Journal of Applied Finance & Banking, vol. 3, no. 3, 2013, 45-64
ISSN: 1792-6580 (print version), 1792-6599(online)
Scienpress Ltd, 2013

An Empirical Investigation of the Relationship between Stock Return and Trading Volume: Evidence from the Jordanian Banking Sector

Mohamed Khaled Al-Jafari[1] and Ahmad Tliti[2]

Abstract

This study investigates the dynamic relationship between stock return and trading volume in the banking sector of Amman Stock Exchange (ASE). In addition, it reveals the nature and direction of this relationship. Therefore, several tests were utilized to include: Bivariate regression model, vector error correction model (VECM), variance decomposition technique, impulse responds function, pairwise Granger causality and Johansen's cointegration tests. The empirical results show that there is no significant relationship between trading volume and stock return on the sub-index level. Moreover, our results show a significant relationship between trading volumes and return volatility. Furthermore, Johansen's cointegration analysis demonstrates that stock return is cointegrated with the trading volume indicating long-run equilibrium relationship. VECM provides evidence of long-run causality from return to trading volume. On the other hand, we used variance decomposition technique and impulse respond function to compare the degree of explanatory power of the trading volume over stock return. The evidence supports the influential role of the stock return in Amman Stock Exchange. Finally, pairwise Granger causality test reveals that past values of stock return were useful in predicting trading volume in ASE. The study concludes that stock price changes in any direction have informational content for upcoming trading activities.

[1]The Arab Academy for Banking and Financial Sciences, Banking and Finance Department, Dean of Postgraduate studies,
e-mail: aljafarimohamedkhled@yahoo.com
[2]The Arab Academy for Banking and Financial Sciences, Banking and Finance Department.
e-mail: Ahmad.tliti@gmail.com

Article Info: *Received :* January 21, 2013. *Revised :* February 9, 2013
Published online : May 1, 2013

JEL classification numbers: C22; C32; G12
Keywords: Stock Return, Trading Volume, Johansen's Cointegration Test, VECM, Variance, Decomposition, Impulse Respond Function, Pairwise Granger Causality Test, Amman Stock Exchange

1 Introduction

Empirical investigations on stock markets traditionally focus primarily on stock prices. Due to various undesirable stochastic properties of stock price, especially non-stationarity, most researchers concentrate on stock return rather than prices. Based on the available set of information about a firm, its stock returns reflect investors' expectations on the future performance of that firm. The arrival of new information causes investors to adapt their expectations, making that the main source for price and return movements. However, since investors are heterogeneous in their interpretations of new information, stock return may remain unchanged even though new information is revealed to the market. This will be the case if some investors interpret it as good news whereas others find it to be bad news. Changes in prices therefore reflect the average reaction of investors to news. On the other hand, stock return may only change if there is positive trading volume.

As with return, trading volume and volume changes mainly reflect the available set of relevant information on the market. Unlike stock price and return, however, a revision in investors' expectations always leads to an increase in trading volume which therefore reflects the sum of investors' reactions to news. Various studies reported that there are significant relationship between volume and stock price movement and volatility, due to the fact that trading volume is a source of risk because of the flow of information. For example, Saatccioglu and Starks (1998) found that volume led stock price changes in four out of the six emerging markets.

There are many reasons why traders pay attention to trading volume. Theoretically, low volume means that the market is illiquid; this also implies high price fluctuation. On the other hand, high volume usually implies that the market is highly liquid, resulting in low price variability. This also reduces the price effect of large trades. In general, with an increase in volume, broker revenue will increase, and market makers have greater opportunity for profit as a result of higher turnover. Many researches have been performed worldwide on different stock markets, especially in the USA, to investigate the relationship between stock return/price and trading volume. Karpoff (1987) summarize importance of understanding this relationship as the following: First, it helps predict various volume-price/return relations that depend on the level of information and the extent to which market prices/volumes convey this information. Second, the price/return-volume relation is important for event studies that use a combination of price and volume data

from which to draw inferences and will increase the power of these tests. Third, the price-volume relationship is critical to the debate over the empirical distribution of speculative prices. When sampled over fixed calendar intervals (e.g. days), rates of return appear platykurtic compared to the normal distribution. Two competing hypotheses to explain this are: rates of return are best characterized by a member of a class of distributions with infinite variance (the stable Paretian hypothesis), and the distribution of rates of return appears platykurtic because the data are sampled from a mixture of distributions that have different conditional variances (MHD). And, fourth, price-volume relationship has significant implications for research into futures markets.

Researchers in this area have examined the volume-price/return relationship in a variety of contexts and by employing a range of analytical techniques. Early studies examined the correlation between volume and the price change as well as volume and the absolute value of the price change (Granger and Morgenstern (1963), Godfrey et al., (1964), Crouch (1970)). More recent studies were interested in investigating the causal relationship between these two market variables (Smirlock and Starks (1988), Chordia and Swaminathan (2000), Chen et al., (2001)).

The linear and non-linear causality between stock prices and trading volume has also received a substantial amount of attention in the literature (Campbell et al., (1993), Martikainen et al., (1994), Hiemstra and Jones (1994)). Many studies report a correlation between these two market variables; but whether they demonstrate a causal relationship in one direction is still unclear.

Although there has been extensive research into the empirical and theoretical aspects of the stock return–volume relationship, most of these researches have focused almost exclusively on the well-developed financial markets, usually the U.S. markets. Taking into consideration that finance theory predicts that there are potential gains from international portfolio diversification if returns from investment in different stock markets are not perfectly correlated and the correlation structure is stable, it will be useful to obtain an investigation of an alternative set of financial markets, in particular, emerging markets.

The advantages of employing emerging markets for such a study are several. Because of their generally low correlations with the more developed markets, the information flows in emerging markets are not equivalent to the information flows in the more developed markets and there are significant institutional differences across the markets. Moreover, a seminal study Harvey (1995), showed that adding portfolio of emerging markets to a diversified developed markets portfolio would result in a reduction of six percentage points in the total portfolio’s volatility, while keeping the expected returns unchanged.

In recent years, a number of new equity markets have emerged in Europe, Latin America, Asia, the Middle East and Africa. Little is known about these markets other than that the expected returns can be impressive and these markets are highly volatile. Importantly, the correlations of these equity returns with developed countries' equity returns are low. As a result, it may be possible to lower portfolio risk by participating in emerging markets.

