FINANCIAL MARKET EFFICIENCY: A STUDY OF THE TIME SERIES PROPERTIES OF THE JORDANIAN STOCK MARKET

Muhannad Atmeh
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Department of Accounting and Finance
University of Newcastle upon Tyne Business School

ABSTRACT

The ASE has developed greatly since its establishment and has succeeded in accomplishing several of its goals by mobilising capital into the productive sectors of the economy. ASE appears to be well organised, attractive, and aims to attract international investments in order to increase the depth of the market.

The aim of the study is to explore the efficiency of this emerging market and investigate the integration with other capital markets in the region. Conventional tests beside recent econometric techniques are implemented.

The thesis starts with a review of the development of the efficient market hypothesis, followed by an overview of the development of the Jordanian Financial Market. The autocorrelation and runs test - runs up and down, distributions of runs by length, and runs above and below –are applied to the daily price indices of ASE to examine whether ASE is weak form efficient. The empirical results reflect significant positive dependency patterns in stock prices and suggest that the price behaviour in ASE does not follow the random walk model over time. However, further investigation is applied to find whether these results could be exploited, through technical analysis, to outperform the simple buy and hold policy. Filter rules and moving average techniques are used. Furthermore, and for the results of moving average techniques, standard statistical testing is extended through the use of bootstrap techniques. According to the moving average rule, buy and sell signals are generated by two moving averages of the level of the index (long and short period averages). The conditional returns on buy or sell signals from actual data are

compared to the conditional returns from simulated series generated by a range of models (random walk with a drift, AR (1), and GARCH-(M)). The results of this part of the study generally suggest that technical analysis helps predict stock price changes in the Jordanian stock market.

In the next part of the thesis, recent econometric procedures are employed to investigate the behavioural properties of ASE indices. The Box-Jenkins estimation, irrespective of the index examined produced different models with a high prediction performance, violating the EMH conditions. The unit-root test also confirmed these results as the return series for all indices did not exhibit unit root, and all processes were stationary. The GARCH-M(1,1) model is estimated and present mix results cross the indices. To a certain limit, the results support the existence of a significant link between conditional volatility and stock returns, and the conditional variance is found to change over time as a result of volatility clustering effects.

The last part of the thesis applies the cointegration and Granger causality tests to investigate the concept of market integration and comovements. These techniques are applied using, firstly, the five Jordanian daily indices, and secondly, the weekly price indices for ten MENA (Middle East and North Africa) markets. The cointegration test between the Jordan index and every other market index is applied. Moreover, different groups of markets (GCC, Africa, and Europe) are composed and the cointegration test is applied for each group. Results suggest that the Jordanian stock market does not exhibit a long run relationship with most other markets, and there is an advantage for investors looking for diversification in the Middle East markets.

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CHAPTER 1

Introduction

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1.1 Motivation for the Study

A functioning stock market is an essential component in a competitive economy, as it provides a mechanism for allocating the economy's capital stock. In an ideal situation, the stock market steers capital in a manner that maximises the total utility of the economy. The growing trading volumes in stock markets globally imply that the importance of stock markets is increasingly pronounced.

Financial markets, or exchanges, play a crucial role in facilitating the intermediation between savers and investors, thereby helping translate savings into investments. The more efficient this process is, the less the cost of investing, and subsequently, the higher the rate of investment/saving. This, in turn, usually leads to higher rates of economic growth for any given country. Moreover, financial markets contribute to economic development by attracting foreign portfolio capital and foreign direct investment.

increasing domestic resource mobilisation, and, as a result, expanding resources available for investment.

Recently, the increasing globalisation of financial markets has heightened interest in emerging markets. However, much of the research in finance focused on the most developed markets in the world, in particular, the US and European markets. The conditions of these developed markets are most likely to be consistent with the assumptions of theoretical models. This feature does not exist in emerging markets. Hence, emerging equity markets provide a challenge to existing models. The interest in emerging markets has provided impetus for both the adaptation of current models to new circumstances in these markets, and the development of new models (Bekaert and Harvey, 2002).

Amman Stock Exchange (ASE), as an emerging market, is expected to play an increasingly important role in helping the country compete for domestic, regional and international capital needed for economic development and growth. To achieve this, significant studies need to be conducted to investigate the properties and functioning of such a market. Studies on ASE, as is the case in most emerging markets, are very few, if any, and literature on this area is hardly found.

Investment risk and market efficiency need to be investigated since investors, both international and domestic, assess these factors before committing funds to a particular market. In addition, the relative efficiency of the stock market will indicate whether or not new regulations should be considered, and if some government intervention may be necessary.

Hussain (1996) stated that "A realization of inefficiencies inherent in command and control policies and the tighter lending policies of international creditors have led the developing countries to re-define the role of domestic equity markets in their economies. Most countries have adopted policies that make the allocation of equity capital more responsive to market forces. These policy changes have resulted in remarkable growth in the size of the equity markets in the developing world, commonly known as Emerging Stock Markets (ESMs)"[1].

The primary motivation for this study is to investigate the stochastic properties and efficiency in ASE, one of the emerging markets, as there is a lack of such studies in this market (and other emerging markets in general). Another powerful motivation for the thesis is to investigate the issue of internationalization of the ASE, examining the possibility of earning arbitrage profits by trading in more than one national market. By doing so, we hope to gain some insight into the situation of the ASE by itself and within the context of emerging equity markets in the Middle East region.

[1] The Amman Financial Market was set up in 1976 to create a market for the trading of securities and to regulate this process. However, this dual role of a regulator and market could only be borne for a limited time by the AFM. As part of Jordan's push to upgrade its capital markets, a new Securities Law was enacted in 1997. It called for the separation of the supervisory and legislative roles from those entailed in operating an exchange (more details can be found in Chapter 3).

1.2 Objectives of this Study

As previously mentioned, the primary objective of this study is to investigate the stochastic properties as well as the efficiency of the ASE using the daily return indices. This study will help enhance the understanding of this important Middle-eastern market. This objective is also important since the issues of efficiency and randomness of this market are essential in the context of market integration and globalization[2].

This objective, to examine stochastic properties of the ASE as well as its efficiency, deals with the question of normality, volatility, randomness and efficiency. There are various justifications for using the assumption of normality in finance. The most substantial one is that the normal distribution is fully described by only two parameters: the mean and the variance. That is, an asset is fully described by its expected rate of return (mean) and its expected risk (variance). If expected asset returns are normally distributed, then since the return on a stock index is a weighted sum of returns on individual stocks, and the sum of normal variables is normally distributed, the index return is also normally distributed. The validity of the normality assumption is examined for the five sub index returns of the ASE, by applying the coefficients of skewness and kurtosis, and the Jarque-Bera (1987) tests. The autocorrelation and runs test - runs up and down, distributions of runs by length, and runs above and below –are also applied to examine whether the ASE is weak-form efficient. The empirical results obtained suggest that the return behavior in the ASE does

[2] The distribution of stock returns is an important issue in finance, as asset returns in finance are usually modeled as generated by a stochastic process with certain characteristics, and concepts such as return and risk depend on assumptions regarding the distribution of asset returns.

not follow the random walk model over time. The ASE reflects a high degree of positive temporal dependency patterns, thereby violating the assumption of random walk model. Following this, the positive temporal dependency patterns are examined to determine whether they can be used to outperform the simple buy and hold strategy. Filter rules and moving average techniques are used to achieve this objective, and the bootstrap technique is used to robust the results.

Next, recent econometric procedures are employed to investigate some behavioural properties of ASE indices. The Box-Jenkins estimation, irrespective of the index examined, produces different models with a high prediction validity, contradicting the EMH conditions. The unit-root test also confirms these results, where the return series for all indices did not exhibit unit root, and all processes were stationary. The GARCH-M(1,1) model is estimated and present mix results cross the indices. The results generally support the existence of a significant link between conditional volatility and stock returns, and the conditional variance is found to change over time as a result of volatility clustering effects.

Given this, cointegration and Granger causality techniques are employed, between ASE indices, to test the concept of static efficiency. If the efficient market hypothesis holds[3], then, and according to MacDonald and Power (1993), the prices of different shares can not be cointegrated. The reason is that, if prices are cointegrated, this would imply that there must be Granger causality running in at least one direction between the different

[3] The market is efficient if all prices fully reflect all relevant information (Fama, 1970)

price series, and hence, one share price could help to predict others, violating the Efficient Market Hypothesis.

Another main objective for this thesis is to investigate the issue of internationalisation of the ASE, examining the possibility of earning arbitrage profits by trading in more than one national market. Cointegration and Granger causality tests are thus also applied to investigate the concept of market integration and comovements among the weekly price indices for ten MENA (Middle East and North Africa) markets. The cointegration test between the Jordan index and every other market index is applied. Moreover, different groups of markets (GCC, Africa, and Europe) are composed and the cointegration test is applied for each group. By including a sufficient number of stock markets, two hypotheses are investigated. The first is that the strong economic relationships among countries that are in the same region are expected to exhibit a higher degree of integration. The existence of a common feature among stock markets would lead them to be cointegrated. Second, a lesser degree of market segmentation, manifested through increased cross-country stock investing and reduced foreign ownership restriction, tends to integrate one market with the others. Results suggest that the Jordanian stock market does not exhibit a long run relationship with most other markets, and as a consequence, there is probably an advantage for investors looking for diversification in the Middle East markets to include the Jordanian market in their portfolios.

1.3 Organisation of the Thesis

The main body of the thesis is organized into six chapters, in addition to the concluding chapter. In the next chapter, the theory of market efficiency, its development and the main concepts it relies on, are discussed. A review of martingale theory, random walks, capital asset pricing models, arbitrage, and the anomalies relating to market efficiency is conducted. The last section of this chapter, Chapter 2, sheds light on stock market efficiency for developing markets, focusing on the differences between developed and developing markets in terms of the financial effects of market integration and liberalisation, corporate finance, market microstructure, and privatisation.

In Chapter 3, a detailed review of the history and development of the Amman Stock Market is presented. First, the establishment and the objectives of the market are discussed, and then the major developments of the market and its divisions are displayed, supported by statistics for the different activities covering most of the period. Next, different microstructural properties of the market are highlighted, including: the trading system, transaction costs, available information, market indices, and along with an outline of the legislative environment. Finally, the chapter provides a comparison of the ASE with other markets in the region.

Chapter 4 reviews, firstly, past empirical studies that have applied autocorrelation and runs tests in different markets. The review is divided into two sections: the developing and the emerging markets. Afterward, autocorrelation and runs tests - runs up and down, distributions of runs by length, and runs above and below –are applied to examine whether the ASE is weak-form efficient. The results suggest that price behaviour in the ASE does not follow the random walk model over time.

Chapter 5 examines whether the results obtained in Chapter 4 can be exploited to outperform the market. It applies technical analysis rules for this purpose. A brief review of Technical Analysis Theory and empirical studies are presented. Next, various filter rules and moving average rules are applied. The results suggest that technical analysis helps predict stock price changes in the ASE, as one might expect, given the results from Chapter 4.

As found in Chapters 4 and 5, the daily returns for the five indices of ASE do not follow the random walk model, and the first order autocorrelation coefficients are high and significant for all indices. Therefore, several forecasting techniques, available to identify patterns in time series data, can be used. Chapter 6 used the Box-Jenkins (ARMA) methodology, which considers the statistical dependence of observations from one time period to the next. The Box-Jenkins method of forecasting is different from other methods in that it does not assume any particular pattern in the historical data of the series to be forecast. Afterwards, the stationary and the random walk processes for the price indices series are investigated. Another issue discussed in the chapter is the time dependent conditional variance. Returns based on equity prices or indices are most often found to have time dependent conditional variance, and hence ARCH and GARCH models are used to take care of the volatility observed in the time series of returns. The

GARCH(1,1)-M model for the daily return indices is estimated in order to investigate the link of stock returns to risk factors expressed by volatility.

In Chapter 7, since the price indices series were found to have a unit root, cointegration and Granger causality tests are used to investigate the concept of market integration and comovements. These techniques are applied using, firstly, the five Jordan daily indices, and secondly, the weekly price indices for ten MENA (Middle East and North Africa) markets. The cointegration test is performed for each pair of Jordan indices using two techniques: the Engle-Granger two step method and the Johansen approach. The cointegration test is also applied for a group containing all indices; the result confirmed the previous results indicating no long relationship among the indices. The last test for daily price indices for the ASE is the Granger causality test which shows a short run relationship between all pairs of indices. The same procedures applied for the ASE indices are reapplied for the ten Middle Eastern markets' price indices. The unit root tests are performed firstly for these indices to investigate the stationarity and to detect the order of integration. All indices are found to be I(1), and hence, appropriate to perform cointegration tests. Pair-wise cointegration between the Jordan price index and each other market's price indices are achieved by the Engle-Granger two step method and the Johansen approach. In the last part of this section, the ten indices are divided into three groups: GCC, Africa, and Europe. The cointegration tests are then employed twice for each group: once including the Jordan index, and once excluding it. The results for the first two groups indicate one cointegration equation when the Jordan index is excluded, and reject any cointigration equation once the Jordan index is included. The third group has one cointegration equation whether or not the Jordan index is included.

Finally, Chapter 8 concludes the study. It contains a discussion of the main results emerging from the research. The chapter also presents recommendations and directions for further research in this area, and potential implications of the results.

