

Volatility Persistence in Palestine Exchange Bulls and Bears: An Econometric Analysis of Time Series Data

Dr. *Ibrahim M. Awad* (Correspondence Author)

Faculty of Business and Economics, Al-Quds University, P.O. Box 51000, Jerusalem, PALESTINE

Tel: +970-599-707-737 E-mail: iawad@staff.alquds.edu

Web: <http://erf.org.eg/affiliates/ibrahim-awad/>

Abdel-Rahman Al-Ewesat

Faculty of Business and Economics, Al-Quds University, P.O. Box 51000, Jerusalem, PALESTINE

Tel: +970-568-069-452 E-mail: aewesat@gmail.com

Abstract: This study aims at investigating volatility persistent in Palestine Exchange (PEX) bulls and bears. It also attempts to explore whether or not stock market volatility present a different behavior during PEX bulls and bears, which is likely to provide investors with a background information for more feasible investment in the PEX. Toward that end, the study employs Rescaled Range (R/S) to calculate the values of difference to find evidence of long memory behavior for the daily data observations from August, 1997 to December, 2014. The study finds that volatility isn't persistent in the PEX bear markets. Co-integration results show that there is an existence of co-integration, which indicates a long run equilibrium association between PEX bull and bear markets. The ECM results reveal that the speed of adjustment toward long run equilibrium is very low for PEX bull markets while the speed of adjustment toward long run equilibrium is unlikely to be attained for PEX bear markets. Further, the PEX bears markets are longer than PEX bulls markets, so that prudent investors should take volatility in PEX bulls and bears into account.

Keywords: PEX bulls and bears; Persistence; Moving average; Long memory; Volatility

JEL Classifications: G10, G11, G23

1. Introduction

The concept of volatility in stock prices is central to the professionals, investors, financial literature, and econometricians for many years. To measure financial markets' performance, long memory in stock market volatility and in returns is considered. PEX is still young and lacking of empirical studies focus on long memory behavior for stock volatilities using trading data from the PEX. Through this investigation in bull and bear phases in PEX, this study can help investors with a better understanding of PEX bullish and bearish periods. Trading data to develop an empirical study on how stock prices behave in both bull and bear phases will be used.

The study will investigate PEX stock prices behavior in order to facilitate translating of savings decision into investment decisions and therefore supporting economic growth. Accordingly, it aims at investigating the long memory stationarity for the volatility process and its persistence in PEX bull and bear stages in order to find evidence that PEX is efficient. It investigates the characteristics of volatility during the PEX bulls and bears over the period 1997 to

2011. Several specific research objectives is likely to be met in this study, they are to: (1) detect bull and bear phases in the PEX; (2) investigate the long memory behavior in volatility and stock returns in financial time series; and (3) determine whether or not the stock volatility is persistent in both bullish and bearish PEX.

Some of empirical papers indicate that stock market volatilities are related to the business cycle (Gasarin and Trecroci, 2006), while others indicate that volatilities are related to bull and bear phases (Cunado *et al.*, 2008). Further, Chordia *et al.* (2001) states that the different observed behavior in the stock market liquidity in bull and bear markets may be related with volatility. Moreover, they concluded that bull markets are subject to more investments and liquidity whereas bears markets are characterized by higher volatility and liquidity problems. Albuquerque *et al.* (2015) reveal that there is a high correlation between stock returns and fundamentals across bull and bear episodes. Therefore, volatility has been considered across bull and bear stages and forecasted so as to detect its characteristics from financial time series.

Based on the abovementioned, this paper is important for investors in Palestine, especially bear markets cost them money. Investors need to know that stock prices fall generally during this phase, so that they need to know when to buy or sell for maximizing their profits. This paper will also introduce a policy of recommendations to investors about how to time the market by using statistical techniques to gauge when a bear market begins and when it ends and the same during the bull market phases.

2. Literature Review

The term volatility and its persistence in stock prices are frequently examined in the Global financial markets such US, Turkish, Thailand, Euro, and Asian markets. As a consequence of increased interest in stock markets, market trends, and volatilities in stock prices and its persistence in bull and bear markets have been extensively investigated and several econometric techniques were employed to measure that. In particular, long range dependence is widely used in financial literature to measure volatility persistence in bull and bear markets and to measure market efficiency. The overall findings of different studies related to volatility focused on long memory stationarity in stock returns for volatility persistence. They tried to detect long memory patterns by using long range dependence measures (parameters) during bullish and bearish periods (Cunado *et al.*, 2008; Gursakal, 2010; Maheu and Mccurdy, 2000; Enders, 2010; and Triacca, 2009). Further, if stock returns have long memory behavior, the stock returns is likely to have positive autocorrelation.

The behavior of stock prices listed in global financial markets has been investigated in numerous empirical studies and it is at the center of academic and business attention and most of these studies have focused on measuring stock market volatility. In particular, characteristics of long memory behavior are investigated during bull and bear markets to find the evidence of volatility persistence during these phases. Nyberg (2013) concludes that the evidence of the predictability of bear and bull markets, as shown in his study, have many interesting further implications and potential extensions in empirical finance research.