In the last three decades, a large number of countries have initiated reform process to open their markets. Emerging markets have received huge inflows of capital and became a valuable alternative for investors seeking for international diversification. Among the emerging markets Amman Stock Exchange (ASE) has received its share of foreign investment. Financial sector of ASE had received the highest foreign investment with more than 51% end of 2009 of total investment in the sector.

Building on what was mentioned before; the purpose of this paper is to examine the relationship between stock return and trading volume in the banking sector of Amman Stock Exchange (ASE) to realize one of the following two Wall Street adages: The first one indicates that volume is relatively heavy in bull market and light in a bear market (i.e. return cause volume), while the second one states that it takes volume to make price change (i.e. volume cause return).

In addition, this study contributes to finance literature in several ways. First, it fills the gap created by the scarcity of researches that investigated this issue on emerging financial markets such as ASE. Second, it utilized several econometrical techniques on more recent data to derive a conclusion if there is a relationship between stock return and trading volume in the banking sector of ASE. Third, it will help investors considering investing in the banking sector of ASE as choice of diversification to take an action or not.

This paper is organized into the following sections: Section 2 addresses the previous studies while section 3 illustrates the scientific methods that are employed. Section 4 displays the empirical findings while section 5 provides the concluding remarks.

2 Literature Review

The literature on trading volume and stock return relationship is extensive, but is mostly concerned with the relationship between volume and the volatility of stock returns. Numerous researches have documented the fact that high stock market volume is associated with volatile returns. In the following section, we summarize previous researches related to these issues.

Early empirical examination of the volume-price relationship was conducted by Granger and Morgenstern (1963) where they founds no correlation between prices or absolute price changes and volumes using weekly or daily transaction data for stock market price index data and for individual stocks. On the other hand, Karpoff (1987) tried to find out answers for two old Wall Street adages that "It takes volume to make prices move." i.e. volume movement causes price changes and "volume is relatively heavy in bull markets and light in bear markets", i.e. price changes cause volume movements. He also proposed a simple model of the price-volume relationship called "asymmetric volume-price change hypothesis", showing that the relationship is fundamentally different for positive and negative price changes.

Several theoretical models attempt to explain the relationship between trading volume and stock returns. For instance, Blume, Easley, and O'Hara (1994) investigate and develop a model that links trading volume to stock price behavior. In their model, the aggregate supply is fixed, and traders receive signals of different quality about assets' fundamental values. In their analysis, trading volume indicates the quality or precision of information in past price movements. The main implication of their model is that investors who focus on past trading volume can obtain additional profits and perform better return than those who use only price measures.

Similarly, Llorente, Michaely, Saar and Wang (2002) consider a simple model in which investors trade in the stock market for both hedging and speculation motives. They use the model to investigate the dynamic relation between volume and returns. According to their model, returns generated by hedging-motivated trades reverse themselves, while returns generated by speculation-motivated trades tend to continue themselves. Their empirical results support the predictions of the model on the nature of the dynamic volume-return relation. Stocks that are associated with a high degree of informed trading exhibit more return continuation on high-volume days, and stocks that are associated with a low degree of informed trading show more return reversals on high-volume days.

On the other hand, Podobnik, Horvatic, Petersen and Stanley (2009) investigate the possible relations between price changes and volume changes, by analyzing the properties of the logarithmic volume-price changes. Using a daily price–volume data from Standard and Poor’s (S&P) 500 Index, the New York Stock Exchange (NYSE) and 28 other worldwide financial indices. They propose that the underlying processes for logarithmic price change and logarithmic volume change are similar. Consequently, by using de-trended cross-correlation analysis (DCCA) to analyze changes in trading price to analyze changes in trading volume, they find power-law cross-correlations between the logarithmic volume-price changes.

Further researches try to investigate the dynamics (causal) relationship between trading volume and stock return. For instance, Smirlock and Starks (1988) examine empirically, the lagged relationship between absolute price changes and volume in equity markets and investigate the implications of this relationship for the microstructure of these markets. Using Granger causality tests their results indicate that there is a significant causal relationship between absolute price changes and volume at the firm level. Furthermore, relationship is stronger in periods surrounding earnings announcements. Also, Bauer and Nieuwland (1995) try to investigate this issue by using daily stock return and volumes for 30 stocks listed in Frankfurt stock market in Germany. They find that trading volume has exploratory power and can be used as a proxy for information arrival.

On the other hand, Lee and Rui (2002) examine the causal relation between trading volume and stock return and volatility. Utilizing VAR analysis, they fail to prove the causal relationship between volume and return in the same market. However, they find positive feedback between trading volume and stock return in the three markets. As for cross-country, their findings show causal relationship between New York market variables (trading volume, stock return and volatility), Tokyo and London markets variables.

Similarly, Assogbavi, Schell and Fagnissè (2007) analyze the stock price-volume relationship of individual equities in the Russian Stock Exchange. They use a Vector Auto-Regression analysis on weekly individual equity data on the Russian Stock Exchange. Their empirical findings show a strong evidence of bi-directional causality, which indicating that stock price changes adjust to lagged trading volume over a one week trading time and that trading volume adjusts to lagged price changes over the same time period.

More recent researches try to investigate the informational content of trading volume and its feasibility to predict stock return. For instance, Chordia and Swaminathan (2000) study the possibility of using the trading volume to forecast short horizon returns on stocks traded on the US stock markets. Their sample includes daily and weekly stock return and average trading volume from January 1963 to December 1996. Using vector autoregression tests with pairs of high and low volume portfolio return. Their findings show that daily or weekly returns of stocks with high trading volume lead daily or weekly return of stocks with low trading volume. They performed additional tests to proof that this effect is related to tendency of high volume stock to respond rapidly and low volume stock to respond slowly to new market information.

Also, Ciner (2002) investigates the information content of trading volume on the Toronto Stock Exchange before and after the move towards fully electronic trading. The empirical analysis supports more accurate price discovery under electronic trading. Results from both the structural and vector autoregression models indicate that the predictive power of volume for price variability disappears after full automation.

In contrast to the trading volume-expected return theories, the link between trading volume and volatility is mostly related to a “mixture of distribution” or “information flow” hypothesis, introduced by Clark (1973). This hypothesis posits a joint dependence of returns and volume on an underlying information flow variable. Since there is a wide consensus that the trading volume is highly positively autocorrelated, one of the implications of this theory is that the stock return volatility should also be positively related to the lagged trading volume.