CHAPTER 2

A Review of Financial Market Efficiency Development

Contents:

Summary

This chapter investigates and discusses the theory of market efficiency, its development and the main concepts it relies on. Anomalous behaviour which appears to be inconsistent with market efficiency is also reviewed. Finally, the conditions and the main special characteristics of emerging financial markets, which cause emerging equity markets to behave rather differently from developed markets, are highlighted.

2.1 Introduction

The concept of market efficiency[1] is central to finance, since a functioning stock market is an essential component in a competitive economy. Primarily, the term efficiency is used to describe a market in which relevant information is impounded into the price of financial assets. Fama (1970) articulates the ideal of a well functioning stock market as: "In general terms, the ideal is a market in which prices provide accurate signals for resources allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time fully reflect all available information". Hence, prices have a key role in a stock market as allocation decisions depend on the prices of the traded stocks[2].

The concept of market efficiency had been anticipated at the beginning of the century by the work of Bachelier (1900), and the empirical research of Cowles (1934). Bachelier began the study of market prices assuming this was a source of time series that would exhibit discernable patterns. Very soon, he began to notice that the price changes, which he had assumed would be predictable, where simply random, and he stated that "past, present and even discounted future events are reflected in market price, but often show no

[1] The term efficiency is used hereafter to describe informational efficiency; loosely, this means relevant information is impounded into the price of financial assets. However, efficiency could refer to operational efficiency, emphasizing the way resources are employed to facilitate the operation of the market.
[2] The current observed market price for an asset plays two distinct roles in financial economics:

- The price represents an opportunity cost. An asset's price appears in the budget constraint as the amount that has to be paid, or received, per unit of the asset. This is the conventional of an individual role for prices in economic analysis.
- The price conveys information. Today's asset price reveals information about prices in the future. The information conveyed by prices affects investors' beliefs and hence their actions (portfolios selected). Investors' actions determine the demand to hold assets and hence influence the assets' observed market prices.

apparent relation to price changes". Cowles also found that there was no discernable evidence of any ability to outguess the market. After the work of Cowles, little work was done on pricing phenomena until 1959. However, two outstanding papers were published: Working (1934) which suggested random pattern in price changes of agriculture commodities, and Kendall (1953) which suggested no predictable pattern could be found in stock and commodity price series.

Two major papers were published in 1959 that formalized the basic framework of later studies of market efficiency. The first was Osborne (1959) which found that the physicist's model of random Brownian Motion[3] described successfully stock price movements. This model has been since used by academics in the field of finance to model stock prices, and it is often called the Random Walk Model. The other paper, Roberts (1959), had the title of "Stock Market Patterns and Financial Analysis". This was the first paper to take aim at the claims of Technical Analysis that they could profit by studying patterns in stock price movements. The study showed clear evidence that technical analysis had no predictive power. Alexander (1961) examined the idea of Technical Analysis and presented evidence that a great many technical strategies could be quite profitable. However, Alexander (1964) replicated the earlier study, after adjusting for transactions cost, and found only minimal evidence of profitable opportunities. Samuelson (1965) tried to prove why properly anticipated prices fluctuate randomly.

Fama (1965) reviewed and added some new tests to the previous technical analysis, and also discussed the value of the useful life of new information coming into the market.

[3] Brownian Motion is the observed movement of small particles as they are randomly bombarded by the molecules of the surrounding medium. This was first observed by the biologist Robert Brown.

Fama (1970) also put forward a classification of different information sets and three forms of efficiency:

- Weak form Efficiency: The prices reflect the information available from the series history. Market efficiency tests that use univariate time series models are an example of a test of weak form efficiency.
- Semi-Strong form Efficiency: The prices reflect all publicly available information.
- Strong form Efficiency: The prices reflect all public and private information available up to the moment. The possibility of insider trading is contemplated in this set

Early tests of the Semi-Strong Form of Market Efficiency were conducted by studying stock splits and dividend announcements. Fama et. al. (1969) tested semi-strong form efficiency and suggested that returns do not increase after stock split announcements. Fama (1970) assembled a comprehensive review of the theory and evidence of market efficiency. Though this paper proceeds from theory to empirical work, it outlines most of the empirical work that preceded the development of efficient market theory.

Fama (1970) stated that in an efficient market, prices always fully reflect all available information. A fully efficient market is characterised by:

- Zero transaction costs,
- All relevant information is costlessly available to all market participants,
- All agree on the implications of current information for the current price and the distributions for future prices.

So, in an efficient market, the current price of a security fully reflects all available information. These conditions ensure that investors possessing available information cannot earn above-competitive returns. However, a violation of any of the conditions does not immediately imply inefficiency.

It is obvious that much of the theoretical work in finance and economics is conducted to understand the behavior of securities prices and the efficiency of the market. The efficient market usually means that stock prices and returns are determined as the outcome of supply and demand in a competitive market, with rational traders. Rational traders instantaneously adjust the security prices to any relative piece of information. Therefore, individuals do not have a comparative advantage in the acquisition of information, since prices reflect fully and very quickly this information. In other words, there should be no opportunities for making abnormal profits. This chapter reviews the development of the concept of the efficient market hypothesis.

Section 2.2 presents the development of the martingales and random walk concepts. The martingale hypothesis suggests that the changes in the prices of assets cannot be systematically forecast. However, it does not account for risk and the trade off between risk and expected returns. Hence, the martingale property is neither a necessary nor a sufficient condition for rationally determined asset prices, but it leads to the development of a closely related random walk model. According to random walk models of asset prices, one can show that if returns are properly adjusted for risk then the martingale property should hold for adjusted returns. Two equilibrium models are presented in the following two sections. Section 2.3 demonstrates Capital Asset Pricing Model (CAPM) which states that the expected return of an asset must be linearly related to the covariance of its return with the expected return on the market portfolio. A brief summary of the assumptions and implications of the model are also conducted. Section 2.4 outlines another equilibrium model, the Arbitrage Pricing Theory (APT). APT does not assume that shareholders evaluate decisions within a mean-variance framework as in the CAPM. Rather, it assumes that the return depends partly on macroeconomic factors and partly on events specific to the company, and that it is the researcher's task to identify these risk factors.

Section 2.5 presents the role of rational expectations and the rational use of publicly available information in explaining asset prices. The concept of noise is also introduced as the opposite of the rational model. Noise traders are investors assumed to act in random ways that are difficult to explain as the outcome of consistent behavior. Section 2.6 deals with the arbitrage concept as the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices. According to this concept, the original case for efficient markets probably leaned too heavily on the notion of risk-free, costless arbitrage to eliminate all profitable trading strategies immediately. Moreover, and relying on this concept, market efficiency is tested in the context of cross market integration. Hence, with perfect cross-market integration there are no cross-market arbitrage opportunities.

Section 2.7 focuses on anomalies; that is, empirical results that seem to be inconsistent with market efficiency. Some of the well known anomalies are listed: the value effect, the size effect, the momentum effect, and calendar anomalies (the January anomaly, the turn of the year effect, day of the week, and time of day and holiday effects). Section 2.8 outlines the main characteristics of emerging financial markets and what distinguishes them from developed markets. Much of the research in finance focuses on the most developed markets in the world; conditions in these markets are more likely to be consistent with the assumptions of the theoretical models. Most studies show that many emerging equity markets do not behave like developed markets. Market integration and liberalisation, corporate finance, market microstructure, and privatization are highlighted as important characteristics of the emerging markets. Summary and conclusion are then presented in Section 2.9.

2.2 Development of the Concept: Martingales and Random Walk

2.2.1 Martingales

The oldest and most important theory about asset pricing is known as the Martingale Model, and its origin dates back to Cardano's manuscripts (1565), whose modern formulation was established by Bachelier[4] (1900) and Samuelson[5] (1965). In brief, this theory postulates that the changes in the prices of assets (returns) cannot be systematically forecast. This is the same as to say that, statistically, the returns of any assets are supposed to be a random i.i.d (independent and identically distributed) process. According to this model, any attempts to predict the future prices of an asset will not have a statistically significant explanatory power.

[4] He stated that "past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes".
[5] He showed that: "...competitive prices must display price changes...that perform a random walk with no predictable bias. Therefore, price changes must be unforcastable if they are properly anticipated".

Let P_t represent an asset's price at date (t), and Ω_t a set of information available at date t, and let Ω_t consist of all the past prices of the asset, i.e. $\Omega_t = \{P_t, P_{t-1}, P_{t-2}, \ldots\}$. The martingale hypothesis denotes that tomorrow's price is expected to be equal to today's price, given the asset's price history. That is, if P_t is considered as a stochastic variable then P_t is said to be a martingale when it satisfies the following condition

$$E[P_{t+1}|\Omega_t] = P_t \tag{2-1}$$

In some applications, Ω_t is assumed to contain additional information (e.g. the prices of other assets, or companies' earnings data).

The crucial features of Ω_t for the analysis below are: (a) that it contains only things that are known at date t; and (b) that it contains, at least, the current and all past prices of the asset.

From (2.1):

$$E[P_{t+1} - P_t|\Omega_t] = 0 \tag{2-2}$$

The fair game[6] (2.2) has the property that the expected return is zero given the asset's price history.

In summary, assumptions which imply that the asset price evolves according to (2.1) or (2.2) are:

- investors believe that holding the asset is just like playing a fair game, and
- they have access to the information contained in the set Ω_t.

[6] Bachelier came to the conclusion that "The mathematical expectation of the speculator is zero" and he described this condition as a "fair game."

The next property of martingale hypothesis is that nonoverlapping price changes are uncorrelated at all leads and lags, so all linear forecasting rules for future price changes based on historical prices alone have no predictive power.

Depending on martingale concept, in an efficient market, the current prices reflect all historical prices, and it should not be possible to make profit by expectation of future price changes from price history. Hence, the market is efficient when price changes are random and unpredictable. However, in finance, there is a trade-off between risk and return, and the martingale hypothesis does not involve risk considerations in any way. Some economic models (like CAPM) determine the equilibrium return of the asset according to the risk of the asset, so there is a trade-off between risk and expected return, but the martingale hypothesis puts a restriction on expected return, and does not take risk into consideration, which means the martingale property is not a sufficient condition for rationally determined asset prices.

Nevertheless, the martingale assumption has become a powerful tool in modern theories of asset prices (Campbell, 1997). Theoretically, once asset returns are adjusted properly for risk then the martingale property does hold. For instance, an asset's risk may imply that it must offer some level of positive return to an investor. As a result, in an efficient market, the asset's price change is expected to be positive but the actual return is still unforecastable. This leads to a random walk models of the asset price where one can show that if returns are properly adjusted for risk (given the equilibrium model) then the martingale property holds for the adjusted returns.

2.2.2 Random Walks

A model that is associated with the martingale process and which is widely represented in tests for the forecastability of returns is the Random Walk. A Random Walk is represented by:

$$p_{t+1} = \mu + p_t + \varepsilon_{t+1} \quad \textbf{(2-3)}$$

This model shows that the asset price at time t+1 is given by the price at the immediately previous moment, a term of expected change known as drift[7] plus an unpredictable error component. The random walk model can be obtained through the Martingale process by restrictions on the error term ε_t. The behaviour of error term ε_t is extremely important, and restrictions on the behaviour of this term produce three versions of the Random Walk model, as stated by Campbell, Lo and Mackinlay (1997).

2.2.2.1 Random Walk I - IID Increments

The stronger version of the random walk model is the one in which increments at price P_t given by error term ε_t belong to the same distribution (identically distributed) and are independent. In addition, the original distribution can be used, which in the most common cases is the same as assuming that ε_t belongs to a normal distribution with zero mean and constant variance σ^2. Random Walk I, also known as RW1, is even more restrictive than the Martingale Model, since in the latter model the increments are nonlinearly

[7] The drift coefficient, μ, reflects how prices change on average to provide the expected rate of returns from holding the asset over time.

uncorrelated and any nonlinear combination of the increments should also be uncorrelated[8].

2.2.2.2 Random Walk II - Independent Increments

The RW1 model is extremely restrictive; therefore, it should not be used in real financial series because it rules out the possibility of structural changes in the data generating process, such as parameter changes, of which the most relevant are the changes in volatility[9]. A more appropriate version, known as Random Walk II (RW2), only requires that the increments should be independent, but not necessarily originate from the same distribution. This maintains the characteristic of linear unpredictability and allows for changes in unconditional volatility[10].

2.2.2.3 Random Walk III - Uncorrelated Increments

The most general form of the random walk model requires only that ε_t be uncorrelated over time - this is referred to as RW3. For instance, financial series with ARCH effects can respect the behaviour of RW3, since level returns may be uncorrelated. As this is the least restrictive form of random walk, it is more likely to prove consistent with the

[8] Runs tests are conducted in Chapter 4 of this study as a test of RW1.
[9] The assumption of identically distributed increments is not plausible for financial asset prices over long time spans, due to changes in the economic, social, technological, institutional and regulatory environment in which stock prices are determined.
[10] Filter Rules are conducted in Chapter 5 of this study as a test of RW2.

behaviour observed in real financial series. RW3 is usually the most widely tested form of random walk[11].