Volatility refers to variances in stock prices over time and it is known that stock prices experience periods of high and low volatilities. Triacca (2009) defines volatility persistence as a stylized statistical property of financial time series data such as exchange rates and stock returns. Garvey (2010) reveals that during a market downswing, volatility increases and conversely, as asset

prices increase volatility become muted. Added to that, the authors are also indicated that a more statistical analysis to measure volatility in bulls and bears markets can help investors for improved the timing of their investment decisions. Investors should consider the probability for risk diversification across bull and bear phases, not on a daily or monthly basis. However, this study not only seeks to find long memory property in the volatility of stock market during bull and bear phases of PEX, but also it tries to investigate long memory behavior in stock returns to find evidence of market efficiency.

Wu (2006) described long memory process as a stochastic process whose auto covariance function decays very slowly as the distance between observations tends to infinity. That is, long memory is a property of certain stationary stochastic processes. Also, Sibbertsen (2004) indicates when the difference parameter is more than 0 and less than 0.5, and then observations far away from each other are still strongly correlated and therefore long-memory time series allow for long-term forecasts. Further, Tolvi (2003) revealed that long memory in time series can be defined as autocorrelation at long lags, of up to hundreds of time periods. Long memory in volatility occurs when the effects of volatility shocks decay slowly which is often detected by the autocorrelation of measures of volatility, such an absolute or squared return. The ability to forecast future returns corresponds to market efficiency. Typically, long memory in volatility not only point to market efficiency, but also it is adopted to indicate volatility persistence during bull and bear markets. In financial literature the upwards and downwards trends in stock prices correspond to “bulls” and “bears” markets respectively.

Historically, the term bull and bear have been used since 1900's. The financial market crash in 1929, presents a good example of the great bear market in the history. One of the most popular examples that identify how bull and bear markets behave is Standard and Poor's 500 Index (S&P 500). Barsky and De Long (1990) indicate that major long-run stock price fluctuations, however-episodes like the major bull markets of 1949-1966 or 1921-1929 and the major bear markets of 1929-1933 or 1973-1975 – are larger than and appear unconnected to fluctuations in realized fundamental values.

Ramos, *et al.* (2011) stated that bulls markets correspond to a generalized upward trend (positive returns) and bears markets correspond to periods of a generalized downward trend (negative returns). If the prices are increasing, then we will enter bull phase. While if the prices are decreasing, then we will enter bear phase. That is, bull phase is located between trough and peak points, because prices are going up, whereas bear is located between peak and trough because prices are going down. Maheu and McCurdy (2000) discussed that as the bull market persists, investors could become more optimistic about the future and then they wish to invest more in the stock market which indicates that the probability of switching out of the bull market decreases with duration. Thus bulls and bears markets are common ways to describe changes in stock prices. For instance, Practitioners use a general rule: if the stock market has fallen more than a 20% this is identified with *bear* phase, on the contrary if the stock market has increased more than a 20% this is called *bull* phase (Biscarri *et al.*, 2004). On the other front, causality relationships between stock exchanges are considered in the international finance literature and it is fundamentally linked to economic growth.

The importance of stock volatility stems from the risk associated with it. Bull markets are characterized by confidentiality and higher probability of returns, whereas bear markets characterized by higher probability of losses. Commonly, more volatility in stock prices makes securities more risky. Researchers have observed upwards and downwards trends in stock prices (volatilities) and therefore they tried to investigate the behavior of long memory in volatility of

daily returns. Tolvi (2003) indicated that the potential presence of long memory in stock market returns has been a popular research topic, although the results of these studies have been mixed. Raung and Scharler (2010) stated that the economic uncertainty associated with financial crashes (periods where the prices of many stocks traded in the market suddenly drop dramatically) is typically reflected in high levels of stock market volatility. That is, increased volatility results in higher uncertainty about future economic conditions. Besides that, Maheu *et al.* (2009) stated that the positive and negative low frequency trends have been labeled as bull and bear markets respectively. If these trends do exist, then it is important to extract them from the data to analyze their properties and consider their use as inputs into investment decisions and risk assessment. As such, investigating bull and bear properties can be used to improve investors' cash positions and help them to sell, hold or buy.

The study focuses on stock volatilities and it attempts at answering these questions: (1) Does the PEX present periods of bullish and bearish phases? (2) Are bullish and bearish periods in PEX characterized by long memory in volatility?

Through this investigation in bull and bear phases in PEX, this study can help people with a better understanding of PEX bullish and bearish periods. The study is built on an investigation of long memory process for volatility process in financial time series because its existence supports market efficiency and predictability. Further, Investors are interested in the volatility in stock prices during the holding period because they depend on capital gains for their returns as well as volatility presents opportunities to buy low priced stocks and sell overpriced stocks. Added to that, volatility is important issue and crucial to success in trading for investors. Candelon, *et al.* (2008) stated that it is common sense that investors rebalance their portfolios by purchasing cheap stocks during bearish periods and selling expensive stocks when stock markets are bullish.

It is likely to be a real need for using trading data to develop an empirical study on how stock prices behave in both bull and bear phases. It will investigate PEX stock prices behavior since it facilitates translating of savings decision into investment decisions and therefore supporting economic growth. Bekaert *et al.* (2002) indicate that economic growth is related to financial development in developed countries.