Similarly, Lamoureux and Lastrapes (1990) provide empirical support for the notion that auto-regression conditional heteroskedasticity (ARCH) in daily stock return data reflects time dependence in the process generating information flow to the market. They use daily trading volume as proxy for information arrival time and show that it has significant explanatory power regarding the variance of daily return. Furthermore, ARCH effects tend to disappear when volume is included in the variance equation.

On the other hand, Connolly and Stivers (2005) study volatility clustering in daily returns for the aggregate US equity market and 29 large firms from 1985 to 2000. They find that the relationship between today's index return shock and future volatility is weaker when there was an unemployment news release of that day. Moreover, they find that the relation between today's index return shock and future volatility varies positively with today's market-level turnover shock. Finally, they suggest that turnover shocks have more effect on index level than firm level on volatility.

Several studies related to volume-price-return relationship were also performed on emerging markets. Saatcioglu and Starks (1998) study the relationship between trading volume and stock return in Latin America's stock markets. Using monthly index data, they document a positive relation between volume and both the magnitude of price change and price change itself. They also apply vector autoregressive model to test for Granger-causality between price changes and trading volume. Their findings show a unidirectional relationship where trading volume changes lead to price changes but not the opposite. Similarly, Kamath and Wang (2006) empirically examine the relationship between daily rates of return and trading volumes on the stock market indices of six developing markets from Asia over the recent 34-month period ending in October 2005. The evidence of these markets supports the view that rising markets are accompanied by rising volumes and vice versa. The volume-return relation is found to depend on the direction of the market itself. The volume-absolute return relation is found to be significantly positive. The Granger-causality tests find the absence of causality running in either direction in four of the six markets.

On the other hand, Léon (2007) examines the relationship between trading volume and stock returns volatility in the regional stock market of the West African Economic and Monetary Union called the Bourse Régionale des Valeurs Mobilières (BRVM). His finding reveals a one-way causality running from trading volume to stock returns volatility regardless of the measures of volatility used. Similarly, Khan and Rizwan (2008) investigate empirical causal relationships between trading volumes, stock return and return volatility in Pakistan's stock market. Using data from the Karachi Stock Exchange (KSE-100 Index) covering the period from Jan 2001 until May 2007, they perform Granger-causality tests to examine whether trading volume precedes stock returns, or vice versa. Moreover, GARCH model was employed to test whether the positive contemporaneous relationship between trading volume and stock returns still exists after controlling for non-normality of error distribution. Their findings show a positive contemporaneous relationship between trading volume and return preserves after taking heteroscedasticity into account. Moreover, VAR finds a feedback relationship between stock returns and trading volume, i.e., returns cause volume and volume causes returns which is consistent with the theoretical models that imply information content of volume affects future stock returns. Similarly, Mubarik, and Javid (2009) used the ARCH and the GARCH-M models to test the relationship between return, volatility and trading volume of Pakistan stock market. Their results showed a significant relationship between trading volume and return volatility. In addition, they found a significant effect of the previous day trading volume on the current return.

Also, Al-Khouri and Al-Ghazawi (2008) investigate the impact of the electronic trading system (ETS) on the Amman Stock Exchange (ASE) with respect to volatility and liquidity before and after the implementation of the ETS. Their sample covers the period from 2 January 1996 to 2 January 2004 and they use the GARCH model to test the volatility level on the ASE. Furthermore, they examine the behavior of trading volume as proxy for liquidity. Empirical results show that electronic trading seemed to decrease the volatility of the ASE. In addition, the ETS showed a positive effect on market liquidity, based on daily trading volume. Also, they find an increase in the relative volume of stocks after the adoption of the ETS.

On the other hand, Sabri (2008) studies the impact of trading volume on stock price volatility in eight Arab stock markets, including the Amman Stock Exchange. The sample included four oil Arab states and four non-oil Arab states. His findings indicate that volume volatility represents the most predicted variable of increasing price volatility, and both volume and prices are integrated with each other. Similarly, Alsubaie and Najand (2009) examine the relationship between the abnormal change in trading volume of both individual stocks and portfolios and short-term price autoregressive behavior in the Saudi Stock Market (SSM). They evaluate whether the abnormal change in lagged, contemporaneous, and lead turnovers affects serial correlation in returns. Their result show a reversal in weekly stock returns when conditioned on the change in lagged volume in the SSM. Moreover, they find that reversal is more pronounced with the loser portfolio as specified by filter-based methodology.

A more recent study by Mehrabanpoor, Bahador and Jandaghi (2011) investigates the empirical relationship between the stock exchange indices and turnover volume in the Tehran Stock Exchange. Using monthly indices, value and turnover for the period from 2003 to 2009, they can prove that there is positive relationship between exchange turnover value and stock exchange indices in the Tehran Stock Exchange. Although they could prove the positive correlation between volume and stock exchange indices, they fail to develop a useful model to capture the relationship between stock market indices and volume. Moreover, they use other market factors in the research during the test without a clear explanation about its effect on the relationship.

Similar study by Tripathy (2011) investigates the relationship between trading volume and stock returns using data from Indian Stock Market during the period from January 2005 to January 2010. By using Bivariate Regression model, VECM Model, VAR, IRF and Johansen’s cointegration test. His findings support the existence of significant contemporaneous relationship between return volatility and trading volume indicating that information may flow simultaneously rather than sequentially into the market. Moreover, the study also found that trading volume is associated with an increase in return volatility and that this relationship is asymmetrical. This implied that daily new information in the market may have a significant impact on price volatility, which indicates that bad news generates more impact on volatility of the stock return and trading volume. Additionally, variance decomposition and impulse response function are also estimated to understand the dynamic relationship between stock return and trading volume. The results of this test revealed that shocks in stock returns impact trading volume in the expected direction over a short horizon. However, cointegration analysis shows that stock return volatility is cointegrated with the trading volume, indicating long-run equilibrium relationship. On the other hand, the error correction model indicates the existence of a long-run causality between the stock return volatility and trading volume of the study.

3 Data, Hypotheses and Research Methodology

3.1 Data

The sample consists of trading data and sub-index value of the banking sector in ASE that cover the period from July 2006 until the end of December 2011. It takes into consideration the change in calculation of indices by changing the base value from 100 to 1000 as of 1 January 2004. Daily data were retrieved from Amman Stock Exchange web site: http://www.ase.com.jo.