Whilst tests for Fama's Efficient Market Hypothesis (EMH) usually meant testing the null hypothesis that the autocorrelation coefficients (linear dependence) of different lags are statistically insignificant, other researchers tested for the nonlinear dependence which, if present, could help in forecasting, especially over short time intervals. Granger and Anderson (1978) and Sakai and Tokumaru (1980) have shown that simple nonlinear models exhibit no serial correlation while containing strong nonlinear dependence. This has, in fact, led several researchers like Granger and Anderson (1978), Hinich and Patterson (1985) and Scheikman and LeBaron (1989) to look for nonlinear structures in stock returns. It may be noted in this context that one of the most important and useful tests available in the literature for detecting nonlinear patterns i.e. the existence of potentially forecastable structures, is due to Brock et al. (1987, revised 1996). With increasing power of computers, coupled with advances in both nonlinear dynamics and chaos, the volume of research into the re-examination of the behaviour of security returns from the standpoint of market-efficiency has increased considerably, and most of these (see Hsieh, 1991; Willey, 1992; Sewell et al., 1993; Opong et al., 1999; among others) have cast doubts on the conclusion of market efficiency based only on the lack of serial correlation in returns.

However, many other studies documented that when the conditional variance of stock returns is not constant over time, some of the tests for (linear) autocorrelation mentioned

[11] Autocorrelation tests are conducted in Chapter 4 of this study as a test of RW3

earlier perform poorly. This fact has led to the development of autoregressive conditional heteroscedasticity (ARCH) and generalised ARCH (GARCH) models (Engle, 1982; Bollerslev, 1986). Returns based on equity prices or indices are most often found to have time dependent conditional variance and hence ARCH/GARCH models are used to take care of the volatility observed in the time series of returns. In fact, Diebold (1986), Lo and MacKinlay (1988), Silvapulle and Evans (1993), and others have noted that in the presence of ARCH, the serial correlation tests, if not corrected, can result in misleading inferences.

2.3 The Capital Asset Pricing Model (CAPM)

Any investment decision must be evaluated in terms of its risk and return. Common sense suggests that risky investments such as the stock market will generally yield higher returns than investments free of risk. Markowitz (1952) is the first to introduce variance as a measure of risk in a way that gave meaning to economists. He argued that the variance of the portfolio, as well as the expected return, needs to be considered. Markowitz (1952) also developed formulas to consider portfolio risk and expected return which is considered the foundation to the modern portfolio theory. However, the problem with the Markowitz (1952) formula for calculating expected portfolio return, is how to estimate expected return for each security in the portfolio. Simply averaging the returns of the last few years, along the lines in Markowitz (1952), will not yield reliable estimates of the return expected in the future (Miller, 1999)[12].

[12] For example, a sample of historical data could produce negative average returns, whilst the expected return must be positive.

In spite of the limited practical usefulness of the Markowitz (1952) mean-variance approach[13], his work is the starting-point of the capital asset pricing model (CAPM). Sharpe (1964) and Linter (1965) derived the CAPM[14]- which states that the expected return of an asset must be linearly related to the covariance of its return with the returns of the market portfolio- assuming the existence of lending and borrowing at a risk free rate of interest, so the expected return of asset i, is:

$$E(R_i) = R_f + \beta_i \left[E(R_M) - R_f\right] \tag{2-4}$$

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{2-5}$$

where $E(R_i)$ is the expected return on asset i, R_f is the return on risk free asset, and R_M is the return on the market portfolio (the average expected return from holding all assets in the optimal proportions).

It can be shown that this implies that the expected return on any security equals a risk free rate plus a risk premium that is equal to the market risk premium times an index of

[13] Markowitz (1952) stated that investors would choose the mean-variance efficient portfolio, which has the highest expected return for a given level of variance.

[14] The most important assumptions which the predictions of the model are derived from are, in brief (Pike and Neal, 1999):

- All investors aim to maximize the utility they expect to enjoy from wealth -holding, operate on a common single period planning horizon, select from alternative investment opportunities by considering expected return and risk, are rationally risk-averse, arrive at similar assessments of the probability distributions of returns expected from traded securities, can lend or borrow unlimited amounts at a common rate of interest, and are price-takers which means no investor can influence the market price by the scale of his or her own transactions
- All such distributions of expected returns are normal.
- There are no transaction costs entailed in trading securities.
- Dividends and capital gains are taxed at the same rates.
- All securities are highly divisible, i.e. can be traded in small parcels.

the systematic risk of this security (the so-called beta)[15]. In this model, unsystematic risk will not be priced by the market (because it can be diversified). Implications that can be inferred from CAPM about equilibrium returns on individual securities in the stock market are:

- The market risk premium (Er_m - r_f) is positive, otherwise investors choose to invest purely in the risk-free asset since they could earn more by doing that (under the assumption that investors are risk averse).
- Returns on individuals stocks tend to move in the same direction, which means cov (r_i, r_m) ≥ 0 and $ß_i \geq 0$. The expected return of stocks with $ß_i = 0$ is the risk-free rate, while, stocks with a high ß (large positive covariance with market return) have high expected returns.
- Stocks with $ß_i = 1$ are expected to have a return move 100% with the market portfolio. If $ß_i$ is bigger than 1, the stock return moves more than changes in the expected market returns, and conversely when $ß_i$ less than 1.

If the CAPM is correct, the model makes it possible to calculate the expected return for a security, based on the security's systematic risk. But the model has several assumptions which limit the usefulness of the model in tests of the EMH. Among others, the model requires Markowitz efficient investors and all investors to have homogeneous expectations. This means that all investors want to be on the efficient frontier and that all investors have identical probability distributions for future rates of return. Identical

[15] There is by now a growing literature arguing against the use of the CAPM to estimate required returns on equity in emerging markets (EMs). One of the characteristics of this model is that it measures risk by beta, which follows from an equilibrium in which investors display mean–variance behavior. In that framework, risk is assessed by the variance of returns, a questionable and restrictive measure of risk.

probability distributions require identical relevant information available to all investors. But if all investors have the same information and interpret the information in a Markowitz efficient way, the securities market must be efficient. In other words, the market must be efficient for the CAPM to be valid and as a consequence the model cannot be used in tests of market efficiency.

2.4 Arbitrage Pricing Theory (APT)

Arbitrage Pricing Theory (APT), founded upon the work of Ross (1976, 1977), aims to analyze the equilibrium relationship between assets' risk and the expected return just as the CAPM does. However, APT does not assume that shareholders evaluate decisions within a mean-variance framework as CAPM does. Rather, it assumes that the return depends partly on macroeconomic factors and partly on events specific to the company. Firm specific risk, since it is easily diversified out of any well-diversified portfolio, is not relevant in determining the expected returns of securities (similar to CAPM), leaving only the macroeconomic risk as the determinant of required security returns (Pike and Neal, 1999). The APT specifies the share's returns as a function of macroeconomic factors upon which the market portfolio depends. Hence, the expected risk premium of a share would be:

$$E(R_i) - R_f = \beta_1 \left[E(R_{factor1}) - R_f \right] + \beta_2 \left[E(R_{factor2}) - R_f \right] + \ldots\ldots + u_i \qquad \textbf{(2-6)}$$

where $E(R_i)$ is the expected return on asset i, $E(R_{factor1})$ is the expected return on macroeconomic factor 1, β_i is the sensitivity of security i to factor 1 and u_i is the random deviation based on unique events having an impact on the security's returns.

The APT does not require investors to hold any particular portfolio and there is no special role for the market portfolio. On the other hand, there is a need to identify the macroeconomic risk factors that affect the returns of well-diversified portfolios. It is the researcher's task to identify the risk factors. Such risk factors might happen to be unexpected changes in industrial production, inflation, real interest rates, etc., and there must be a linear relationship between the risk exposure or sensitivity (its loadings on the risk factors) and expected return of a security.

2.5 The Role of Rational Expectations

The definition of market efficiency is related to the rational use of publicly available information. Suppose the price change between time (t) and time (t+1) depends on the arrival of information, where this is viewed as a random variable. The rational expectation[16] under EMH can then be presented as:

[16] The importance of expectations formation in financial markets is illustrated by a famous passage in Keynes's General Theory " professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one's judgement, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligences to anticipating what average opinion expects average opinion to be. And there are some, I believe, who practise the fourth, fifth and higher degrees." (Keynes, 1936, p. 156). Hence, asset prices affect expectations, expectations affect decisions, decisions affect prices, and so on.

$$P_{t+1} = E_t P_{t+1} + \varepsilon_{t+1} \quad \textbf{(2-7)}$$

where $E_t(.)$ is the expected value operator (with expectations formed at time t), and the expected value of the forecast error is zero,

$$E_t \varepsilon_{t+1} = E_t\left(P_{t+1} - E_t P_{t+1}\right) \equiv E_t \varepsilon_{t+1} - E_t \varepsilon_{t+1} \equiv 0 \quad \textbf{(2-8)}$$

The error term ε_{t+1} is considered a measure of unexpected profit (or loss) between time (t) and (t+1), and its expected value is zero. According to EMH, the stock price P_t incorporates all relevant information available at time (t), and the prices change between time (t) and time (t+1) depending on the arrival of 'news' which itself is a random variable, sometimes good sometimes bad.

The forecast error $\left(E_t \varepsilon_{t+1}\right)$ must be independent of any information set available at time (t), thus it is already incorporated in P_t. On the other hand, if the forecast error is dependent on the information set at time (t) (ε_t is serially correlated), then this violates the EMH in that information available at time (t) is not fully incorporated in P_t and helps to forecast future prices. An example of serially correlated error term is the first order autoregressive process, AR (1)

$$\varepsilon_{t+1} = \rho \varepsilon_t + V_t \quad \textbf{(2-9)}$$

where V_t is a (white noise) random element. This equation implies that period (t's) error ε_t has a predictable effect on the next period's forecast error ε_t which helps in forecasting the next period prices as mentioned in the above equation. As a conclusion, under the EMH there must not be a serial correlation in ε, hence we cannot use information available today to predict tomorrow's prices. If stock returns are considered instead of stock prices (2-10), then no one can predict future returns from today's return, which means there will be no abnormal profits by buying and selling stocks.

$$R_{t+1} = E_t R_{t+1} + \varepsilon_{t+1} \tag{2-10}$$

The forecast error has a mean of zero $(E_t \varepsilon_{t+1} = 0)$. Thus the actual return could be above or below the expected return but on average unexpected returns (ε_{t+1}) are zero.

The concept of noise was introduced by Black (1986) in an attempt to account for some of the imponderable features of price fluctuations. In this context, the noise traders are some investors assumed to act in random ways that are difficult to explain as the outcome of consistent behavior. On the other hand, rational traders are assumed to behave according to more coherent precepts, or have better information, or have better ways of processing the available information, than noise traders.

Investors behave according to many and various criteria, hence, the simple model that investors make decisions based on past asset prices alone may not be sufficient. Some investors devote great energy and skill to their portfolio choices and do not depend solely

on past prices[17]. However, as Keynes cautions, no amount of effort can completely eliminate human ignorance about what the future may bring forth:
"The game of professional investment is intolerably boring and over exacting to anyone who is entirely exempt from the gambling instinct; whilst he who has it must pay to this propensity the appropriate toll." (Keynes, 1936, page 157). Thus, the concept of noise traders, empirically, imposes limitations on the assumption of rational expectations and market efficiency.

2.6 Arbitrage

One of the fundamental concepts in finance is arbitrage, defined as "the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices" (Sharpe and Alexander, 1990). In its simplest form, arbitrage implies the law of one price; that is, the same asset exchanges for exactly one price in any given location and at any given instant of time.

Roughly speaking, arbitrage strategies are patterns of traders motivated by the prospect of profiting from discrepancies between the prices of different assets but without bearing price risk. Arbitrage opportunities occur whereby a trader can buy a security and sell it simultaneously at a higher price. If arbitrage opportunities are not absent, then investors could design strategies that yield unlimited profits with certainty and with zero initial capital outlays. Their attempts to exploit arbitrage opportunities are predicted to affect

[17] Seeking out potential investment opportunities, examining the strategies of individual companies, monitor the markets in which the companies operate, and studying the performance of investments are criteria used by some investors other than past prices.

observed market prices[18] (even though each investor, individually, is assumed to be too small to influence prices). The ensuing price changes then eradicate the potential for arbitrage profits. That is, in an efficient market, arbitrage activity will continue until the price differential is eliminated (Pike and Neal, 1999).

However, in real markets, arbitrage is neither easy nor effective as it had been assumed. For one thing, financial markets are not complete and frictionless[19], so arbitrage in general is risky and costly. In addition, it is not realistic to assume that the number of informed arbitrageurs or the supply of financial resources they have to invest in arbitrage strategies is limitless.

