices, ***Applied Financial Economics***, 4: 241-247.

Ross, Sheldon. M. (2014). V***ariations on Brownian Motion. Introduction to Probability Models*** (11th ed.). Amsterdam: Elsevier.

Rousan, Raya, and Ritab Al-Khouri. (2005). Modeling Market Volatility in Emerging Markets: The Case of Daily Data in Amman Stock Exchange 1992-2004, ***International Journal of Applied Econometrics and Quantitative Studies***, 2-4: 99-118.

Sarno, Lucio, and Mark P. Taylora. (1999). Moral Hazard, Asset Price Bubbles, Capital Flows, and the East Asian Crisis: The First Tests, ***J. Int. Money Finance***, 18 (4): 637–57.

Sharma, Susan Sunila, Paresh Kumar Narayan, and Xinwei Zheng. (2014). An Analysis of Firm and Market Volatility, ***Economic Systems***, 38 (2): 205-220.

Taylor, James W. (2004). Volatility Forecasting with Smooth Transition Exponential Smoothing, ***International Journal of Forecasting***, 20: 273-286.

Timmermann, Allan G. (1993). How Learning in Financial Markets Generates Excess Volatility and Predictability in Stock Prices, ***Quarterly Journal of Economics***, 108: 1135-1145.

Luciani, Matteo, and David Veredas. (2015). Estimating and Forecasting Large Panels of Volatilities with Approximate Dynamic Factor Models, ***Journal of Forecasting***, 34 (3): 163–176.

West, Kenneth D. (1988). Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation, ***Journal of Finance***, 43 (3): 639-56.

Włodarczyk, Aneta, and Iwona Otola. (2016). Analysis of the Relationship between Market Volatility and Firms Volatility on the Polish Capital Market, ***Dynamic Econometric Models***, 16: 87-116.

Wongswan, Jon. (2006). Transmission of Information across International Equity Markets, ***Review of Financial Studies***, 19: 1157-1189.

Yom, Chiwon. (2000). ***Fundamentals of Fads: Explaining Price Volatility of Emerging Market***s. Market Paper, University of California, Irvin.

Zumbach, Gilles, Olivier V. Pictet, and Oliver Masutti. (2002). Genetic Programming with Syntactic Restrictions Applied to Financial Volatility Forecasting, 557-581, In: Kontoghiorghes, E.J., Rustem, B. and Siokos, S. (Eds.), ***Computational Methods in Decision-Making, Economics and Finance,*** Springer, Boston, MA.

عمومية التذبذب: هل توجد في بورصة عمان للأوراق المالية؟

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ملخص

كشف *Sharma et al. (2014)* دليلاً هاماً عن العلاقة ما بين التذبذب في سعر السهم والتذبذب في السوق ككل في بورصة نيويورك. قدمت هذه الدراسة الدليل الأول على عمومية التذبذب في الأسواق المتقدمة. قد تكون هذه الظاهرة أكثر أهمية في الأسواق الناشئة لما تتصف به هذه الأسواق من ارتفاع في معدل العوائد ومستويات التذبذب المرتفعة في أسعار الأسهم. تبحث هذه الدراسة في العلاقة ما بين التذبذب في سعر السهم والتذبذب في السوق ككل في الدول الناشئة. تتكون بيانات الدراسة من المشاهدات اليومية لمائة وخمس شركات مدرجة في بورصة عمان للأوراق المالية على الفترة (2006–2015). قدرت نماذج الانحدار جارش *GARCH (1, 1)* ذات السلاسل الزمنية لكل سهم على حدى. تشير النتائج إلى وجود دليل قوي لعمومية التذبذب في بورصة عمان حيث أن 76%–89% من الشركات التي تم دراستها أظهرت علاقة إيجابية ذات دلالة إحصائية ما بين التذبذب في أسعار أسهمها والتذبذب الكلي لأسعار الأسهم في السوق ككل. ولكن وعند إضافة التذبذب القطاعي لنماذج الدراسة أصبح دليل التذبذب مع السوق ككل أقل أهمية للشركات في القطاع المالي والصناعي حيث أن أسهم الشركات في هذين القطاعين تظهر علاقة أقوى ما بين التذبذب في أسعارها والتذبذب الكلي في أسعار الأسهم في القطاع ككل من تلك العلاقة مع التذبذب الكلي في أسعار الأسهم في السوق ككل. إضافة إلى ذلك أظهرت النتائج أنه لا يوجد تأثير لحجم الشركة على ظاهرة عمومية التذبذب وكذلك فإنه لا يوجد فروق هامة بين محافظ الأسهم المصنفة حسب الحجم. تعتبر نتائج هذه الدراسة ذات أهمية للمستثمرين ومدراء المحافظ الاستثمارية والباحثين وجميع الأطراف المهتمة في الأسواق المالية. تعتبر هذه الدراسة (على حد علم الباحث) الأولى في الأردن التي تتناول ظاهرة عمومية التذبذب.

الكلمات الدالة: العمومية، التذبذب، السوق، أثر الحجم، العمومية القطاعية، بورصة عمان للأوراق المالية.

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تاريخ استلام البحث 2017/4/5 وتاريخ قبوله 2017/7/10.