3.2 Hypotheses

This study tests the following five hypotheses, seeking to reveal the relationship between trading volume and stock return in ASE banking sector:
H_{01}: There is no statistical significant relationship between trading volume and return.
H_{02}: There is no statistical significant relationship between trading volume and return volatility.
H_{03}: There is no cointegration between stock return and trading volume.
H_{04}: Stock return does not Granger cause volume.
H_{05}: Trading volume does not Granger cause the stock return.

3.3 Methodology

The first step is to calculate return for banking sector (R_i). The return is defined as the logarithm of the first difference of closing sub-index at each day.

$$R_i = Ln\left(\frac{P_t}{P_{t-1}}\right) = Ln(P_t) - Ln(P_{t-1}) \tag{1}$$

Where: $\ln(P_t)$ stands for the natural logarithm of the closing sub-index at time t.
Trading volume could be measured in different manner. Turnover ratio, value traded and shares volume are the most used measures throughout reviewed literatures. In this research, trading volume is defined as a log of daily total sub-sector.

$$V_t = Ln(Vol_t) \tag{2}$$

Where Vol_t is the value of the shares traded at time t. The utilization of the natural logarithm of the volume series will improve their normality.
Descriptive statistics are carried out as the second step. This displays various summary statistics for both of the two series (return-volume). It contains basic statistics like mean, standard deviation, range, skewness and kurtosis. Jarque-Bera test were also applied to test whether the series is normally distributed.
To investigate the relationship between stock return and volume data, we simply start by calculating bivariate correlation coefficients for the banking sector. Before commencing

analysis and applying various models to the data, stationarity must be tested as third step. Stationarity means that the mean and variance of the series are constant through time and the auto covariance of the series is not time varying. One of the most famous tests of stationarity (or non-stationarity) is the unit root test.

To perform unit root tests or for the purpose of this study, we use the model proposed by Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test. The unit root test is carried out by using the Augmented Dickey-Fuller (ADF) test for both return and volume series for the banking sector. The general model of the ADF test is:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{j=1}^{m} \alpha \Delta Y_{t-j} + \varepsilon_\tau \quad (3)$$

Where: *Yt* is the variable tested for unit root, which, in our study, is for both return and volume. Δ is the first difference operator ε_t is a pure white noise error term, β is the constant term and t is the time trend and m is the lags number. The number of augmenting lags (m) was chosen on the basis of the Akaike Information Criterion (AIC).

The ADF test takes care of possible serial correlation in the error terms by adding the lagged values for the dependent variable. The null hypotheses for this test is $\delta= 0$ (i.e. there is unit root and the series is not stationary) against the alternative hypothesis of $\delta < 0$ (i.e. there is no unit root and the series is stationary).

Phillips-Perron use nonparametric statistical methods to take care of the serial correlation in the error terms without adding lagged difference terms. To make up for the shortcomings of the ADF test we apply the Phillips-Perron test, which allows the error disturbances to be weakly dependent and heterogeneously distributed. Phillips-Perron test is shown by the following equation:

$$\Delta Y_t = \alpha Y_{t-1} + \beta X_t + \varepsilon_\tau \quad (4)$$

Where: Y_t is data series being tested for unit root. X_t is optional exogenous regressed variable that can either be trended or non-trended. β are the parameters to be estimated and ε_t are the error terms. The null and alternative hypothesis of this test is the same as in ADF test.

To test the relationship between stock returns and trading volume, we apply the model proposed by Lee and Rui (2002), which is defined by the two equations:

$$R_t = \beta_0 + \beta_1 V_t + \beta_2 V_{t-1} + \beta_3 R_{t-1} + \varepsilon_t \quad (5)$$
$$V_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 V_{t-1} + \mu_t \quad (6)$$

Where V_t and R_t is the trading volume and stock return at time *t*. α_i and β_i (i = 0, …, 3) are the model parameters and ε_t and μ_t respectively, denote white noise variables.

Price fluctuations (return volatility) often reported to increase in contemporaneity with high trading volume, and such phenomena can be spotted especially in times of bullish markets. It may happen due to the relationship between higher orders moments of stock returns and trading volume. We explore this relationship by extending the model proposed by Brailsford (1996), which relates trading volume to squared stock returns, as a measurement of volatility, by the following regression:

$$V_t = \alpha_0 + \phi_1 V_{t-1} + \phi_2 V_{t-2} + \alpha_1 R_t^2 + \alpha_2 D_t R_t^2 + e \tag{7}$$

Where D_t is a dummy variable that is equal to 1 if the R_t is positive i.e. bull market, and 0 if R_t negative. The estimated parameter α_1 measures the relationship between return volatility and trading volume, irrespective of the direction of price change. The estimated parameter α_2 measures the degree of asymmetry in that relationship.

The next step is testing for cointegration between trading volume and return series. Cointegration between trading volume and stock return suggests that over the long-run, they move in tandem with each other although the behavior of trading volume could be different from that of return in the short-run. To investigate the long-run relationship between stock return and trading volume, we employed the Johansen cointegration test.

Johansen developed two likelihood ratio tests for testing the number of cointegration vectors (r): the trace and the maximum Eigen value test shown in equations (8) and (9) respectively:

$$J_{trace} = -T \sum_{i=r+1}^{n} Ln\left(1-\hat{\lambda}_i\right) \tag{8}$$

$$J_{\max} = -TLn(1-\hat{\lambda}_{r+1}) \tag{9}$$

Where T is the sample size an*d* λ_i is the largest canonical correlation. The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors. The maximum eigenvalue test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r +1 cointegrating vectors. Neither of these test statistics follow~~s~~ a chi square distribution in general; asymptotic critical values can be found in Johansen and Juselius (1990).

If there is evidence of a cointegrating relationship, causal inferences can be made by estimating the parameters of the vector error correction model (VECM) equation. The purpose of the error correction model is to indicate the speed of adjustment from the short-run equilibrium to the long-run equilibrium.

The short-run vector autoregression in the error correction model (VECM) can be expressed as follows:

$$\Delta R_t = \alpha_0 + \sum_{i=t}^{m} \beta_i \Delta R_{t-i} + \sum_{j=1}^{n} \beta_j \Delta V_{t-j} + \lambda_1 ECT_{t-1} + \varepsilon_{1t} \tag{10}$$

$$\Delta V_t = \alpha_0 + \sum_{i=t}^{m} \alpha_i \Delta V_{t-i} + \sum_{j=1}^{n} \alpha_j \Delta R_{t-j} + \lambda_2 ECT_{t-1} + \varepsilon_{2t} \tag{11}$$

Where Δ is the first difference operator; ECT_{t-1} is the error correction term lagged one period, λ is the short-run coefficient of the error correction term and ε is the white noise.