3. Main Hypotheses

As mentioned above, this study looks at investigating the behavior of stock volatilities of Al-Quds index to detect long memory behavior in PEX bulls and bears in order to find evidence of volatility persistence. Two hypotheses were developed regarding volatility and its persistence in PEX bulls and bears:

Hypothesis 1: PEX stock prices have long-memory properties;

H_0 : Time series for stock indices don't display long memory behavior, and the series are no longer covariance stationary, so $0.5 \leq d$; where d is the fractional differencing parameter.

Hypothesis 2: the volatility is persistent in PEX bears rather than bulls;

H_0 : Volatility isn't persistent index bear phases.

However, in our study, we expect to find that volatility is more persistent in PEX bull rather than bear markets, so in this case d_{bull} is greater than d_{bear} , and we have

H_0 : Volatility isn't persistent in PEX bull phases.

4. Research Methodology

In this study, we used daily stock values of Al-Quds index to measure volatility. Time series observations of Al-Quds index will be divided into bull and bear phases using 200-day moving average. The study undertakes easy ways to find evidence of long memory in the financial time series, namely rescaled range statistics.

In the course of this study, we will undertake and apply various econometrics tests to investigate bullish and bearish periods in PEX and market efficiency, and to measure the volatility in each period depending on cyclical daily financial time series data¹, following an approach similar to that of Cunado *et al.* (2008), Gursakal (2010), Biscarri and Gracia (2004), Pagan and Sossounov (2003), Gonzalez *et al.* (2006), Candelon *et al.* (2007), and Khan *et al.* (2010). Many economic time series data have not a constant mean and most exhibit phases of relative tranquility followed by periods of high volatility (Walter Enders, 2010). As such, the study employs specific econometrics models that can deal with time series data to determine whether the data are stationary or non-stationary. Afterwards, volatilities in bull and bear markets will be modeled in order to investigate the behavior of volatility as well as market efficiency. The study will also use correlation and Granger causality models to investigate short and long run interdependency relationships between PEX, ASE, and TASE.

4.1 Data

Stock price are always observed at daily, weekly and monthly manners so we have time series data. The data used in this study consisted of time series of daily closing values of Al-Quds Price index over the study period from 8/1997 to 3/2012. This period is selected because the data includes all observations of daily closing values for PEX.

4.2 Methodology

In our study we focus on measuring volatility during PEX bull and bear phases. Therefore, it is necessary to look for the characteristics of the data to develop the test. For measuring volatility during PEX bull and bear phases, this firstly requires locating peaks and troughs in time series to obtain PEX bulls and bears.

Cunado *et al.* (2008), Gursakal (2010), Tudor (2011), Thomas and Laosethakul (2010), Khan *et al.* (2010) and others used the natural logarithm of daily closing values. We consequently used the natural logarithm of the daily closing values in each market to produce time series of continuously compounded returns. The advantage of looking at log returns of a series is that relative changes in the variable can be investigated and compared directly to other variables. Thus it is enabling evaluation of analytical relationships among them despite the fact that these log returns generated from price series of unequal values. Another advantage is that taking natural logarithm of the daily closing values versus prices, enhances normalization of data. Therefore the returns in each market (R_t) are computed as the first differences of the stock price indices. That is,

$$R_t = \ln(P_t) - \ln(P_{t-1}) = \ln(P_t / P_{t-1})$$

where P_t is the price index at time t and R_t is the natural logarithm stock price returns at time t .

¹ A time series data set is a sequence of numerical data in which each item is associated with a particular instant in time (Maddala, 1992).

Variances in time series decompose into two categories; conditional and unconditional. That is, time series are called conditionally heteroskedastic if the unconditional (or long run) variance is constant, but there are periods in which the variance is relatively high.

4.3 Identifying market phases

Technical analysts use moving average technique to find peaks and troughs. Thomas and Laosethakul (2010) showed that moving average is a technique used to determine direction of stock prices. On the basis of moving average technique traders, it is possible to decide whether to buy, sell or hold. Further, the moving average is based on the notion that time series data should be smoothed in order to highlight longer term trends or cycles. Moving averages are also called running means or rolling averages. The moving average is calculated based on two procedures: 1- the number of data points in each average remain constant, 2- each average is computed by excluding the oldest observation and including the next observation. The arithmetic moving average is the arithmetic average of prices of a stock (SP) over the most recent period of n days:

$$MA = \sum_{i=0}^{n-1} (SP_{t-i}) / n$$

The moving average generates a forecast from the past prices of a security. Also, the increasing moving average indicates that, on average over time, prices are trending higher. The degree of sensitivity for the technique is determined by the value of n , the number of days in the period. Whereas, if n is too small, there is too much sensitivity to changes in daily prices, but if n is too large, the moving average will not be sensitive enough, so Bry and Boschan (1971) considered the elimination of outliers or extreme observations.