Recently, market efficiency is being tested in the context of cross market integration[20]. With perfect cross-market integration there are no cross-market arbitrage opportunities and the law of one price –i.e. portfolios with the same payoffs should have the same price in different markets– holds. The main advantage of this approach is that it relies on the condition of absence of arbitrage opportunities –which is directly related to the idea that more integration means fewer barriers to trade across markets- and does not depend on any particular asset pricing model. If markets are completely integrated and, therefore, there are no arbitrage opportunities, returns on different assets can be divided into a common component and an idiosyncratic one. Chen and Knez (1995) developed a measurement theory of market integration that relies directly on the concept of the law of

[18] When an arbitrageur buys a cheaper security and sells a more expensive one, his net future cash flows are zero for sure and he gets his profits up front. Hence, arbitrage plays a critical role in the analysis of securities markets, because its effect is to bring prices to fundamental values and to keep markets efficient.
[19] The frictionless assumption has two elements; zero transaction costs and no institutional restrictions on asset traders (e. g. short sales are allowed).
[20] In Chapter 7, a brief review of this topic is presented, and a cointegration test is conducted for different Middle Eastern countries.

one price and the condition of absence of arbitrage opportunities, and does not depend on any particular asset pricing model.[21]

2.7 Anomalies

Anomalies[22] are empirical results that seem to be inconsistent with theories of asset pricing behavior. They indicate either market inefficiency (profit opportunities) or inadequacies in the asset-pricing model. This raises the question of whether profit opportunities existed in the past, but have since been arbitraged away, or alternatively, they were statistical aberrations that attracted the attention of academics and practioners.

In an efficient market, publicly available information should already be reflected in the asset price. In a stock market, for example, public information on price-earnings ratios, cash flows or other measures of value should not have implications for future share returns (unless these variables are revealing information about the riskiness of the asset). The history of asset prices should also have no predictive power for future asset returns. Some of the well known anomalies are listed below.

2.7.1 The Value Effect

Portfolios constructed from value stocks appear to produce superior investment returns over long horizons. Value stocks are those with high earnings, cash flows, or tangible

[21] In the literature other approaches that test for integration based on the notion of absence of arbitrage have been developed (for instance, Adler and Dumas (1983) use an international CAPM). However, as pointed out by Chen and Knez (1995), the main shortcoming of these approaches is that any test of market integration is, at the same time, a test of the particular asset pricing model used.

[22] Some anomalies referred to public information about stocks which helps to predict excess returns.

assets relative to the current share price. Basu (1977, 1983) noted that firms with high earnings/price (E/P) ratios earned positive abnormal returns relative to the CAPM. Many subsequent papers have noted that positive abnormal returns seem to accrue to portfolios of stocks with high dividend yields (D/P) or to stocks with a high book/market (B/M) value of common stock.

Ball (1978) made the observation that such evidence was likely to indicate a fault in the CAPM, rather than market inefficiency, because the characteristics that would cause a firm to enter a trader's portfolio following this strategy would be stable over time and easy to observe. In other words, turnover and transaction costs would be low, as would information collection costs. If such a strategy earned reliable abnormal returns, it would be available to a large number of potential arbitrageurs at a very low cost.

More recently, Fama and French (1992) showed that two variables, the book to market ratio and size, captured much of the cross-sectional variation in stock returns over the period 1963-1990. These results have been confirmed for a wide variety of non-US markets as well; see, for example, Arshanapalli, Coggin and Doukas (1998)[23].

DeBondt and Thaler (1985) constructed portfolios ordered across various measures of value, such as book-to-market, cash-flow-to-price and price-earnings ratios, sales growth and past returns history, using historical data on US stock returns. Along each of these

[23] However, recent results cast doubt on Fama and French (FF) results. Wright, Mason, and Miles (2003) argued that the risk premia on the two factors used by (FF) are of marginal statistical significance in (FF) study; when the sample period is extended to include later data, the premia are not statistically significant. Also, the inclusion of the factors in the asset pricing model has the general effect of moving the CAPM beta towards 1.

dimensions, portfolios constructed from value stocks exhibit high future returns relative to glamour portfolios over investment horizons of between one and five years (glamour stocks have the opposite characteristics to value stocks). Lakonishok, Shleifer and Vishny (1994) reached similar findings, and also presented evidence that the variability of returns from value portfolios is no greater than that for glamour portfolios. Thus, the higher returns earned by value portfolios do not appear to be due to a higher level of risk.

Fama and French (1996), with their three-factor model[24], suggest that there are three explanations for their results

- CAPM is incorrect and a three-factor model is the correct specification of the world.
- CAPM is correct but investors are irrational.
- CAPM is correct but has not been tested properly.

Trecartin (2001) shows that the BV/MV effect is not reliable over short time horizons. He holds that the BV/MV variable is not an adequate measure of risk, as it does not predict return on a consistent basis. Trecartin (2001) holds investor overreaction as a plausible explanation, as investors favour different types of stocks at different times.

[24] Fama and French (1993) found that three specific factors, the excess return on market portfolio, the size anomaly, and the book-to-market anomaly, to a large extent explain empirical return patterns. This model is called the three-factor model.

2.7.2 The Size Effect

Small stocks exhibit higher average returns (Banz 1981) although (Chan and Chen 1991) suggest this may reflect a distressed-firm effect. Since small firms include a disproportionate number of companies in financial distress, the higher expected returns experienced by small stocks may be a compensation for exposure to the risks associated with these distressed firms. While there is some relationship between anomalies, they do appear to be distinct phenomena. For example, small firms generally have lower price-earnings ratios and relatively poor past earnings growth (Chan, Hamao and Lakonishok 1991) and thus are more likely to be classified as value stocks. Nevertheless, measures of share value still have a predictive power for stock returns even after controlling for firm size (Lakonishok, Shleifer and Vishny, 1994).

2.7.3 The Momentum and the Contrarian Effects

Although value stocks produce superior returns over long investment horizons, in the short run the opposite seems to hold. Jegadeesh and Titman (1993) find that portfolios with high returns in the recent past continue to produce above-average returns over a 3-12 month horizon, and hence, the recent past winners (portfolios formed on the last year of past returns) out-perform recent past losers, which is a 'continuation' or 'momentum' effect. Chan, Jegadeesh and Lakonishok (1996) provide evidence that this momentum in stock returns can be partially accounted for by the slow adjustment of the market to past profit surprises that affected stock prices earlier. On the other hand, DeBondt and Thaler

(1985) suggest that past losers (low stock returns in the past 3-5 years) have higher average returns than past winners (high stock returns in the past 3-5 years), referred to as "contrarian" effect. A simple interpretation of these results would be that markets take a few weeks to react to new information, but having reacted, then continue to overshoot until an ultimate correction occurs some years down the line. In other words, investors initially underreact and, ultimately, overreact to new information (e.g. Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), Hong and Stein (1999)).

2.7.4 Calendar Anomalies

Calendar studies question whether it is possible to find regularities in the rates of return during the calendar year. There is extensive research material on these effects, and this brief review is limited to presenting some important findings on the January anomaly, the turn of the year effect, the day of the week effect, time of day and holiday effects.

2.7.4.1 The January Anomaly and the Turn of the Year Effect

The January anomaly is the effect that stock returns are unusually high in early January. The turn of the year effect is related to the January anomaly. It is the phenomenon that small stocks have unusually high returns in January, with the effect decreasing during the month. Branch (1977) reported a January anomaly and explained the effect by investors wanting to establish losses on stocks that have declined, and thus earning tax benefits.

Investors will sell out stocks in November and December and then buy them back in the beginning of January creating a positive pressure on the stocks. Keim (1983) and Reinganum (1983) showed that much of the abnormal return to small firms (measured relative to the CAPM) occurs during the first two weeks of January. Roll (1983) hypothesized that the higher volatility of small capitalization stocks caused more of them to experience substantial short-term capital losses that investors might want to realize for income tax purposes before the end of the year. This selling pressure might reduce prices of small cap stocks in December, leading to a rebound in early January as investors repurchase these stocks to reestablish investment positions[25].

Ritter (1988) investigates the January anomaly, and finds that value-weighted portfolios have no January effect. He found that earlier research was performed on equal-weighted portfolios, which made small firms over represented. Ritter (1988), however, found that small stocks have abnormal returns in January, a turn of the year effect. He viewed the effect as a function of institutional factors such as portfolio rebalancing. Schwert (2001) supported the existence of a turn of the year effect. However, he found that the abnormal returns of the turn of the year effect from 1980 to 2000 are about half of the abnormal returns from 1962 to 1979. The turn of the year effect was still present, but it was small.

[25] There are many mechanisms that could reduce the size of such an effect, including the choice of a tax year different from a calendar year, the incentive to establish short-term losses before December, and the opportunities for other investors to earn higher returns by providing liquidity in December.

2.7.4.2 Day of the Week, Time of Day and Holiday Effects

Another calendar anomaly is the day of the week effect, the effect that certain days consistently may exhibit different returns than others. French (1980) and Gibbons and Hess (1981) documented daily patterns in returns, in particular on average returns on Mondays tending to be negative. Further Harris (1986) has documented small but significant intra-day patterns in returns. Wang et al.(1997) found a Monday effect on the fourth and fifth week of the month, but no effect in the three first weeks. Again, relating the effect to a tick it was very small. However they made a point that when an investor has already decided to buy a stock, he should make the transaction on a Monday in the fourth or fifth week of the month.

The above studies anomalous behavior in stock returns, which appears, at first sight, to be inconsistent with market efficiency. Ball (1978) pointed out that such evidence may equally well be interpreted as indicative of shortcomings in the models of expected returns. Indeed, Fama (1997) took issue with the view that apparent anomalies require new behaviorally based theories of the stock market. Rather, they are indicative of a need to continue the search for better models of asset pricing. The last two decades have witnessed an onslaught against the efficient markets hypothesis. Yet as Roll (1994) observed, it is remarkably hard to profit from even the most extreme violations of market efficiency. Stock market anomalies are only too often chance events that do not persist into the future. The importance of the efficient market hypothesis is demonstrated by the fact that apparently profitable investment opportunities are still referred to as anomalies.

The efficient market model continues to provide a framework that is widely used by financial economists[26].

2.8 Stock Market Efficiency for Developing Markets

Much of the research in finance focuses on the most developed markets in the world; the conditions in these markets are most likely to be consistent with the assumptions of the theoretical models. In such markets, rich empirical tests can be carried out using data as granular as individual transactions. However, this feature does not exist in emerging markets[27] and the data are not nearly as extensive. Hence, there is a chance to develop new models which perform better, in emerging markets, than existing models. Bekaert and Harvey (2003) mentioned that standard models are often ill suited to deal with the specific circumstances arising in these markets. For example, emerging market returns are found to be highly non-normal (see Bekaert et. al., 1998, and Susmel, 2001) and highly volatile, and the samples are short. Bekaert and Harvey (2002) showed that many emerging equity markets do not behave like developed markets; some studies documented that emerging market equity returns have a higher serial correlation than developed market returns, and this serial correlation is symptomatic of infrequent trading

[26] Several interpretations have been proposed for explaining the anomalies, including investor behaviors (e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hisshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)), risk differentials between winner and loser stocks (Fama and French (1996)), problems in measuring portfolio performance (Ball, Kothari, and Shanken (1995)), biases in computed returns (Conrad and Kaul (1993)), industry effects (Moskowitz and Grinblatt (1999)), cross-sectional differences in mean returns of stocks (Conrad and Kaul (1998)), and investors' herding behavior (Grinblatt, Titman, and Wermers (1995)), among many others.

[27] The term emerging market is associated with the World Bank. A country is classified as emerging if its per capita GDP falls below a certain hurdle that changes through time. The basic idea behind the term is that these countries emerge from a less-developed status and join the group of developed countries. In development economics, this is known as convergence (Bekaert and Harvey, 2002).

and slow adjustment to information (Harvey, 1995 and Kawakatsu, 1999). Emerging market returns are also less likely to be impacted by company-specific news announcements than developed market returns. The evidence suggests that insider trading occurs well before the release of information to the public. Moreover, there is literature on stock selection in emerging markets that suggests that relatively simple combinations of fundamental characteristics can be used to develop portfolios that exhibit considerable excess returns relative to the benchmark (Fama and French, 1998, Rouwenhorst, 1999). These findings suggest that emerging markets are relatively less informationally efficient than developed markets.

A comprehensive review of emerging markets finance is conducted by Bekaert and Harvey (2003); they highlighted the following issues as important characteristics of the emerging markets:

- Financial effects of market integration and liberalization
- Corporate finance
- Market Microstructure
- Privatization

These are now discussed .

2.8.1 Financial Effects of Market Integration and Liberalisation[28]

Numerous articles have measured the effects of the liberalization process on financial variables. Although it is early to make inferences, a few robust findings emerge: the liberalization[29] process has led to a very small increase in correlations with the world market and a small decrease in dividend yields. This decrease could represent a decrease in the cost of capital or an improvement in growth opportunities. Bekaert and Harvey (2000), Henry (2000), and Das and Mohapatra (2003) all found that aggregate investment increases significantly after liberalizations, providing one channel for this increased growth.

2.8.2 Corporate Finance

Overall, research has characterized the degree of external corporate governance in emerging markets as weak. Both shareholder rights and the legal enforcement of the rights that do exist are generally lacking in emerging markets (La Porta et al., 1998), and the use of corporate takeovers as a disciplining mechanism is almost nonexistent. Furthermore, as mentioned above, it is frequently the case that insiders possess control rights in excess of their proportional ownership. This is usually achieved through pyramid structures in which one firm is controlled by another firm, which may itself be

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[28] Markets are considered integrated when assets of identical risk command the same expected return irrespective of their domicile. In theory, liberalization should bring about emerging market integration with the global capital market.