Once the VECM system is estimated, we then employ two short-run dynamic analyses: Variance Decomposition (VDC) and Impulse Response Function (IRF).Variance Decomposition and impulse response function have been utilized for drawing inferences.

The VDC is an estimate of the proportion of the movement of the n-step ahead forecast error variance of a variable in the VAR system that is attributable to its own shock and that of another variable in the system.

Similarly, the IRF shows impulse responses of a variable in the VAR system to the time path of its own shock as well as that of the shock to another variable in the system. While impulse response functions trace the effects of a shock to one endogenous variable to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR.

To examine the causal relationship between stock returns and trading volume, we have used Granger causality Test. The Granger causality test is used to investigate whether the past information of return is useful to improve the prediction of trading volume and vice versa. We test whether trading volume causes return or return causes trading volume by employing the Engle-Granger causality model. This model was applied by Chen et al., (2001) to explore the same relationship, and the model is as follows:

$$R_t = \alpha_0 + \sum_{i=1}^{5} R_{t-i} + \sum_{j=1}^{5} \beta_j V_{t-j} + \varepsilon_t \tag{12}$$

$$V_t = \alpha_0 + \sum_{i=1}^{5} V_{t-j} + \sum_{i=1}^{5} \delta_j r_{t-j} + \varepsilon_t \tag{13}$$

Where R_t, V_t respectively are the stock return and trading volume on time t. If β_j coefficients are statistically significant then past values of volume and return yield a better forecast of future return and trading volume causes stock return. The F test is used to test the hypothesis that $\beta_j = 0$ for all lagged values (j), if β_j not equal to zero, then volume causes return.

4 Data Analysis and Hypotheses Testing

Table 1 displays the descriptive statistics to include the mean, median, maximum, minimum, standard deviation, skewness and kurtosis and Jarque-Bera (JB) test of normality. It's clear that return mean was negative with high volatility around the mean. Return series was skewed to the left and the kurtosis was higher than 3 reflecting a leptokurtic profile. The JB test fails to reject the null hypothesis indicating that return series was normal in the banking sector of ASE. On the other hand, trading volume series has much less volatility around its mean compared to return. Moreover, trading volume series has positive small skewness and platykurtic profile (kurtosis less than 3). For normality the JB test fails to reject the null hypothesis indicating that trading volume series for the banking sector was normal.

Table 1: Descriptive Statistics for Stock Return and Trading Volume

	Return	Volume
Mean	-0.0002	15.022
Median	-0.0003	14.956
Maximum	0.047	19.665
Minimum	-0.047	12.480
Std. Dev.	0.009	1.029
Skewness	-0.092	0.285
Kurtosis	7.169	2.616
Jarque-Bera	985.984	26.729
Observations	1359	1359

The correlation coefficient between trading volume and stock return is 0.075 and significant at 1% confidence level.

For the test of unit root the present study employs the Augmented Dickey-Fuller test and PP test with null hypothesis that series have unit root (non-stationary). The optimal number of augmented lags for Augmented Dickey-Fuller (ADF) test was chosen on the basis of the Akaike Information Criterion (AIC). Table 2 reports values of ADF test and PP test of both trading volume and stock return for the level and the first difference.

Table 2: Unit Root Test for Trading Volume and Stock Return

At Level		
	Return	Volume
ADF	-0.63	-0.48
PP	-0.68	-0.35
At First Difference		
	Return	Volume
ADF	-7.38	-12.52
PP	-31.29	-73.92

ADF critical values with no intercept and no trend are: -2.56, -1.94 and -1.61 at 1%, 5% and 10% levels; PP critical values are: -2.56, -1.94 and -1.61at 1%, 5% and 10% respectively. Null of unit root existence is accepted if the tests statistic is less than the critical value. The number of augmenting lags (m) was chosen on the basis of the Akaike Information Criterion (AIC).

The results of ADF test at the level suggest that both return and trading volume has a unit root (non-stationary at the level). The Augmented Dickey-Fuller requires the error term (ET) be Independent Identically Distributed (IID) and stationary homoskedostic which may not be true for all-time series data. Therefore, Phillips-Perron (PP) test is applied to test for the existence of unit roots in data. PP test confirms the results derived from Augmented Dickey-Fuller (ADF) showing that both of trading volume and stock return are non-stationary at the level.

However, when we applied ADF test and PP test to the series but at first difference, the results show clearly that both trading volume and stock return become stationary to the first difference, which means that they are both integrated to I(1).

In order to test our first null hypothesis, we apply regression models (5) and (6); with the estimated regression coefficient and their related t-statistic values, P-value, F-statistic and adjusted R-Square reported in Tables (3) and (4) respectively.

From Table 3, we can see that the coefficient is still positive, but not significant either in current or lagged values. Lagged return coefficient is positive and significant at 1% level of significance. Additionally, F-statistic is significant at 1% level of significance, but adjusted R-Square is very small.

Table 3: Regression Results for Model (5) $R_t = \beta_0 + \beta_1 V_t + \beta_2 V_{t-1} + \beta_3 R_{t-1} + \varepsilon_t$

	V	V_{t-1}	R_{t-1}	*F-statistic*	*Adj. R-Square*
Coefficient	0.0005	0.0001	0.142^{**}		
t-statistic	1.330	0.399	5.290	12.27^{**}	0.024
P-value	0.180	0.689	0.000		

Dependent variable: return. Independent variables: trading volume. One lagged period (trading-volume and return)
** Significant at the 0.01 level (2-tailed).
 * Significant at the 0.05 level (2-tailed).
For trading volume-return relationship, Table 4 reports the results for this relationship, results are the same as model (5) as the coefficient is still positive, but not significant either in current or lagged values; lagged trading volume coefficient is positive and significant at 1% level of significance. Additionally, F-statistic is significant at 1% level of significance and adjusted R-Square is relativity high.
To sum up, there is no sharp evidence of a lagged relationship between stock returns and trading volume, since the parameter is insignificant. The strong dependency of trading volume is documented by highly significant return coefficients in model (6) and a higher adjusted R-Square.
Based on the previous results and discussions we cannot reject the null hypothesis in the case of the banking sector, as coefficients were not significant in both models.