In our study, the PEX 200-day moving averages (8 months excluding public holidays) are adopted rather than 50-day moving averages. The 50-day moving average is an indicator of the secondary market trend and therefore it considers the short term changes in price direction within a primary trend and the duration is few weeks or a few months. However, the long term 200-day moving averages are an indicator of the primary trend and it considers changes in stock prices throughout the entire market lasting for a year or more. During primary trend based on 200-day moving averages, investors and analysts can locate peaks and troughs in time series, so they identify bull and bear phases.

4.4 Testing the long memory in stock volatility and returns

As aforesaid, long memory parameter is used to find the evidence of volatility persistence as well as market efficiency. Sibbertsen (2004) mentioned that a stationary time series $X_t, t=1, \dots, N$ exhibits long memory or long range dependence when the correlation function $\rho(k)$ behaves $\lim_{k \rightarrow \infty} \rho(k) / c_\rho k^{2d-1} = 1$, here c_ρ is a constant and $0 \leq d \leq 0.5$ denotes long memory parameter. This means that observations far away from each other are still strongly correlated. The long memory properties of such series depend on the value of d .

To measure long memory, squared returns and absolute returns were calculated. The return, squared return, and absolute return are calculated as $R_t = \ln Y_t - \ln Y_{t-1}$, $SqrR_t = (R_t)^2$, and $AbsR_t = |R_t|$, respectively.

Gursakal (2010) investigated whether or not stock volatility present different patterns of persistence in bulls and bear phases. It estimated long memory behavior by using the absolute and squared returns in the Istanbul Stock Exchange (ISE). The study used wavelet methods for estimating long term memory parameter of d which provide more robust estimates of d than the other methods. That is, estimating and testing the fractional differencing parameter and he

concluded that volatility is persistent during bear stages. Hsu, Nan-Jung (2006) stated that wavelets for long memory studies provide more robust estimates of d than the other methods.

As mentioned above, long memory parameter is considered in the literature to investigate volatility persistence as well as market efficiency. The analysis of long memory process in time series depends on the value of d . In this process if $d = 0$ then $x_t = \varepsilon_t$, and there is a short run memory, when $d = 1$, x_t follows a unit process and memory is infinite. If $0 < d < 0.5$ the auto covariance function of x_t declines to zero, indicates long memory process and when $0.5 \leq d < 1$ x_t will revert to its mean or trend in the very long run. In addition, for $d \in (0.5, 1.0)$ the autocorrelations are all positive. For $d \in (-0.5, 0)$ the series is said to exhibit intermediate memory. When $d \geq 0.5$ the series are no longer covariance stationary, and have infinite variance.

There are currently a significant number of estimation methods for testing long memory behavior in stock returns and volatility. We consider one of the most widely used estimators and tests: The Rescaled Range Statistic as a parametric approach.

4.5 Nonparametric approach: The rescaled range statistics

The statistical measurement of long memory introduced by Hurst (1951), and subsequently used by Mandelbrot (1972) is the R/S statistic (rescaled range statistic). The rescaled range is calculated from dividing the range of values exhibited in a portion of the time series by the standard deviation of the values over the time series. Giraitis *et al.* (2003) stated that Hurst (1951), Mandelbrot and Taqqu (1979) and others developed a non-parametric R/S type test, which has become widely applicable in empirical literature. The Hurst exponent is used as a measure of the long term memory of time series when it relates to the autocorrelations of the time series.

The rescaled range statistic $R(t,s)/S(t,s)$ (Hurst, 1951; and Mandelbrot, 1972) is defined as:

$$R_T = \text{Max} \{ \sum_{j=1}^k (X - \bar{X}) \} - \text{Min} \{ \sum_{j=1}^k (X - \bar{X}) \}$$

$$S_T = [(1/T) \sum (X - \bar{X})^2]^{1/2}$$

$$R_T / S_T (n) = (1/S_T) [\text{Max} \{ \sum_{j=1}^k (X - \bar{X}) \} - \text{Min} \{ \sum_{j=1}^k (X - \bar{X}) \}]$$

where R_T is the range, S_T is the sample standard deviation, and \bar{X} is the sample mean.

The values of rescaled range statistic are used to find value of d which is the difference parameter. These equations present statistical features of the price indices. After bull and bears have been detected with Bry and Boschan algorithm (1971), the study estimates the long memory parameter d of each phase for the series volatilities. If the estimates of d are above 0 and below 0.5, this implying long memory stationarity for the volatility processes. In addition, when d bull is less than d bear, this indicates that the volatility is more persistent in the bear than in the bull market. That is, this stage is characterized by higher uncertainty and risk with decline in equity values and it is subject to falling liquidity. Then investors are advised to buy stocks in bear stages and sell in bull stages since bull stage is characterized by less volatility and so more liquidity. The story is to determine whether volatility behaves similarly in the PEX bull and bear markets. Further, when $0 < d < 0.5$, this indicates long memory behavior and stationarity which indicates the stock market isn't efficient at weak level, and stock prices didn't randomly move. However, if $0.5 < d$, this indicates non-stationarity time series, and therefore stock market is efficient at weak level.

4.6 Co-integration model

The co-integration model is used because the independent variables are actually correlated while multiple regression analysis indicates that they aren't correlated. It tries to discover multicollinearity among variables.