[29] Financial liberalization means allowing inward and outward foreign equity investment. In a liberalized equity market, foreign investors can, without restriction, purchase or sell domestic securities. In addition, domestic investors can purchase or sell foreign securities.

controlled by some other entity, and so forth (Shleifer and Vishny, 1997; La Porta et al., 1998; and Claessens et al., 2000,). Finally, irrespective of pyramid structures, managers of emerging market firms sometimes issue and own shares with superior voting rights to achieve control rights that exceed their cash flow rights in the firm (Nenova, 2003). Taken together, the net result is that a great number of firms in emerging markets have managers who possess control rights that exceed their cash flow rights in the firm, which, fundamentally, gives rise to potentially extreme managerial agency problems.

2.8.3 Market Microstructure

Market microstructure is the branch of financial economics that investigates trading and the organization of markets. Market microstructure directly affects price discovery (the trading process should lead to fair and correct prices), and liquidity (trading should occur at a low transaction cost, high speed, and large quantities should trade without affecting the price). Eventually, microstructure research is especially interested in transaction costs and liquidity, which differ greatly across emerging markets (see Glen, 2000 for an introduction to microstructure in emerging markets). Obtaining estimates of liquidity and transaction costs is important because: illiquid assets and assets with high transaction costs trade at low prices, relative to their expected cash flows. It follows that liquidity and trading costs may contribute both to the average equity premium in stocks and to the time-variation in expected returns if there is systematic variation in liquidity. Liquidity effects may be particularly acute in emerging markets. In a survey by Chuhan (1992), poor liquidity was mentioned as one of the main reasons for foreign institutional investors not investing in emerging markets. If the liquidity premium is an important feature of the data, emerging markets should yield particularly powerful tests and useful independent evidence. Moreover, the recent equity market liberalizations provide an additional verification of the importance of liquidity for expected returns since, all else equal (including the price of liquidity risk), the importance of liquidity for expected returns should decline post liberalization. This is important, since when focusing on the U.S. alone, the finding of an expected return variation due to liquidity can always be ascribed to an omitted variable correlated with liquidity.

2.8.4 Privatization

Privatization [30] shifts residual income and control to private investors, restricting redistribution and improving incentives; thus rapid privatization should be desirable. Empirically, however, the transfer of ownership, as opposed to control, is very gradual depending on investors' concern about future interference. However, when a large government stake conflicts with the transfer of control, underpricing may be necessary for separation (Perotti, 1995).

[30] Jordan's privatization program commenced in 1996 with the aim of rebalancing the role of the public sector in the economy by reducing the Jordanian government's stake in sectors dominated by state controlled enterprises.

The goals to be achieved for the wide-scale privatization program encompassed increasing the efficiency and hence production levels of privatized firms, creating a competitive market where demand and supply can freely interplay, attracting foreign direct investments, allowing the private sector to participate in infrastructure investments, deepening and developing the Jordanian financial market, and most importantly, limiting the government role to that of the regulator rather than that of the inefficient producer of goods and services.

The overall performance of the privatization program has been a grand success according to the World Bank, which has played a major role in devising and supporting the overall implementation of the program. However, the major criticism regarding the manner in which the program was handled was that the government chose not to conduct its privatization transactions through the Amman Stock Exchange, which denied Jordan's small and illiquid capital market from a golden opportunity to further develop and deepen. By failing to do so, private citizens were also deprived from directly taking part in investing in privatized SOEs. Although a technically and financially capable strategic partner was in dire need in most cases, we believe that a substantial portion of offered shares should have been made available to local private investors and floated on the Amman Stock Exchange.

A large-scale privatization program is one of the most critical policy steps in a transition economy. Following establishment of equity markets, some transition countries become able to carry out privatization sales through stock exchanges. As a result, a boost in a stock market, indicated by increases in capitalization, can be taken as a direct effect of launching privatization programs. Privatization also produces indirect effects on developing stock markets. New listings of privatized firms help to resolve a low-listing trap and expand diversification possibilities. Increased diversification potential creates an externality for all investors that is further reinforced through induced entry and reduced volatility of the market (Pagano, 1993).

Recent studies also found special tasks carried out by the privatization process (Perotti and van Oijen, 2001). It is argued that a consistent privatization program results in resolution of regulatory and legal uncertainty, e.g. by strengthening property rights and institutional reliability. The authors showed that reduction of political risk is achieved by the actual implementation of sustained privatization which is perceived as irreversible. Using panel data on emerging markets, they found the impact of decreases in political risk on stock market development to be considerable.

In general, privatization programs impact emerging capital markets through various mechanisms. For instance, share issued privatizations (SIPs) increase the market capitalization and the value traded on local exchanges. Moreover, SIPs can change the investment opportunity set of portfolio investors. Public offers of state-owned economic enterprises (SOEs) whose cash flows are not perfectly correlated with pre-existing companies help investors to achieve gains through diversification. Under this scenario, SIPs may help to lower the risk premium investors require for holding the market portfolio of publicly traded equity. Other methods of privatization, the direct sale of former SOEs, the direct sale of an SOE asset, or concessions of public sector monopolies, alter the dynamics of local capital markets in less obvious ways. For example, the direct sale of an SOE to a private investor does not increase the market capitalization or value traded on the local exchange. However, the sale may alter the real investment opportunity set of the private investor.

As viewed from this perspective, all forms of privatization can impact on local capital market dynamics. The common component of privatization that impacts capital markets is the transfer of productive resources from the public sector to the private sector. This transfer may allow investors to achieve benefits through diversification and may affect the cost of capital in emerging markets. Even if private investors do not benefit from the transfer of resources, i.e. their investment opportunity set does not change; privatization programs may still influence capital markets. Privatization programs can help the government signal its commitment to free market policies (see also Perotti, 1995). For most emerging market governments, the implementation of a privatization program reverses decades of state-led economic development. Successful privatization of politically sensitive industries may convince investors to reduce the ex ante perceived risk of government interference in investment decisions and expropriation of productive assets. As a result of sustained privatization efforts, the sovereign risk premium inherent in the governments fixed income liabilities may be reduced. As this chain of events ripples through the economy, local market entrepreneurs eventually benefit in their ability to obtain debt financing at a lower cost.

2.9 Conclusion

One of the earliest and most enduring questions of financial economics is whether financial asset prices are forecastable. The concept of efficient market hypothesis which asserts that the asset price changes are unforecastable, can be traced back at least as far as the pioneering theoretical contribution of Bachelier (1900) and the empirical research of Cowles (1933).

The efficient market hypothesis is simple in principle, but it became the dominant paradigm in finance during the 1970s. A discussion of market efficiency is closely related to asset pricing models, such as the capital asset pricing model. The empirical work testing the efficient market hypothesis is enormous. Although the efficient market hypothesis was supported by a growing body of empirical research demonstrating the difficulty of beating the market, testing for market efficiency is difficult. In the literature, different studies indicated anomalous behaviour which appears, at first sight, to be inconsistent with market efficiency. Ball (1978) pointed out that such evidence may equally well be interpreted as indicative of shortcomings in the models of expected returns. Yet as Roll (1994) observed, it is remarkably hard to profit from even the most extreme violations of market efficiency. Stock market anomalies are only too often chance events that do not persist into the future. Fama (1997) takes issue with the view that apparent anomalies require new behaviourally based theories of the stock market. Rather, he argues that anomalies are indicative of a need to continue the search for better models of asset pricing. However, making inference of market efficiency is difficult for the joint hypothesis issue and since small adjustments in the test methodology can also give large impacts on the results.

Although the last two decades have witnessed an onslaught against the efficient market hypothesis.. The importance of the efficient markets hypothesis is demonstrated by the fact that apparently profitable investment opportunities are still referred to as anomalies. The efficient market model continues to provide a framework that is widely used by financial economists. In general, the efficient market hypothesis is supported, although certain studies find anomalies that cannot be explained by the efficient market hypothesis or an asset-pricing model.

The chapter also highlighted the special characteristics of emerging financial markets that may produce assumptions differing from the assumptions of the standard theoretical models. Bekaert and Harvey (2003) mentioned that standard models are often ill suited to deal with the specific circumstances arising in these markets. However, the interest in emerging markets has provided impetus for both the adaptation of current models to new circumstances in these markets, and the development of new models. The most important of these characteristics are: market integration and liberalisation, corporate finance, market microstructure, and privatization.

CHAPTER 3

An Overview of the Development of Jordanian Financial Market

Contents:

Summary

This chapter presents an overview of the ASE, considering the objectives, properties, divisions, and the legislation environment for this market. The major developments of the market are displayed, supported by statistics, for the different activities, covering most of the period. Next, different microstructural properties of the market are highlighted, including: the trading system, transaction costs, available information, market indices and its methodology, and the legislation environment. Finally, the chapter provides a comparison of the ASE with other markets in the region. It concluded that the ASE has developed greatly since its establishment and has succeeded in accomplishing several of its goals by mobilising capital into the productive sectors of the economy. The ASE appears to be well organised, attractive, and well managed with much potential for growth when compared with other emerging markets. Despite the accomplishments so far, the ASE has much room for improvement, in order to become a regional financial market in the future.

3.1 Introduction

The financial sector is perhaps the most important factor determining any country's level of development, and the World Bank has shown increased attention in promoting and encouraging the establishment of stock markets. Jordan established Amman Financial Market (AFM) in 1976. The establishment of this stock exchange proved to be a major contribution towards improving the Jordanian financial sector. This consequently enabled a better utilisation of financial resources through:

-Mobilization of foreign and local savings.

-Steering such resources towards productive projects.

The AFM was one of the most sophisticated and active stock markets in the Middle East in particular, and among the emerging markets in general (emerging stock markets are defined by the International Financial corporation as stock markets in developing countries)[1]. AFM attracted the attention of numerous national and even international institutions. Additionally, the peace process in the Middle East which commenced with the Madrid Peace Conference on October 30, 1991, had generated interest in investment opportunities in Jordan (Maghyereh, 2001).

Section 3.2 gives an overview of the establishment and objectives of Amman Financial Market and its role in the Jordanian economy. This section discusses the major

[1] The term emerging market is associated with the World Bank. A country is classified as emerging if its per capita GDP falls below a certain hurdle that changes through time. The basic idea behind the term is that these countries emerge from a less-developed status and join the group of developed countries. In development economics, this is known as convergence (Bekaert and Harvey, 2002)

developments that occurred, focusing on the Securities Law of the year 1997, which restructured the Jordanian capital market and is considered as a turning point. A brief display of the new institutions formed by the new law and its role is also presented. Section 3.3 describes the segmentation of the market according to previous and current regulations. It starts with the primary market, then the secondary market, dealing in detail with former and current divisions. Some historical and statistical data that track the growth of the market is presented in this section. Section 3.4 deals with Non Jordanian inward investment and its regulation. The new regulations encouraged foreign investments and raised the non-Jordanian ownership ceiling, thereby possibly affecting trading volume and market liquidity, and eventually, market performance[2].

In section 3.5, the properties of the Jordanian market are discussed from different aspects: the trading system (i.e. brokers, entries registration, and transformation of ownership); transaction cost for all instruments, including brokers' commissions, fees for the market, and other taxes and commissions; and the available information for investors, including daily stock price indices. All these aspects play a major role in market performance. Profession and legislative environment, such as regular publication of P/E ratio, accounting standards, investor protection, Securities Commission, and the restriction on the investors are discussed in Section 3.6. Comparison of Amman Stock Exchange with other markets in the region through the last ten years is conducted in Section 3.7. The summary and concluding comments are in Section 3.8.

[2] Depending on allowing foreign investments in AFM, Chapter 7 investigates cross markets investment, including the Jordanian market, and the results suggest that there is an advantage for investors looking for diversification in the Middle East markets to include the Jordan market in their portfolios.

3.2 Amman Financial Market Establishment and Objectives

Public shareholding companies were set up and their shares were traded in, long before the setting up of the Jordanian Securities Market. In the early thirties, the Jordanian public already subscribed to and traded in shares; the Arab Bank was the first public shareholding company to be established in Jordan in 1930, followed by Jordan Tobacco and Cigarettes in 1931, Jordan Electric Power in 1938, and Jordan Cement Factories in 1951. The first corporate bonds were issued in the early sixties (www.ammanstockex.com).

As a result, an unorganized securities market had emerged in the form of non- specialized offices. Realizing this, the government discovered the need to set up a market to regulate issuance of and dealing in securities. By defining a fair price based on supply and demand, this market would ensure safe, speedy and easy trading, and protect small savers. It was hoped that such a market would serve as a creator of and caterer for opportunities for economic growth, thereby stimulating and spurting economic activity. Upon further demands for the establishment of this much needed market, various parties started to prepare, with the government's support, for setting up an organized securities market. In 1975 and 1976, the Central Bank conducted intensive studies, in cooperation with the World Bank's International Finance Corporation (IFC). These studies confirmed beyond doubt what was already known, that the size of the national economy and the share of the private sector in it through public shareholding companies and its broad investor base justified such a step. The Temporary Law No. 31 of the year 1976 was promulgated, and what was known as Amman Financial Market was consequently established. A Cabinet resolution of March 16, 1977 set up an AFM Administration Committee, which immediately went into action. Operation in AFM started on the 1st of January, 1978 (www.ammanstockex.com).