Table 4: Regression Results for Model (6) $V_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 V_{t-1} + \mu_t$

	R_t	R_{t-1}	V_{t-1}	*F-statistic*	*Adj. R-Square*
Coefficient	2.740	2.610	0.75**		
t-statistic	1.330	1.260	41.140	575.91**	0.55
P-value	0.180	0.210	0.000		

Dependent variable: trading volume, independent variables: return, one lagged period (trading-volume and return)
** Significant at the 0.01 level (2-tailed).
 * Significant at the 0.05 level (2-tailed).

To test the second null hypothesis we estimate the model (7) and the results are reported in Table 5. The Table shows a positive significant coefficient at 1% level of significance, but an insignificant negative coefficient in the case of bull markets. F-statistic, which measures that overall significance of the regression model, was significant at 1% level of significance; we chose to report the adjusted R-Square as it increases only if the new term improves the model more than would be expected by chance. Adjusted R-Square indicates that, on average, in 60% our model could explain the variation of trading volume.
To sum up, we can strongly reject the null hypothesis, as our findings document a positive significant relationship between trading volume and return volatility, this relationship disappears in the case of bull markets. This analysis points out that news is having an impact on trading volume. Therefore, good news increases stock return volatility and leads to an increase in trading volume and bad news decreases stock return volatility and reduces trading volume.

Table 5: Regression Results for Model (7)

$$V_t = \alpha_0 + \phi_1 V_{t-1} + \phi_2 V_{t-2} + \alpha_1 R_t^2 + \alpha_2 D_t R_t^2 + e_t$$

	V_{t-1}	V_{t-2}	R_t^2	DR_t^2	*F-statistic*	*Adj. R-Square*
Coefficient	0.49**	0.31**	461.65**	-26.220		
t-statistic	19.260	12.210	4.151	-0.166	535.02**	0.61
P-value	0.000	0.000	0.000	0.867		

Dependent variable: trading volume, independent variables: return volatility, one-two lagged period trading- volume and return volatility with dummy variable for bull market.
** Significant at the 0.01 level (2-tailed).
* Significant at the 0.05 level (2-tailed).

As both trading volume and stock return is found to be non-stationary at level and stationary at the first difference, we can move to test the third hypothesis about cointegration between stock return trading volume.
To test the cointegration between trading volume and return, we apply the Johansen cointegration test to our data at the level (i.e. in the non-stationary situation). Cointegration analysis of Trace Statistics is used to test the null hypothesis of (r) vector of cointegration against the (r) or other vector of cointegration proposed by maximum likelihood based on Johansen (1988, 1991). A lag length interval (first difference) 1 to 4 is chosen in the cointegration equation.
The results of cointegration were reported in Table 6. Trace test where statistics is greater than 1% critical value, therefore, we have one cointegration equation at 1% level of significance among our sample. Analysis of the Max-Eigen value is applied to confirm the long-run relationship. Max-Eigen results were also reported in Table 6. Results on maximum Eigen value statistic indicate one cointegration equation at 1% level of significance.

Table 6: Johansen Cointegration Test for Return and Trading Volume

Variables	*Eigenvalue*	*Trace statistic*	*Critical Value (0.01)*	*Prob.*	*Max-Eigen statistic*	*Critical Value (0.01)*	*Prob.*	*Hypothesized No. OFCE*
Return	0.077074	112.555*	31.1539	0.000	108.681*	23.975	0.000	None*
Volume	0.002856	3.875	16.554	0.760	3.875	16.554	0.760	At most 1

Assumptions: Deterministic trend in the series in levels and intercept in the cointegrating equation**.**
Trace test and Max-Eigenvalue test indicate 1 cointegrating eqn (s) at the 0.01 level.
* denotes rejection of the hypothesis at the 0.01 level

In the previous discussion we managed to prove the cointegration relationship between trading volume and return. However, it's it is possible that cointegrated variables may deviate for this relationship in the short-run, but their association would return in the long-run. According to representation of the Granger theorem, if two variables are cointegrated, then there is an error correction representation (ECM), which effects the short-run adjustment. To evaluate the dynamic adjustment patterns, Vector-Error

Correction Model (VECM) are estimated and the results for this model was reported in Table 7.

Table 7: Vector Error Correction Estimates

	D(Stock Return)	D(Trading Volume)
Cointegrating Eq:		
Return(-1)	1.0000	1.0000
Trading volume(-1)	-1.1719**	-0.8533
t-value	(-36.01)	(-0.65)
C	-0.0010	0.0009
Error Correction:		
CointEq1	-0.00090	-2.2355**
t-value	(-1.02)	(-35.81)
Trading volume(-1)	-0.0003	0.6608**
t-value	(-0.44)	(14.11)
Trading volume(-2)	0.0002	0.2782**
t-value	(0.45)	(10.51)
Return(-1)	-0.5501**	3.5737*
t-value	(-21.22)	(2.27)
Return(-2)	-0.2828**	4.3277**
t-value	(-10.94)	(2.75)
Constant	0.0000	0.0004
t-value	(-0.07)	(0.02)
Adj. R-square	0.25	0.74
F-statistic	92**	782**

**Significant at the 0.01 level (2-tailed)
* Significant at the 0.05 level (2-tailed).

First we run VECM considering stock return as an endogenous variable. It is clear that return is responding to changes in trading volume negatively in the long-run. In other words, the long-run elasticity of the stock return to the trading volume was 1.17, i.e. a one percent deviation in the trading volume decreases the stock return by 1.17 percent. The coefficients on the ECT (Error-Correction Term) give the short-run adjustment to changes in the equilibrium relationship between the variables. The ECT, also called the speed of adjustment coefficient, captures whether a given variable adjusts (via the significance of the coefficient), and how fast the adjustment is (or how much of the short-run disequilibrium is closed in each period). Results show that ECT was insignificant. Out of that we can say that trading volume cannot adjust the long-run relationship with stock return.

In the next part we evaluate trading volume as an endogenous variable. The results of ECTs are significant in all cases at 1% level of significance. The high value of ECTs relatively refer to fast adjustment done by return in the short-run, in other words, return can adjust the deviation in the long-run with trading volume with only one lag (one trading day). Here, the VECMs allow for simultaneous adjustment of all variables in the cointegration relationships.

This indicates the existence of a long-run causality between the market return and trading volume on market level. This is consistent with results from models 5 and 6 as we could prove much stronger dependency of trading volume to return than return to trading volume and this indicates the existence of a long-run causality between the stock return and trading volume.

Both researched variables may be raised due to its own shocks or may be due to other variables shocks. Variance Decomposition (VDC) response analysis is conducted to analyze which part of variable shocks is explained by other. It facilitates some other evidence of cointegration among stock return and trading volume and extends contribution with reference to systematic shocks over the time horizon.