An n -dimensional time series y_t is co-integrated if some linear combination $\beta_1 y_{1t} + \dots + \beta_n y_{nt}$ of the component variables is stationary. The combination is called a cointegration relation, and the coefficients $\beta = (\beta_1, \dots, \beta_n)$ form a cointegration vector. Cointegration is usually associated with systems of $I(1)$ variables, since any $I(0)$ variables are trivially cointegrated with other variables using a vector with coefficient 1 on the $I(0)$ component and coefficient 0 on the other components. The idea of cointegration can be generalized to systems of higher-order variables if a linear combination reduces their common order of integration.

The model can be written as follows (Christiaon *et al.*, 2004):

$$\Delta y_t = - (y_{t-1} - kx_{t-1}) + kx_t + \varepsilon_t$$

Cointegration is distinguished from traditional economic equilibrium, in which a balance of forces produces stable long-term levels in the variables. Cointegrated variables are generally unstable at their levels, but exhibit mean-reverting "spreads" (generalized by the cointegrating relation) that force the variables to move around common stochastic trends. Cointegration is also distinguished from the short-term synchronies of positive covariance, which only measures the tendency to move together at each time step. Modification of the VAR model to include cointegrated variables balances the short-term dynamics of the system with long-term tendencies.

4.7 Error correction model (ECM) and Vector autoregressive model (VAR)

Error Correction Models (ECM) can be used whenever (1) we have time series data, and (2) are interested in both short and long term relationships between multiple time series. In this study we have time series models on the two phases that directly estimate the speed at which a dependent variable (bear phase) returns to equilibrium after a change in an independent variable ($\% \Delta$ in bull phase). The following equation shows how the ECM corrects for disequilibrium (Greene, 2012).

$$\text{Bear market} = \alpha + \beta_1 \% \Delta \text{bull}_{t-1} - \beta_2 \text{EC}_{t-1} + \text{bull}_t,$$

where EC is the error correction component of the model and measures the speed at which prior deviations from equilibrium are corrected.

In this case, ECM can be used to estimate both, the short and long term effects of $\% \Delta$ bull on bear phase. The most important outcomes of the ECM are the α parameters, this to investigate whether the model is stable (returns to equilibrium) and the speed at which it adjusts. The main feature of the ECM is its capability to correct for any disequilibrium that may shock the system from time to time. The error correction term picks up disequilibrium and guides the variables of the system back to equilibrium. The existence of a co-integrating relationship between variables allows us to use the ECM. If not, we will only be able to use VAR model (Greene, 2012), as the study variables were cointegrated so that we applied ECM rather than VAR model. E-views (Econometric Views) was run for econometric analysis.

5. Empirical Results and Analysis

As abovementioned, this study aims at measuring volatility persistence. It adopts data set of daily closing price of Al Quds Index from 08/1997 to 12/2014. The natural logarithm of the daily closing values was utilized, and daily returns are computed as the first differences of the log-transformed series. For this purpose, econometric and statistical techniques are used.

Stock charts enable analysts, investors and traders to study past and present time series observations in order to make reasonable predictions and wise choices. Figure 1 illustrates the changes in Al-Quds Price index including highest and lowest stock prices at which stock are traded

over the last 17 years. This chart plots the daily closing values of Al-Quds price index. The time series observations of Al-Quds index have been connected together in a single line to view changes in stock prices and to detect market trend during the stipulated period. The chart shows that price down days are more than up days, indicating that PEX stock prices move in the opposite directions and their time series data is non-stationary. Also, the PEX exhibit a trend in the mean so that the mean isn't constant. This supports the result that data is non-stationary. Also, the chart shows that stock prices fluctuate along the time period. Stock prices were increasing during before the year 2000. Accordingly, stock prices had decreased with some corrections until 2004. However, stock prices sharply increased during 2005 to reach the highest value of 1336.5 and then decreased followed by many ups and downs.