2.2.1 Major Developments of the Jordanian Capital Market

The establishment of AFM was a major step on the path of developing financial resources through the development of a sound capital market. The objectives of AFM were as follows:

- To mobilize savings by encouraging investment in securities, thereby channeling savings to serve the interests of the national economy.
- To regulate issuance of and dealing in securities such as to ensure the soundness, ease and speed of transactions to safeguard national financial interests and to protect small savers.
- To provide the necessary data and statistics to achieve AFM objectives (www.ammanstockex.com).

AFM was also able to encourage savings and investment, and offer investors the chance to aid in developing the private sector in Jordan, thereby contributing in accelerating Jordan's economic growth.

Before the financial sector was reformed, AFM and as of its inception, was entrusted with a dual task, namely the role of a securities and Exchange Commission (SEC) and the role of a traditional stock exchange. It used to operate under the auspices of the Ministry of

Finance. As revenue and expenditures are treated as entries in the accounts of the general government budget, they were collected and allocated by the Budget Department.

The Jordanian government adopted in 1997 a comprehensive capital market reforming policy, which aimed at boosting the private sector, expanding and diversifying the national economy, and improving regulation of the securities market to reach international standards. Among the most important features of the new orientation were institutional changes in the capital market, use of international electronic trading, settlement and clearance systems, elimination of obstacles to investment, and strengthening capital market supervision to reach optimum transparency and safe trading in securities, in line with globalization and openness to the external world (www.ammanstockex.com).

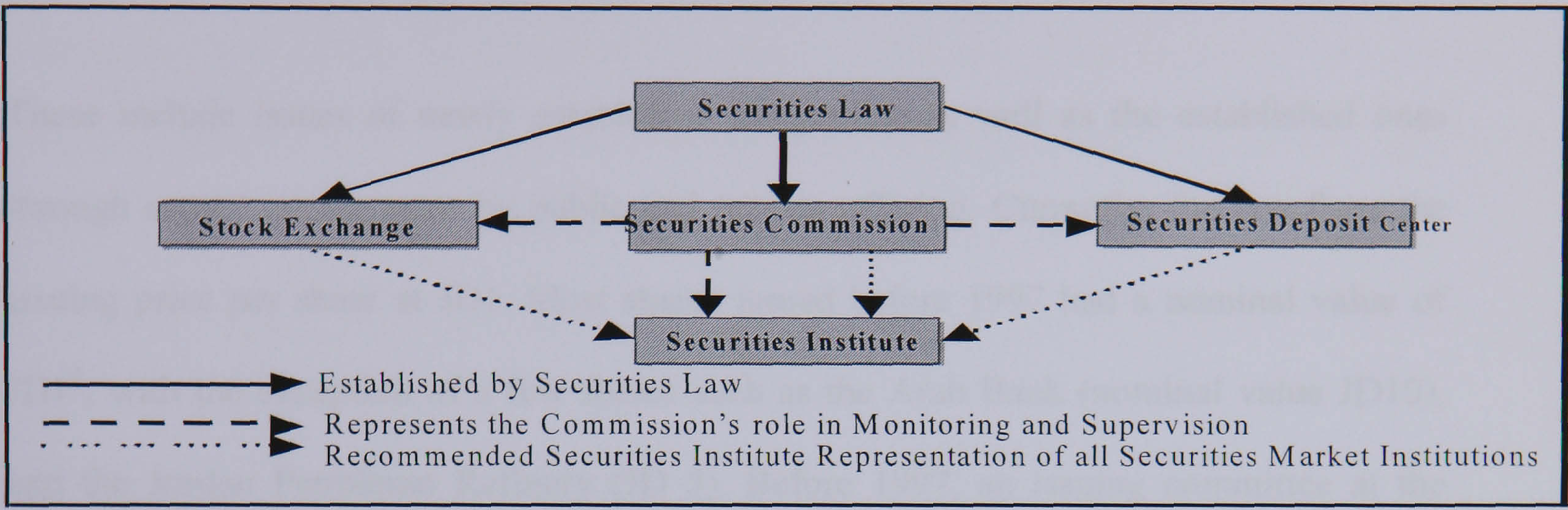
The enactment of the Temporary Securities Law, No. 23 of the year 1997, was a landmark; indeed, it was a qualitative leap and a turning point for the Jordanian capital market. Its aim was to restructure and regulate the Jordanian capital market, and to complete its infrastructure to be consistent with international standards, in order to secure transparency and safe trading in securities. The central feature of this restructuring effort was the separation of the supervisory and legislative role from the executive role of the capital market. The latter was left to the private sector, whereby Amman Stock Exchange/ Securities Market (ASE) and the Securities Depository Center (SDC) played the executive role, and the supervisory and legislative role was entrusted to Jordan

Securities Commission (JSC). This Law provided for setting up three new institutions to replace AFM, namely:

1. Jordan Securities Commission (JSC) implemented in October 1997. It aims at supervising the issuance of and dealing in securities, regulating and monitoring the activities and operations of those organs falling under its supervision. It also aims at regulating and supervising the disclosure of information related to securities, issuers, insider trading and major shareholders. It also regulates and supervises both ASE and SDC (Refer to Figure 3.1), it is a government agency affiliated with the office of the Prime Minister, but has administrative and financial autonomy in order to enhance its independence and efficiency in achieving its objectives (www.jsc.gov.jo, Maghyereh, 2001).
2. Amman Stock Exchange (ASE): It is a non profit legal entity, with financial and administrative autonomy, and it is the only party authorized to act as an organized market for trading in securities in the Kingdom. Its membership is made up of financial brokers, and it is managed by the private sector. It has started its operations on March 11, 1999.
3. Securities Depository Commission (SDC): was established on May 10, 1999 with the aim of ensuring safe custody of ownership of securities; registering and transferring ownership of securities traded on ASE; and settling the prices of securities among brokers. It is a non profit legal entity, with financial and administrative autonomy, and is managed by the private sector.

Since this study covers the period from 1992 to 2001, regulations both before and after the market reforming (1997) will be discussed.

Figure 3-1: Market Institutions Credited by the Securities Law



Source: Maghyereh, 2001

3.3 Amman Stock Exchange (ASE)

The ASE, of all three, is the closest to being a commercial entity. It is controlled by the firms of brokers who are its members, and who ultimately underwrite its liabilities. It is charged with creating and running a fair, efficient and transparent market in securities on a "not for profit" basis. The ASE consists of four main sectors: banking, insurance, services and industries, and it deals with two markets namely: The Primary and the Secondary Market. A brief description of both markets is given below (www.npsc.com.jo/ase/ase.htm, www.jordanembassyus.org/02062001001.htm)

2.3.1 The Primary Market

The Primary Market deals with new issues. These consist of share issues and bond issues:

3.3.1.1 Share Issues

These include issues of newly established companies, as well as the established ones through capital increases or by public and private offering. Currently, the law fixes the issuing price per share at JD1. Most shares issued before 1997 had a nominal value of JD1[3], with the exception of a few shares such as the Arab Bank (nominal value JD10), and the Jordan Petroleum Refinery (JD 5). Before 1997, an issuing committee at the Ministry of Industry and Trade, in co-operation with the AFM, used to determine the price of new share offerings by established companies. The problem was that no formula was used to calculate the price of new issues, and the calculation was usually done based on a purely subjective weight between the book value of the share and its market value. The new Security Law states that the price of new issues should be determined, through a market-based method, by the general assembly and the board of directors. It is claimed that this method allows a good reflection of the value of the securities being floated. It encourages companies to list shares on the exchange, and raises more money through the public issues of the same number of shares. In more developed stock markets, the company selling the shares, together with the investment bank and underwriter, determine the pricing of new issues, based on the company's potential earnings.

Since 1997, companies have been able to raise more equity than before, probably because firms were reluctant to sell shares, with equity issues so underpriced in the past. This led to a huge excess demand for shares, with a reduced chance of getting shares in a company. Additionally, there was typically a big jump in the price on the first day of

[3] The exchange rate at 7/11/2002 was: 1£=1.11 J.D

trading, allowing a capital gain for those able to get shares in the initial location. This benefit was not present in subsequent purchases. This may have improved with the liberalisation and better opportunities for dynamic companies. Furthermore, the new pricing system reduced over-subscription, thereby improving the likelihood of securing shares in the initial allocation and raising expected return (Maghyereh, 2001).

Several distinct phases in the growth of primary issues of shares can be distinguished: During the first phase (1978 to 1982), the value of primary issues increased from JD11.90 million to JD 91.31 million. The second phase lasted for the following 10 years. During this phase, the value of primary market issues declined -mainly due to the slowdown in economy- reaching JD 54.61 million in 1992. A huge increase occurred in the third phase. Primary issues increased in value by 318.2 percent in 1993 to JD 228.39 million, and by further 101.8 percent in 1994 to reach JD 460.92 million. This was attributed to companies increasingly turning to the stock market as a means of raising funds, due partly to a significant increase in market prices. The credit tightening imposed by the Central Bank of Jordan (CBJ) also contributed to this move by making bank loans less available. In addition to signing peace agreement in 1993, which was hoped to increase the political stability in the region (Refer to Figure 3.11 for major economic activity and the political situation that affected the Jordanian economy).

In the fourth phase, there were declines by 29.9 percent in 1995, and another 52 percent in 1996, with primary issues reaching JD 154.88 million. Another huge increase occurred in the fifth phase, where the value of new primary issuing increased by 111.4%

(compared to the 1996 level) reaching JD 327.36 million in 1997. Reductions in market price in 1998 caused the primary issues to decline to JD 47.52 million. A considerable increase in primary issues occurred in 1999 and 2000, reaching JD 105.92 million, the value dropped in 2001 to reach JD 60.730 million (Refer to Figure 3.2 and Table 3.1). (Azzam, 1997).

3.3.1.2 Bond Issues

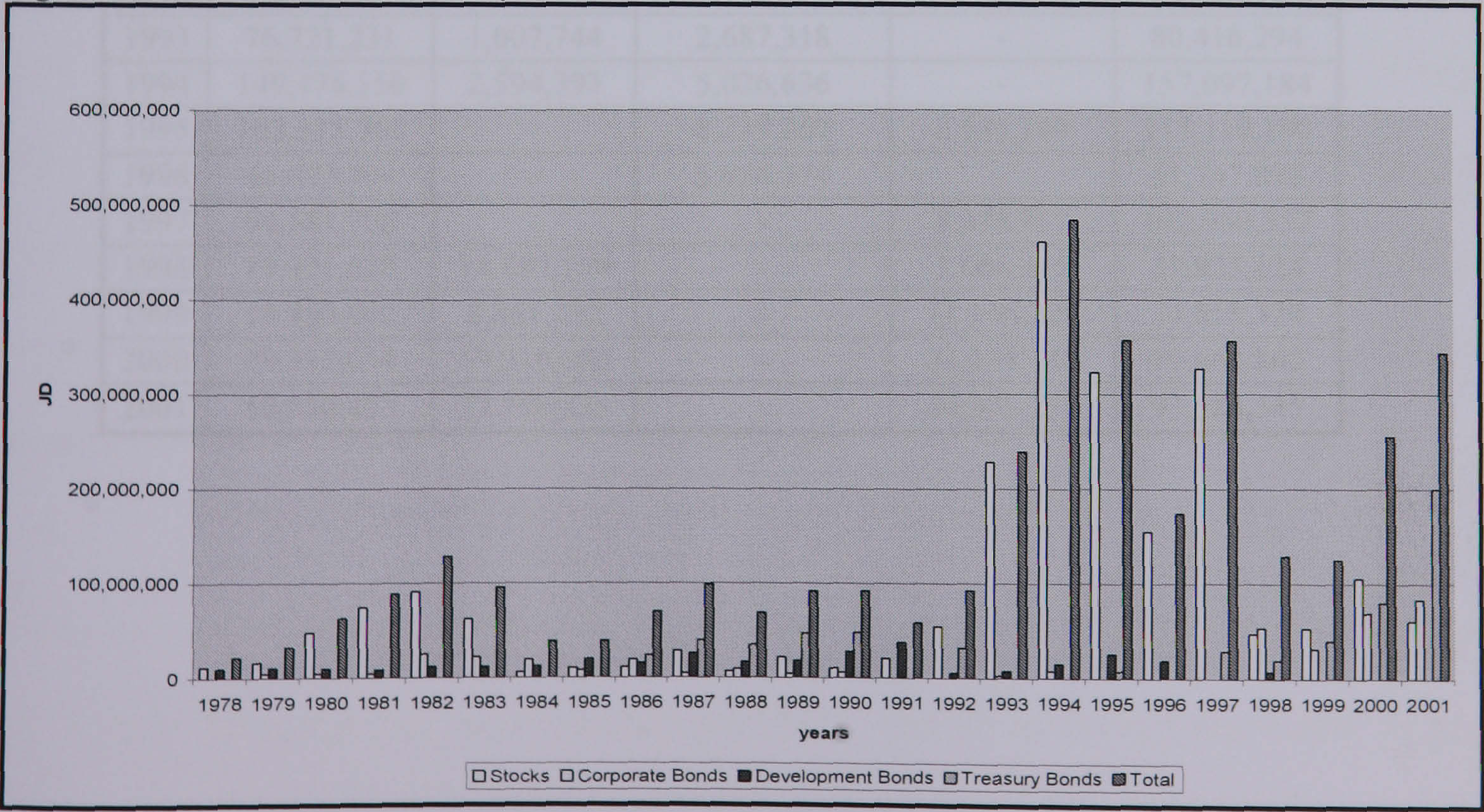
The bond market is still in the early stages of development. Three different types of bonds are issued: corporate bonds, development bonds and treasury bonds (Refer to Figure 3.2 and Table 3.1). Corporate bonds have always registered a small value – zeros in some years- until 1997. A significant increase started in 1998 till 2001 and the highest volume of corporate bond issues was JD 83.50 million in 2001. Most of the development bonds are issued by CBJ for monetary purposes, and are denominated in the local currency. In the last 3 years no development bonds were issued, while treasury bonds issues increased significantly during this period. It reached JD 200 million in 2001, from JD 80 million in 2000. (Maghyereh, 2001, ASE Annual Report 1999 and 2001, ASE website).