The VDC is the best technique to examine the cumulative impact of shocks and to observe significant changes. VDC captured the system wide shocks and volatility between our research variables. VDC was also helpful to determine responses–pattern spread over time and error variance between trading volume and stock return. Results on VDC analysis were reported in Table 8.

Table 8: Variance Decomposition of Stock Return and Trading Volume

	% of the movement in Return explained by the shocks to		% of the movement in Trading Volume explained by the shocks to	
Period	Trading volume	Return	Trading volume	Return
1	0.00	100.00	99.55	0.45
2	0.15	99.85	99.46	0.54
3	0.18	99.82	99.46	0.54
4	0.15	99.85	99.19	0.81
5	0.15	99.85	99.03	0.97
6	0.15	99.85	99.02	0.98
7	0.14	99.86	99.02	0.98
8	0.13	99.87	99.02	0.98
9	0.13	99.87	99.00	1.00
10	0.12	99.88	99.00	1.00

The variability of stock return is explained by its own past movement, the role of trading volume remaining 0.12% after 10 days ahead. The results provide strong evidence in support of the argument that the movements of stock returns are explained by their own shocks rather than the shocks to the trading volume.

Results for the VDC analysis for trading volume show an increasing role for stock return in explaining variability in trading volume, on day one 99% variability in trading volume was explained by its own past movements and 0.45% by stock return, where in day ten return contribution in explaining shocks in trading volume increased up to 1%. In sum, the variance decomposition analysis provides evidence that past shock returns could be useful in predicting future trading volume.

To further investigate the dynamic responses between the trading volume and stock return, the impulse response of the VECM system has been calculated and exhibited in Table 9. Impulse responses show the impact of shocks for various days separately. Impulse response function (IRF) is employed by VECM to capture the time constraint effects of to see behavior of series. Impulse response function (IRF) is used to map the responses of current as well as future values of endogenous (dependent) variables to ascertain at one standard deviation effects due to the value creating by structure of VECM.

It is observed from the Table 9 that a return response to one standard error of trading volume shocks was relatively very small and negative in some cases, while one standard-error shock in return affects stock return positively until approximately 10 days with relatively higher values.

Table 9: Impulse Response Function

	Response of Stock Return		Response of Trading Volume	
Period	Trading volume	Return	Trading volume	Return
1	0.0000	0.0103	0.6209	0.0419
2	0.0004	0.0046	-0.3568	0.0322
3	0.0003	0.0049	-0.0301	-0.0014
4	-0.0001	0.0063	-0.0170	-0.0374
5	0.0002	0.0054	0.1184	0.0314
6	0.0002	0.0055	-0.0533	0.0101
7	0.0002	0.0057	-0.0081	-0.0005
8	0.0001	0.0056	-0.0077	-0.0001
9	0.0002	0.0056	0.0222	0.0086
10	0.0002	0.0056	-0.0072	0.0053

On the other hand, results show that trading volume tends to respond to one standard error shock in return positively with a higher value compared to the previous case.

Both impulse responses fall between the respective standard error bands. We find evidence of distinct asymmetry in the impulse responses between stock returns and trading volume. Shocks to trading volume do not tend to have significant impact on their corresponding returns. On the other hand, shocks to returns are important in predicting the future dynamics of their own return series and the future dynamics of their corresponding trading volume values. According to the previous findings we can confirm that shocks in stock returns impact trading volume in the expected direction over a short horizon.

The final step is to test the last two hypotheses. Of course, the previous analysis has given us a clear vision about the causal relationship. Granger-causality test is used to validate our last findings and judge our last two hypotheses about causality relationship among variables and direction. Lag four is selected to get appropriate results which are user specified. Results are reported in Table 10.

Table 10: Pairwise Granger-Causality Tests between Stock Return and Trading Volume

Null Hypothesis :	Trading volume does not Granger Cause Return		Return does not Granger Cause Trading Volume	
	F-Statistic	P-Value	F-Statistic	P-Value
	2.34	0.05	4.13**	0.000

Results show unidirectional causality from stock return to trading volume as F-value is significant at 1% level of significance when testing the causality from return to volume but not significant at all for the opposite direction, which implies that market return leads trading volume in the banking sector. These findings support VECM results and reveal the dynamic relationship nature between trading volume and stock return in the banking sector in the ASE.

To sum up, we can reject the null hypothesis that stock return does not Granger-cause volume in banking sector in ASE. In other words, Granger-causality test confirms the long-run unidirectional causality from stock return to trading volume.

On the other hand, we cannot reject the null hypothesis that trading volume does not Granger-cause stock return, which means that trading volume past values have no significant effect on prediction of current and future stock return values.

5 Conclusions

This research explores the relationship between two market variables, trading volume and stock return, for contemporaneous, long-run and short-run relationship using the data from the banking sector in the ASE. The main target of this research is to reveal whether past values of one variable can improve the prediction of current and future values of another.

Descriptive statistics reveal much more volatility in stock return compared to trading volume. Moreover, our results proved evidence that stock return is not normal with leptokurtic curves in most cases, which in fact consistent with mixture of distributions model. On other hand, trading volume appears closer to normality with less volatility. Correlation among our variables could be seen at 1% level of significance. Even though the correlation coefficient was positive, it was very small. Unit root was revealed in both series at the original series but this non-stationarity quickly disappeared at the first difference. All the previous analyses highlighted important aspects of both series and allowed us to proceed to our cointegration and causality tests.

The first test targeted the contemporaneous relationship. Our results fail to confirm this relationship which indicates that information may flow simultaneously rather than sequentially into the market.

Moving forward, we tested the relationship between trading volume and return volatility. Our findings suggest that trading volume is responding positively to return volatility, which in turn implied that new daily information in the market may have a significant impact on price volatility.

Cointegration analysis shows that stock return is cointegrated with trading volume indicating a long-run equilibrium relationship. Vector Error Correction Model also indicates the existence of a long-run causality relationship from stock return to trading volume. It is evident in our sample that trading volume moves in sympathy with stock return. Variance decomposition analysis (VDC) was applied to acquire an overall view of the level of change which describes stock return attribute to trading volume and vice versa. Stock return is explained by its own innovation rather than trading volume and does a better job in explaining trading volume movements. Impulse response function (IRF) shows most of the parts of shocks in stock return are explained by its own innovations and also its exerting impact on trading volume.