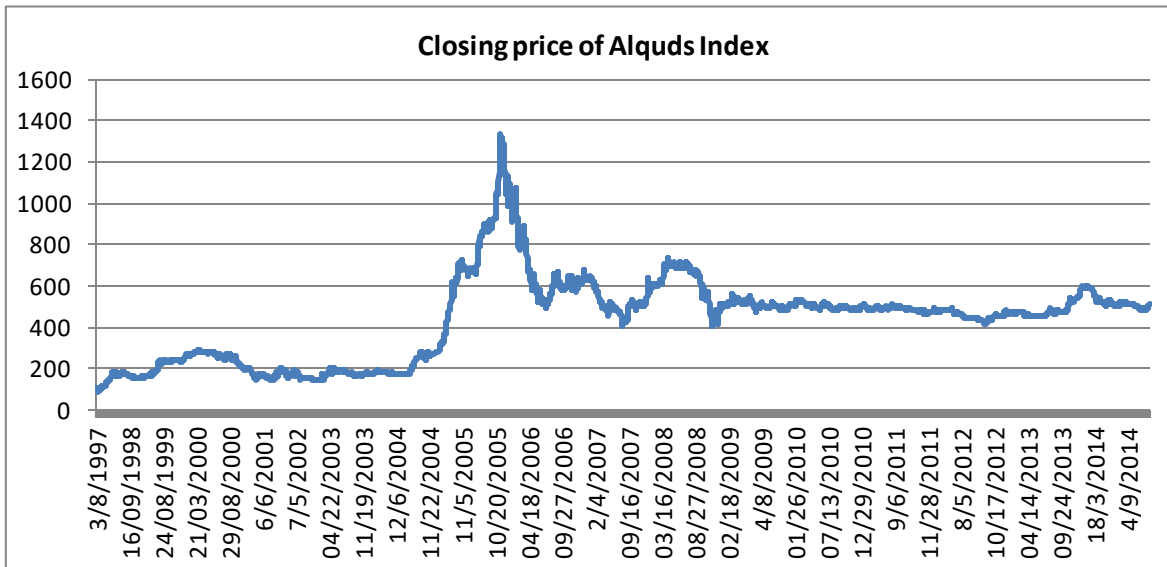


Figure1. Graph of Al-Quds Index for 17 years (1997.08–2014.08)

5.1 Identifying bull and bear phases

PEX bull and bear phases use the technique of the 200 day moving average taking into consideration the assumptions of Bry and Boschan (1971). Troughs and peaks were identified in Al-Quds Index and thus the starting and finishing points of bull and bear markets are identified. Figure 2 shows PEX bull and bear phases along the 17 years. Figure 2 also represents a secular market trend which consists of a series of primary trends. The PEX moved into seven directions over the last 17 years. These trends consist of bull and bear phases. The bull and bear phases represent upward and downward market trends respectively. These directions represent trends to describe PEX as a whole (all sectors).

As depicted in Table 1, there are four cycles consist of four bull phases and three bear phases have been detected for Al-Quds Index. We note that time series consist of smaller bull markets and larger bear markets, which indicates a secular bear market and therefore, downward trends continued for longer time than upward trends. However, there are 6 primary trends-three bears and three bulls- because they lasted for more than year, whereas there is one secondary trend- the third bullish phase in the cycle 3- because it lasted for less than one year. Further, we note that bull phases are shorter than bear phases, which indicates that more risk is associated with volatility during bear phases.

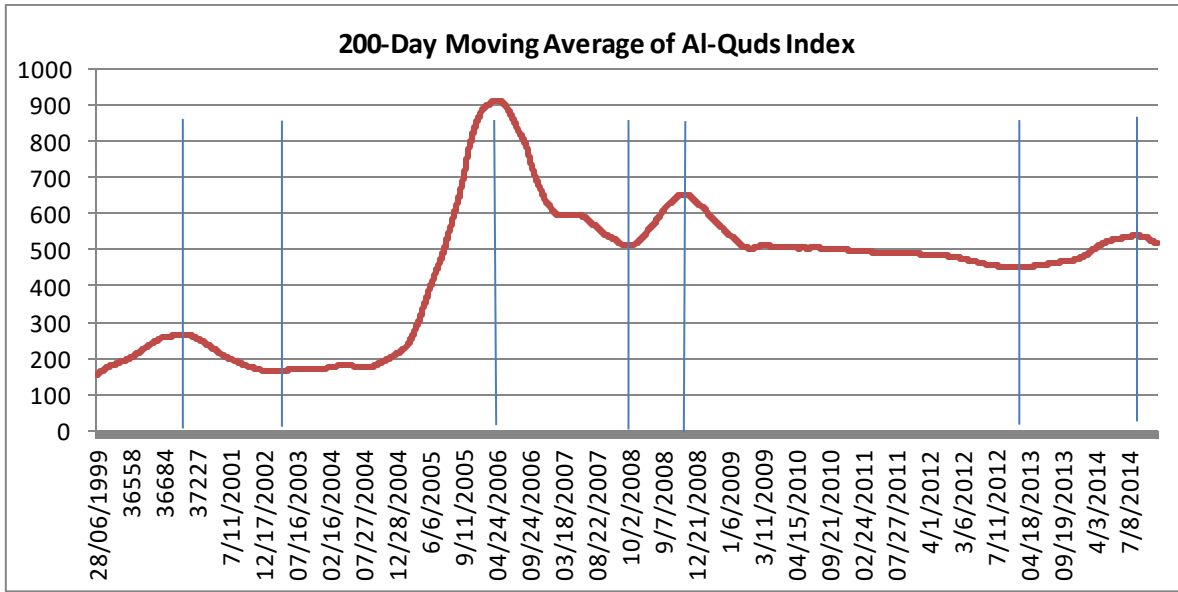


Figure 2. Bull and Bear graphs of Al-Quds Index

Table 1. Al-Quds Index Bull and Bear phases: 1997.08 to 2014.09

Cycles	Bull phase	Bear phase
Cycle 1	1997:08 – 2000:10	2000:10 – 2003:04
Cycle 2	2003:04 – 2006:04	2006:04 – 2008:02
Cycle 3	2008:02 – 2008:10	2008:11 – 2013:02
Cycle 4	2013:02 – 2014:09	---

5.2 Volatility persistence test

The difference parameter of d is calculated on the basis of the returns using R/S statistics. Table 2 below displays the results of ADF and PP unit root tests. Those test shows that the stock prices aren't stationary in most phases at level so they aren't normally distributed whereas the series are stationary at first difference. This implies that we can use nonparametric tests to investigate volatility and its persistence during bull and bear phases. Thus, this study applies R/S test since it is superior for its robustness in capturing long memory (long range dependence) in the presence of non-normality (Yalama *et al.*, 2011).