Table 3-1: Value in JD of Primary Market Issues

Year	Stocks	Corporate Bonds	Development Bonds	Treasury Bonds	Total
1978	11,901,117	_	10,000,000	-	21,901,117
1979	16,887,705	5,000,000	11,000,000	-	32,887,705
1980	47,764,260	5,000,000	10,000,000	-	62,764,260
1981	74,547,574	5,000,000	9,000,000	-	88,547,574
1982	91,308,682	25,000,000	12,000,000	-	128,308,682
1983	62,010,000	22,000,000	12,000,000	-	96,010,000
1984	6,283,630	19,500,000	13,000,000	-	38,783,630
1985	10,675,000	8,500,000	20,000,000	-	39,175,000
1986	11,420,000	19,000,000	15,500,000	24,000,000	69,920,000
1987	28,159,538	5,000,000	26,000,000	40,000,000	99,159,538
1988	7,000,000	9,660,000	17,000,000	35,000,000	68,660,000
1989	21,845,074	5,000,000	18,000,000	47,000,000	91,845,074
1990	10,478,065	6,000,000	28,000,000	48,000,000	92,478,065
1991	20,722,028	-	38,000,000	-	58,722,028
1992	54,608,973	-	6,000,000	32,000,000	92,608,973
1993	228,394,905	3,000,000	8,000,000	-	239,394,905
1994	460,920,711	8,000,000	15,500,000	-	484,420,711
1995	322,932,733	-	26,000,000	8,000,000	356,932,733
1996	154,882,113	-	19,000,000	-	173,882,113
1997	327,356,278	-	-	29,000,000	356,356,278
1998	47,522,780	53,500,000	8,000,000	20,000,000	129,022,780
1999	53,294,587	31,800,000	-	40,000,000	125,094,587
2000	105,924,067	69,450,000	-	80,000,000	255,374,067
2001	60,730,051	83,500,000	-	200,000,000	344,230,051

Source: Amman Stock Exchange, The Annual Report, Various years

Figure 3-2: Value in JD of Primary Market Issues

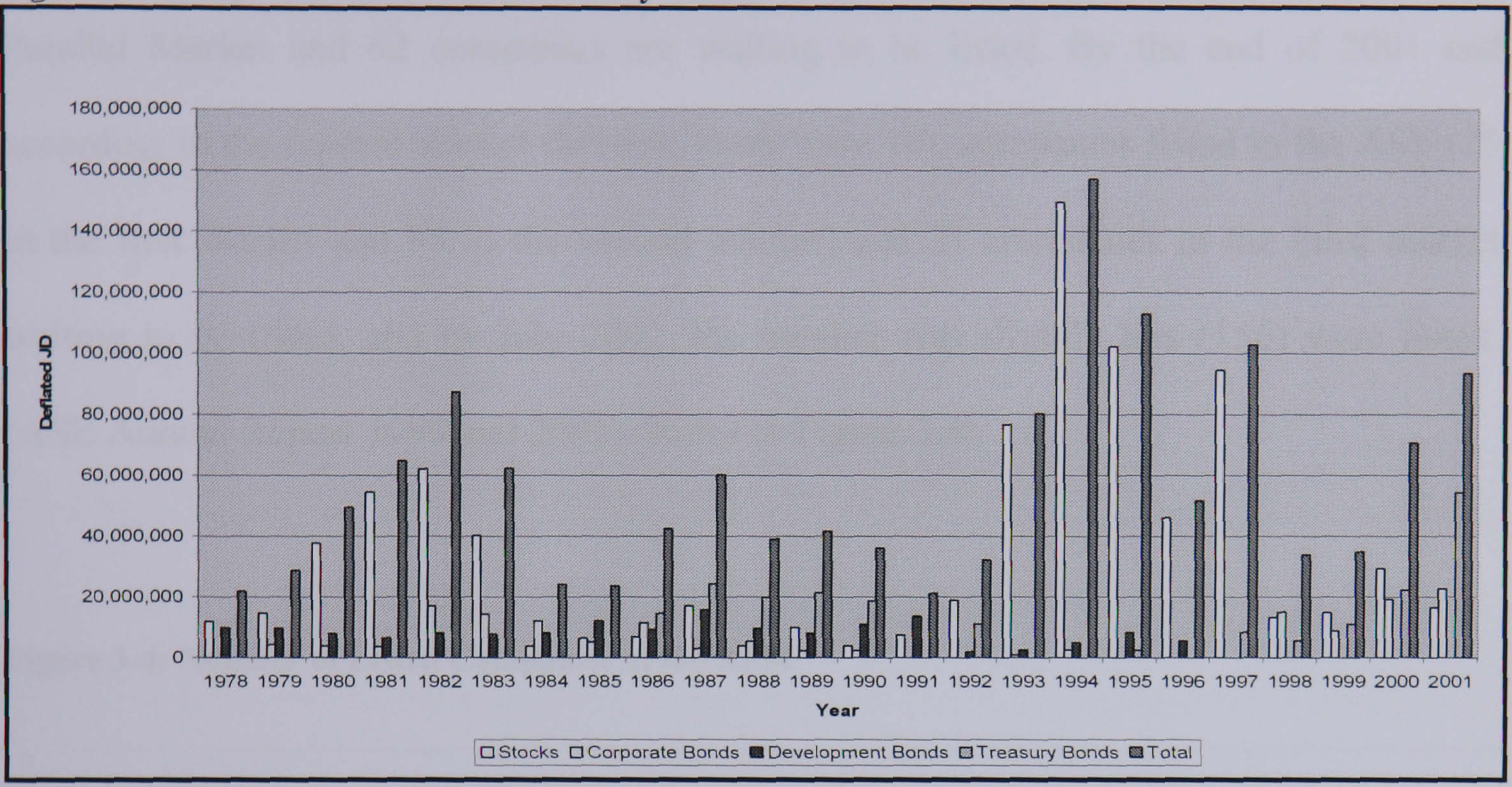


To ascertain that the changes in issues were not due to inflation, prices were deflated using the cost of living index (base year 1978). The results are shown in Table 3.2 and Figure 3.3, it is obvious that even after deflation, the results also revealed the five distinct phases of growth.

Table 3-2: Value in Deflated JD (Base Year 1978) of Primary Market Issues

Year	Stocks	Corporate Bonds	Development Bonds	Treasury Bonds	Total
1978	11,901,117	_	10,000,000	-	21,901,117
1979	14,798,065	4,381,313	9,638,889	-	28,818,267
1980	37,668,632	3,943,182	7,886,364	-	49,498,178
1981	54,573,857	3,660,338	6,588,608	-	64,822,802
1982	62,247,766	17,043,222	8,180,747	-	87,471,734
1983	40,219,570	14,269,159	7,783,178	-	62,271,907
1984	3,928,684	12,191,892	8,127,928	-	24,248,504
1985	6,475,918	5,156,469	12,132,867	-	23,765,253
1986	6,927,867	11,526,224	9,402,972	14,559,441	42,416,503
1987	17,112,714	3,038,529	15,800,350	24,308,231	60,259,824
1988	3,988,506	5,504,138	9,686,371	19,942,529	39,121,544
1989	9,908,811	2,267,974	8,164,706	21,318,954	41,660,445
1990	4,089,863	2,341,957	10,929,134	18,735,658	36,096,613
1991	7,474,578	-	13,706,861	-	21,181,438
1992	18,949,314	-	2,082,000	11,104,000	32,135,314
1993	76,721,231	1,007,744	2,687,318	-	80,416,294
1994	149,476,156	2,594,393	5,026,636	-	157,097,184
1995	102,335,761	-	8,239,269	2,535,160	113,110,190
1996	46,092,704	-	5,654,374	-	51,747,078
1997	94,581,706	-	-	8,378,851	102,960,557
1998	13,321,620	14,997,159	-	5,606,415	33,925,124
1999	14,850,842	8,861,252	-	11,146,229	34,858,324
2000	29,312,034	19,218,680	-	22,138,148	70,668,862
2001	16,510,453	22,700,835	-	54,373,257	93,584,545

Figure 3-3: Value in Deflated JD of Primary Market Issues



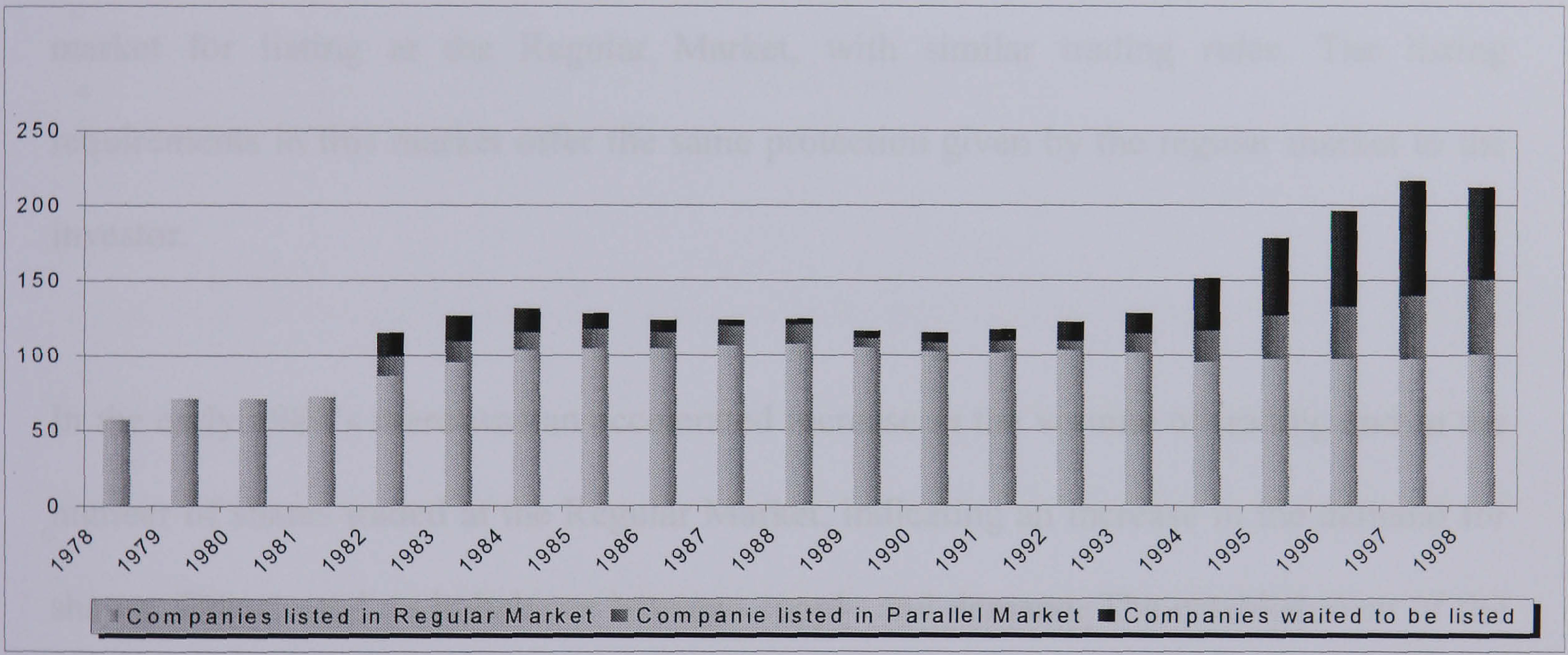
2.3.2 The Secondary Market

This market trades in securities that have already been issued and subscribed. Until fairly recently, the secondary market used to be divided into four markets: The Parallel Market, The Regular Market, Bond Market, and Legal Transfers (transactions off the trading floor). A new classification was implemented in accordance with the Directives for Listing Securities on Amman Stock Exchange/ Securities Market, whereby the secondary market is divided into: First Market, Second Market, Third Market, Transactions off the Trading Floor, and Bonds Market and Mutual Funds.

Since the establishment of AFM, the number of listed companies has almost tripled. In 1978, only 57 companies were listed in the AFM, and all of them were traded in the

Regular Market. In 1998, there were 100 companies listed in Regular Market, 50 in the Parallel Market and 62 companies are waiting to be listed. By the end of 2001 and according to the current market division, there were 161 companies listed in the ASE (75 in the first market and 85 in the second market) and 31 companies in the third market waiting to be listed, and by July 2002, the number was slightly less (156) were listed. (ASE Annual Report 1999 and 2001) (Refer to Figure 3.4).