A unidirectional Granger-causality exists between stock return and trading volume. Hence movement of stock return is responsible for movements in trading volume.

Finally, it can be said that trading volume and stock return have a significant long-term relationship. Therefore**,** changes in stock return will lead towards movements in trading volume and this leads to the adoption of the first adage "volume is relatively heavy in bull markets and light in bear markets" in the banking sector of ASE.

It is worth noting that our findings are consistent with most recent literatures. Studies by Khan and Rizwan (2008), Mubarik and Javid (2009) and Tripathy (2011) documented significant role for stock return in predicting future trading volume.

References

[1] Al-Khouri, R. & N. Al-Ghazawi, The effect of electronic trading on market volatility and liquidity in emerging markets: Evidence from Amman Stock Exchange, Journal of Derivatives & Hedge Funds, **14**, (2008), 222–236.

[2] Alsubaie, A. & M. Najand, Abnormal trading volume and autoregressive behavior in weekly stock returns in the Saudi stock market, Emerging Markets Review, **10** (3), (2009), 207-225.

[3] Assogbavi, T., J. Schell, & S. Fagnissè, Equity price-volume relationship on the Russian stock exchange, International Business & Economics Research Journal, **6** (9), (2007), 107-116.

[4] Bauer, R. & F. Nieuwland, A multiplicative model for volume and volatility, Applied Mathematical Finance, **2**, (1995), 135-154.

[5] Blume, L., D. Easley, & M. O'Hara, Market statistics and technical analysis: The role of volume, Journal of Finance, **49** (1), (1994), 153–181.

[6] Brailsford, T. J., The empirical relationship between trading volume, returns and volatility, Accounting and Finance, **35** (1), (1996), 89-111.

[7] Campbell. Y. J., S. J. Grossman, & J. Wang, Trading volume and serial correlation in stock returns, Quarterly Journal of Economics, **108**(4), (1993), 905-939.

[8] Chen, G., M. Firth & M. O. Rui, The dynamic relation between stock return, trading volume, and volatility, The Financial Review, 38, (2001), 153-174.

[9] Chordia, T., & B. Swaminathan, Trading volume and cross-autocoralations in stock returns, The Journal of Finance, **55**, (2000), 913-935.

[10] Ciner, C., Information content of volume: an investigation of Tokyo commodity futures markets, Pacific-Basin Finance Journal, 10, (2000), 201-215.

[11] Clark, P. K., A subordinated stochastic process models with finite variance for speculative prices, Econometrica, 41, (1973), 135-156.

[12] Connolly, R. & C. Stivers, Macroeconomic news, stock turnover and volatility clustering in daily stock return, The Journal of Financial Research, 2, (2005), 235–259.

[13] Crouch, R. L., The volume of transactions and price changes of the New York Stock Exchange, Financial Analysts Journal, **26**(4), (1970), 104-109.

[14] Godfrey, M. D., J. W. C. Granger & O. Morgenstern, The random walk hypothesis of stock market behavior, Kyklos, 17, (1964), 1-30.

[15] Granger, C. W. J. & O. Morgenstern, Spectral analysis of New York stock market Prices, Kyklos, **16** (1), (1963), 1-27.

[16] Harvey, R. C., Predictable risk and returns in emerging markets, Review of Financial Studies, **8** (3), (1995), 773-816.

[17] Hiemstra, G. & D. J. Jones, Testing for linear and nonlinear Granger causality in the stock price-volume relation, The Journal of Finance, **XLIX** (5), (1994), 1639-1663.
[18] Johansen, S., Statistical analysis of cointegration vectors, Journal of Economic Dynamics and Control, 12, (1998), 231-254.
[19] Johansen, S., Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, Econometrica 59, (1991), 1551-1580.
[20] Kamath, R. & Y. Wang, The causality between stock index returns and volumes in the Asian equity markets, Journal of International Business Research, 5, (2006), 63-74.
[21] Karpoff, M. J., The relation between price changes and trading volume: A survey, Journal of Financial and Quantitative Analysis, **22**(1), (1987), 109-126.
[22] Khan, U. S. & F. Rizwan, Trading volume and stock returns: Evidence from Pakistan's stock market, International Review of Business Research Papers, **4**(2), (2008), 151-162.
[23] Lamoureux, C. G. & W. D. Lastrapes, Heteroskedasticity in stock return data: volume versus GARCH effects, The Journal of Finance, **45** (1), (1990), 221-229.
[24] Lee, C. F. & M. O. Rue, The dynamic relationship between stock return and trading volume: Domestic and cross-country evidence, Journal of Banking & Finance, 26, (2002), 51-78.
[25] Léon, N., An empirical study of the relation between stock return volatility and trading volume in the BRVM, African Journal of Business Management, **1** (7), (2007), 176- 184.
[26] Llorente, G., R. Michaely, G. Saar & J. Wang, Dynamic volume-return relation of individual stocks, The Review of Financial Studies, **15** (4), (2002), 1005-1047.
[27] Martikainen. T., V. Puttonen, M. Luoma & T. Rothovius, The linear and non-linear dependence of stock returns and trading volume in the Finnish stock market, Applied Financial Economics, 4, (1994), 159-169.
[28] Mehrabanpoor, M., B. V. Bahador & G. Jandaghi, Stock exchange indices and turnover value-evidence from Tehran Stock Exchange, African Journal of Business Management, **5**(3), (2011), 783-791.
[29] Mubarik, F. & Y.A. Javid, Relationship between stock return, trading volume and volatility: Evidence from Pakistani stock market, Asia Pacific Journal of Finance and Banking Research, **3**(3), (2009), 1-17.
[30] Podobnik, B., D. Horvatic, M. A. Petersen & E. Stanley, Cross-correlations between volume change and price change, Pnas, **106**(52), (2009), 22079–22084.
[31] Saatcioglu, K. & L. Starks, The stock price–volume relationship in emerging stock markets: The case of Latin America, International Journal of Forecasting, 14, (1998), 215–225.
[32] Sabri, N., The impact of trading volume on stock price volatility in the Arab Economy, Journal of Derivatives & Hedge Funds, 14, (2008), 285–298.
[33] Smirlock, M. & L. Starks, An empirical analysis of stock price-volume relationship, Journal of Banking and Finance, 12, (1998), 31-41.
[34] Tripathy, N., The relation between price changes and trading volume: A study in Indian stock market, Interdisciplinary Journal of Research in Business, **1**(7), (2011) 81-95.