Table 2. Unit root test of PEX bulls and bears at level

Cycles and their bull or bear phases	ADF Test Statistic				PP Test Statistics			
	Level		First Difference		Level		First Difference	
	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
Cycle 1, bull	-0.9585	0.3381	-12.6087	0.0000	-0.8271	0.4084	-27.1365	0.0000
Cycle 1, bear	-2.8331	0.0049	-6.9341	0.0000	-2.7219	0.0069	-17.5351	0.0000
Cycle 2, bull	-0.7719	0.4404	-10.6757	0.0000	-0.6771	0.6771	-16.3341	0.0000
Cycle 2, bear	-2.2436	0.0254	-9.3109	0.0000	-2.1076	0.0357	-18.5649	0.0000
Cycle 3, bull	0.0007	0.9994	-5.6012	0.0000	-0.2420	0.8090	-10.2736	0.0000
Cycle 3, bear	-3.5876	0.0003	-13.7061	0.0000	-3.5364	0.0004	28.7423	0.0000
Cycle 4, bull	1.2902	0.1978	-6.9059	0.0000	0.9234	0.3563	-15.2655	0.0000

As aforesaid, when the parameter d in the interval $(0, 0.5)$, this indicates that the time series are characterized by long memory and stationarity because these values are the relevant cases for the volatility. This means that observations are far away for each other, but they are still strongly correlated. Further, when $d = 0$ then $x_t = \varepsilon_t$, and this indicates short term memory. However, when $d > 0.5$, x_t follows a unit process and this indicates non-stationarity case. Table 3 displays the R/S estimates of long memory parameter d .

In all cases d is more than 0, and the confidence values of some cases are constrained in the interval $(0, 0.5)$ indicating stationary long memory volatility process. The parameter d doesn't take value of 0 in the mentioned cases as well as no minus values of parameter d . In all cases, $d \neq 0$ so there are no exceptions of phases since the null hypotheses of stationarity is not accepted at first difference at the 5% level.

Table3. R/S based estimated parameters of d

Phases	d
1997:08 – 2000:10 (Bull Phase)	1.11
2000:10 – 2003:04 (Bear Phase)	0.93
2003:04 – 2006:04 (Bull Phase)	0.39
2006:04 – 2008:02 (Bear Phase)	0.66
2008:02 – 2008:10 (Bull Phase)	0.41
2008:11 – 2013:02 (Bear Phase)	0.64
2013:02 – 2014:09 (Bull Phase)	0.62

Table 3 shows that systematically higher orders in one case over the other are existed. In 2 out of the 3 cases d -bull is lower than d -bear, and in one case d -bull is higher than d -bear. That is, statistical evidence of d -bull (1.11) is higher than d -bear (0.93) in cycle 1. However, we find in two cases d -bull is lower than d -bear: in cycle number 2, d -bull is 0.39 and d -bear is 0.66, and in cycle 3 d -bull is 0.41 and d -bear is 0.64.

According to the results being presented in table 3, there is no evidence of volatility persistence in bear markets in cycle number 1, 2, and 3 since d -bears > 0.5 in the three cases while d -bulls are 0.39 and 0.41 which means that d -bulls < 0.5 . This implies that volatility is more persistent in PEX bull markets than in PEX bear markets. In the cycle number 1 that d -bull is higher than d -bear and both are more than 0.5 implies that volatility is more persistent in bear than in bull phase in this cycle. In general, time series data during PEX phases are characterized by long range dependence implying volatility is more persistent in PEX bull phases since d is above 0 and below 0.5.

According to the results showed in Table 3, two PEX bulls (volatilities) have long range dependence characteristics. Otherwise, there is a short term memory in volatility. Existence of long memory in volatility financial time series implies that the daily observations of the PEX during bull markets are related to each other, so that the estimates of parameter d are above 0 and below 0.5 implying long memory stationarity for the volatility process. Additionally, the results indicate that the volatility is more persistent in the PEX bull markets than the PEX bear markets. We, therefore, reject the alternative hypothesis in favor of the null hypothesis, so that PEX stock volatility is more persistent in bull markets than in bear markets, and null hypothesis is accepted, which means the volatility isn't persistent during bear phases. However, it has been documented in

the financial literature that stock market volatility is higher during bear markets than in bull markets.

5.3 Results of co-integration

Referring to Table 4, the model of co-integration is used to summarize the results of a co-integration analysis between PEX bulls and bears markets. The results reveal that there is a long run association and stationarity of the error term for the two markets (phases), meaning that there is evidence of co-integration between PEX bull and bear markets and significant at 5 percent level of significance as the P-value is 0.0122. Thus, the existence of co-integration indicates a long run equilibrium association between PEX bull and bear markets.

Table 4. Co-integration between PEX bull and bear markets

Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	Critical value at p=0.05	Prob.
None *	0.225795	19.40269	15.49471	0.0122
At most 1	0.033114	2.256187	3.841466	0.1331

Note: * denotes rejection of the null hypothesis at the 0.05 level of significance.

5.4 Results of error correction model (ECM)

As a foresaid in section 4.7, our target in using this model is to find out how and in what ways PEX bear markets are affected by PEX bull markets. As discussed in section 4.7, the most important outcomes of the ECM are the α parameters so as to investigate whether the model is stable (returns to equilibrium) and the speed at which it adjusts. The main feature of the ECM is its capability to correct for any disequilibrium that may shock the system from time to time. The error correction term picks up such disequilibrium and guides the variables of the system back to equilibrium. The existence of a co-integrating relationship among the variables allows us to use the ECM.

Referring to table 5, the results reveal that the estimated lagged error correction term of Bull phases (Lag 1) is negative and significant at 5 percent level of significance as the P-value is 0.0132 . The speed of adjustment toward long run equilibrium is very low (0.1341%). On the other hand, the estimated lagged ECM of bear phases (Lag 1) is positive and significant at 1 percent level of significance as the p-value is 0.0023, but positive ECM is not the fit sign for the model, it implies that the process is not converging in the long run, so that the speed of adjustment toward long run equilibrium is unlikely to be attained, as the ECM is not violated by autocorrelation.

Table 5. Vector error correction model estimates

Market	Variable	Coefficient (α)	Standard Error	t-value	p-value
PEX	Bull market (-1)*	-0.134126	0.052593	-2.550248	0.0132
	Bear market (-1)*	0.093424	0.029336	3.184665	0.0023

Note: * reflects the percentage of the disequilibria of the earlier period's shock adjust get back to the long run equilibrium in the current.

6. Conclusions, Policy Implications, and Future Research

To the best of our knowledge, this study is likely to be the first one that it empirically aims at investigating long memory in volatility during PEX bulls and bears so as to determine whether or not the volatility is persistent in these phases. Toward that end, the study uses data of daily stock prices of Al-Quds index over the period of August 1997 to December 2014.

According to 200-day moving average technique, we found 4 bulls and 3 bears along the stipulated time period. After determining these 7 phases, we estimated the difference parameter d for each phase. The estimated values of d are between 0 and 0.5 for two bull stages. These values reveal that persistence is found in bull phases implying long memory stationarity for the volatility processes so the volatility is more persistent in the bull market than in bear markets. Long memory behavior in time series implies to risk, asset allocation decision, pricing derivatives, so that long memory in PEX as an emerging stock market is likely to show significant evidence of risk. The volatility persistence during bull markets suggests that long horizon predictability is doubtful. Thus, investors are unlikely to predict future stock returns when they are in bulls markets because of long range dependence in those phases.

The existence of a co-integrating relationship among the variables allows us to use the ECM. The results also reveal that the estimated lagged error correction term of Bull phases is negative and significant so the speed of adjustment toward long run equilibrium is very low while the estimated lagged ECM of bear phases isn't negative so that the speed of adjustment toward long run equilibrium is unlikely to be attained.

The study's conclusions regarding volatility persistence are important for both investors and policy makers. The risk of uncertainty during bull and bear markets and the decline in PEX stock price and liquidity can be related to the volatility observed in the bull and bear markets. Therefore, investors are likely to consider the risk associated with changes in stock prices and decline in liquidity in PEX bear phases. So, they may invest during bear phases, while they sell in bull phases in order to avoid losses and achieve returns. Also, they should carefully investigate market movements and general market trends when they establish their buy and sell decisions since risk and liquidity problems are associated with PEX bear markets. The investors are advised to consider the uncertainty and risk at both index level, and company level. This strategy is likely to apply in short term sale. This can help investors to avoid losses associated with bears markets.

Furthermore, investors may suffer financial losses since volatility is persistent and continues for a long time periods which add more risk and liquidity problems during those phases. Therefore, investors should consider the turning points when bull and bear phases start. It is also important for investors to know when they buy and when they sell securities since stock prices are more volatile during PEX bear phases for long time periods. To reduce the risk of losses, the combination of fundamental and technical analysis is to be used when investors make their investment decisions, because together, they may provide opportunities for enhancing investment results.

Palestinian investors are advised to take these results when they manage their portfolios into account, rather than counting on general movements. Bull and bear phases' characteristics can be considered at index level as well as company level. This study is of importance value to both investors and policy makers in Palestine. The results provide very important information on investment strategies in stock exchanges which in turn enable investors to take profitable decisions and achieve returns. Also, regulators and policymakers are likely to examine the sources of long range dependence in stock markets to improve and enhance market efficiency, so that they should consider volatility persistence as it enhances economic growth.

In Palestine, empirical studies of these topics are still limited. Non-parametric R/S is used to investigate long memory behavior to indicate volatility persistence and market efficiency. The estimates of d parameter indicate that the study is likely to introduce evidence about the possibility of developing investment environment since stock market volatility is persistent during PEX bull phases. As a result, robustness of empirical results of R/S statistics is very necessary to be examined by further semi parametric techniques; GPH estimator and Wavelet based estimator and parametric tests; and ARFIMA Models to investigate long memory behavior in stock volatility and returns.

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