Figure 3-4: Number of Listed Companies at the AFM



Source: Amman Stock Exchange, Monthly Statistical Bulletin, Different Issues

A more detailed description of secondary market divisions – both former and current- follows.

2.3.3 Former Secondary Market Divisions

The Secondary Market previously consisted of: Parallel Market, Bonds Market, Transactions off the Trading Floor, and the Regular Market.

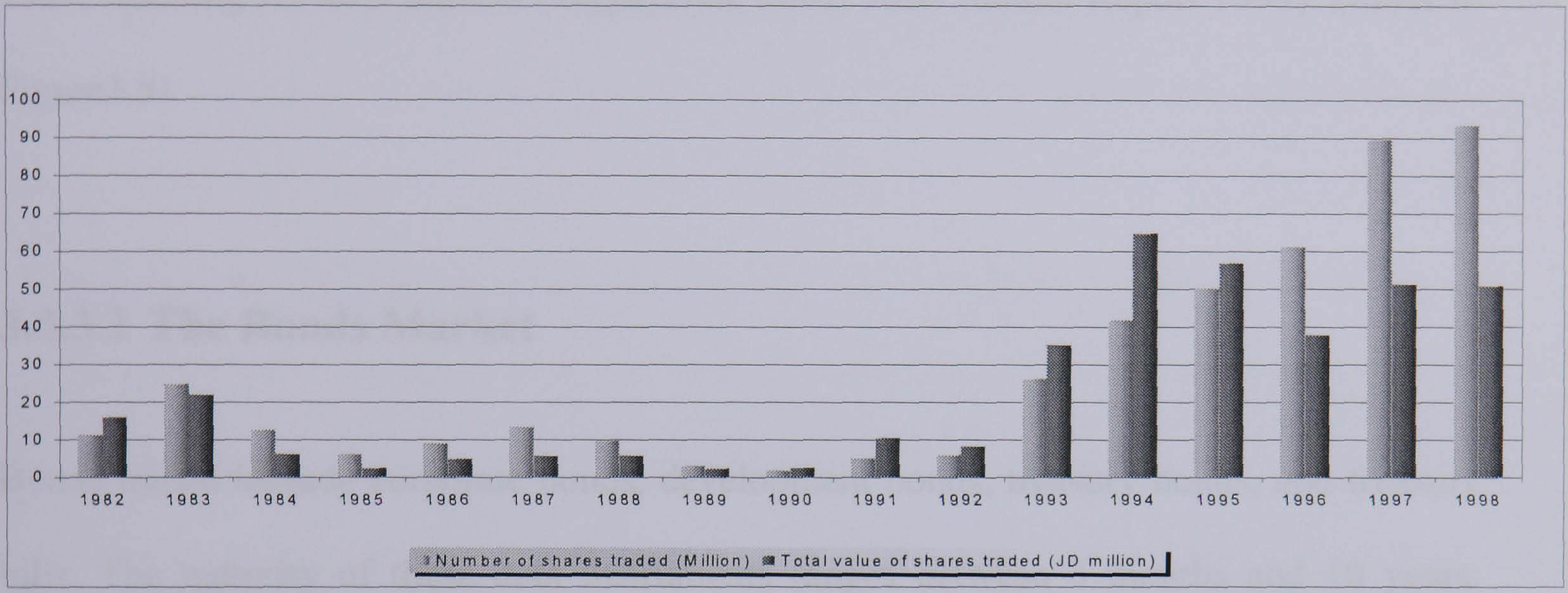
3.3.3.1 Parallel Market

Through this market, newly emerging companies with a liquidity problem were permitted to have their shares traded in an orderly manner while preparing to meet the more rigid requirements of formal listing in the Regular Market. The Parallel Market is a preparatory market for listing at the Regular Market, with similar trading rules. The listing requirements in this market offer the same protection given by the regular market to the investor.

In the early 1980's there was an accelerated increase in the volume of trading and in the number of shares traded at the Regular Market, indicating an increase in the demand for shares. This caused an imbalance between supply and demand. The establishment of the Parallel Market in 1982 solved this problem. It began its first day on February 20th of that year. Since then, it has witnessed distinct phases in growth, in terms of shares traded and volume. The total number of shares traded increased from 11.2 million in 1982 to 24.8 million in 1983 before declining to 12.6 million in 1984 and to 6 million in 1985. Shares then increased in the following two years to reach 13.4 million in 1987, before declining sharply to a trough value of 1.7 million in 1990. After declining during the Gulf Crisis (1990/91), the number of shares traded increased rapidly thereafter reaching a peak of

93.2 million in 1998 and 94.0 million in 1999 (Refer to Figure 3.5) (Maghyereh, 2001, ASE Annual Report 1999).

Figure 3-5: Trading in the Parallel Market (by Number and Values)



Source: Amman Stock Exchange, The Annual Report, Various years

An increase in volume followed the increase in the total number of shares traded. In 1982 the value of traded shares was approximately JD16.4 million. They increased to JD 21.8 million in 1983 or by 32.9 percent, and later declined to JD 6.2 million in 1984 and JD 2.4 million in 1985. During the next two years, the value of traded shares in this market recovered to reach JD 4.7 million in 1986 and JD 5.6 million in 1987. However, as a result of the 1988 economic crisis[4], the volume of shares traded sharply declined to reach

[4] Throughout the late 1970s and early 1980s, Jordan enjoyed unprecedented economic growth patterns boosted by outside assistance and loans, increased exports to regional countries, and workers' remittances of Jordanians working abroad. The inflow of foreign capital instigated extensive consumption and investment behavior, both public and private, which remained bountiful up until the crash in oil prices in 1982, after which this inflow began to decrease. The decline in oil prices instigated a major regional economic slowdown, which adversely affected the performance of the Jordanian economy. To resuscitate a collapsing economy, the government embarked on an extensive spending program financed through external borrowing. The consequence was a deteriorating current account deficit, a general rise in prices, and a rapidly mounting foreign debt. This ultimately led to a serious economic crisis by 1988. Encountering grave difficulties with debt management and repayment of loans, the government was compelled to turn to the IMF in 1989 to negotiate debt rescheduling and succumb to a stern economic restructuring program to reinstate a sustainable economic growth pattern.

JD 2.5 million in 1990 at an average annual rate of 24.4 percent. In the following seven years, the volume of shares traded in parallel market increased at an average annual rate of 25.3 percent, to reach JD 50.8 million in 1998. Trading volume slightly decreased in 1999, reaching JD 46.9 million (Maghyereh, 2001, ASE Annual Report 1999). (Refer to Figure3.5)

3.3.3.2 The Bonds Market

Bonds traded include corporate bonds, development bonds, treasury bonds, and treasury bills. The maturity of these debt instruments ranges between 3 months and 10 years. Trading in bonds and bills at the AFM had been generally slow, with the volume of bonds traded fluctuating between JD 2 million and JD 22.2 million during the years of AFM existence. During the period 1978-99, the volume of bonds traded incorporated an average of 1.47 percent of overall volume in the Secondary Market (Refer to Tables 3.3, 3.4).

There are several reasons behind the underdevelopment of bonds market in Jordan. One is the sudden inflation in the late 1980s, which caused large losses to the holders of fixed-rate bonds. Furthermore, only a few bonds are issued, and most are held until they mature. In most cases, bonds are sold to banks at subsidised rates. This discourages banks from selling the bonds in the secondary market because of the losses this would involve. The lack of institutional and legal infrastructure is another major factor inhibiting the development of the bonds market in Jordan. Jordan lacks financial institutions with sufficient expertise in pricing, underwriting, and selling corporate bond issues. An institutional infrastructure with an efficient clearing and settlement arraignments is essential for supporting the bond market.

Clearing, settlement, custody and payment systems are either absent or underdeveloped; and, consequently, trades run many risks, including those that may be created by the unreliability of counterparts, fraud, and multiple trades of same securities. Jordan needs creative financial institutions that can meet the changing financial requirement of the country. Investment bank services including strong financial analysis, underwriting of bond issues, floating of these bonds to the public at large and making market of these issues, are also needed. Other factors, such as lack of information and market makers with access to liquidity support also hamper bonds market development in Jordan.

3.3.3.3 Transactions off the Trading Floor

The Secondary Market also serves the purpose of legal transfers. The legal department at the AFM provided a setting for special transactions such as sales of unlisted companies, transactions from abroad, or those which involve transfers within families and are related to inheritance. Transactions off the trading floor incorporated on average almost 11.1 percent of the overall volume of trade in the Secondary Market from inception till year 2000. (Refer to Figure 3.6 and Table 3.3)

3.3.3.4 The Regular (Organized) Market

That was the part responsible for regulating and supervising the AFM trading floor. Most companies listed at the AFM were traded on the regular market. Companies listed in this market were divided into four sectors: the banking and financial institutions sector; the insurance sector; the services sector; and the industrial sector. The majority of transactions in equity dealing at the AFM took place at the Regular Market. During the years of AFM existence, the volume of equity traded in this market incorporated 87.4 percent, on average, of the overall volume traded in the Secondary Market (Refer to Table 3.3).

The industrial sector is generally the most active in terms of traded shares, incorporating 49.8 percent of the overall volume traded in this market from inception till the year 2000, followed by the banking sector by 33.6 percent, the services sector with 13.9 percent, and finally, the insurance sector 2.7 percent. During the period 1978-92, Jordan witnessed an exceptional growth in the number of shares traded at the Regular Market. The total number of shares traded in this market increased from 2.4 million in 1978 to a peak value of 344.8 million in 1992, before declining to 244.3 million in 1993 and to 154.6 million in 1998, and slightly increasing to 177.1 million shares in 1999 (Refer to Figure 3.7). The total number of traded shares to the total number of subscribed shares increased gradually from 2.8 percent in 1978 to reach 87.1 percent in 1992 before declining to 57.3 percent in 1998 (ASE Annual Report 1999).

Table 3-3: Trading Value in JD at the Secondary Market at ASE (1978-2000)

Year	Stocks	Mutual Funds	Bonds	Off-Trading Floor Transactions	Total
1978	5,615,891	_	_	4,056,000	9,671,891
1979	15,843,159	_	776,289	3,848,649	20,468,097
1980	41,431,076	_	1,661,015	6,748,813	49,840,904
1981	75,417,027	_	2,324,445	6,569,746	84,311,218
1982	128,288,963	_	1,942,272	9,565,110	139,796,345
1983	141,427,111	_	607,686	13,481,071	155,515,868
1984	59,318,623	_	1,676,497	8,302,526	69,297,646
1985	66,730,872	_	3,607,914	14,425,344	84,764,130
1986	69,522,993	_	2,530,574	26,080,676	98,134,243
1987	148,178,293	_	1,047,321	17,982,136	167,207,750
1988	132,625,222	_	16,656,964	22,194,279	171,476,465
1989	367,589,840	_	22,175,343	164,865,777	554,630,960
1990	268,885,973	_	3,121,014	17,808,353	289,815,340
1991	302,836,729	_	1,448,874	16,001,995	320,287,598
1992	886,950,983	_	4,316,726	15,254,051	906,521,760
1993	968,613,802	_	4,650,449	37,372,182	1,010,636,433
1994	495,076,052	_	4,375,151	46,812,893	546,264,096
1995	418,958,544	_	12,238,519	82,926,204	514,123,267
1996	248,583,344	_	5,141,100	28,919,143	282,643,588
1997	355,244,623	_	2,008,224	67,663,188	424,916,035
1998	464,374,268	_	4,041,085	69,750,893	538,166,246
1999	389,430,783	45,551	4,097,316	109,287,384	503,105,864
2000*	334,724,633	200,749	7,234,782	20,544,292	362,704,456

* Includes Third Market data for stocks

Source: Amman Stock Exchange, The Annual Report, Various years

Table 3-4: Yearly Trading Movement of Bonds Market

Year	No. of Traded Bonds	(%) Change	Traded Bonds (JD)	(%) Change
1978	-	-	-	-
1979	117,124	-	776,289	-
1980	98,440	(16.0)	1,661,015	114.0
1981	217,484	120.9	2,324,445	39.9
1982	184,331	(15.2)	1,942,272	(16.4)
1983	42,813	(76.8)	607,686	(68.7)
1984	127,673	198.2	1,676,497	175.9
1985	337,274	164.2	3,607,914	115.2
1986	121,440	(64.0)	2,530,574	(29.9)
1987	97,074	(20.1)	1,047,321	(58.6)
1988	532,987	449.1	16,656,964	1,490.4
1989	658,652	23.6	22,175,343	33.1
1990	198,926	(69.8)	3,121,014	(85.9)
1991	119,924	(39.7)	1,448,874	(53.6)
1992	406,614	239.1	4,316,726	197.9
1993	437,965	7.7	4,650,449	7.7
1994	437,523	(0.1)	4,375,151	(5.9)
1995	1,223,199	179.6	12,238,519	179.7
1996	514,025	(58.0)	5,141,100	(58.0)
1997	200,760	(60.9)	2,008,224	(60.9)
1998	241,863	20.5	4,041,085	101.2
1999	85,432	(64.7)	4,041,086	0.0
2000	197,626	131.3	7,234,782	76.6
2001	88,959	(55.0)	7,223,212	(0.2)

Source: Amman Stock Exchange, The Annual Report, Various years

Figure 3-6: Trading Values at the Secondary Market

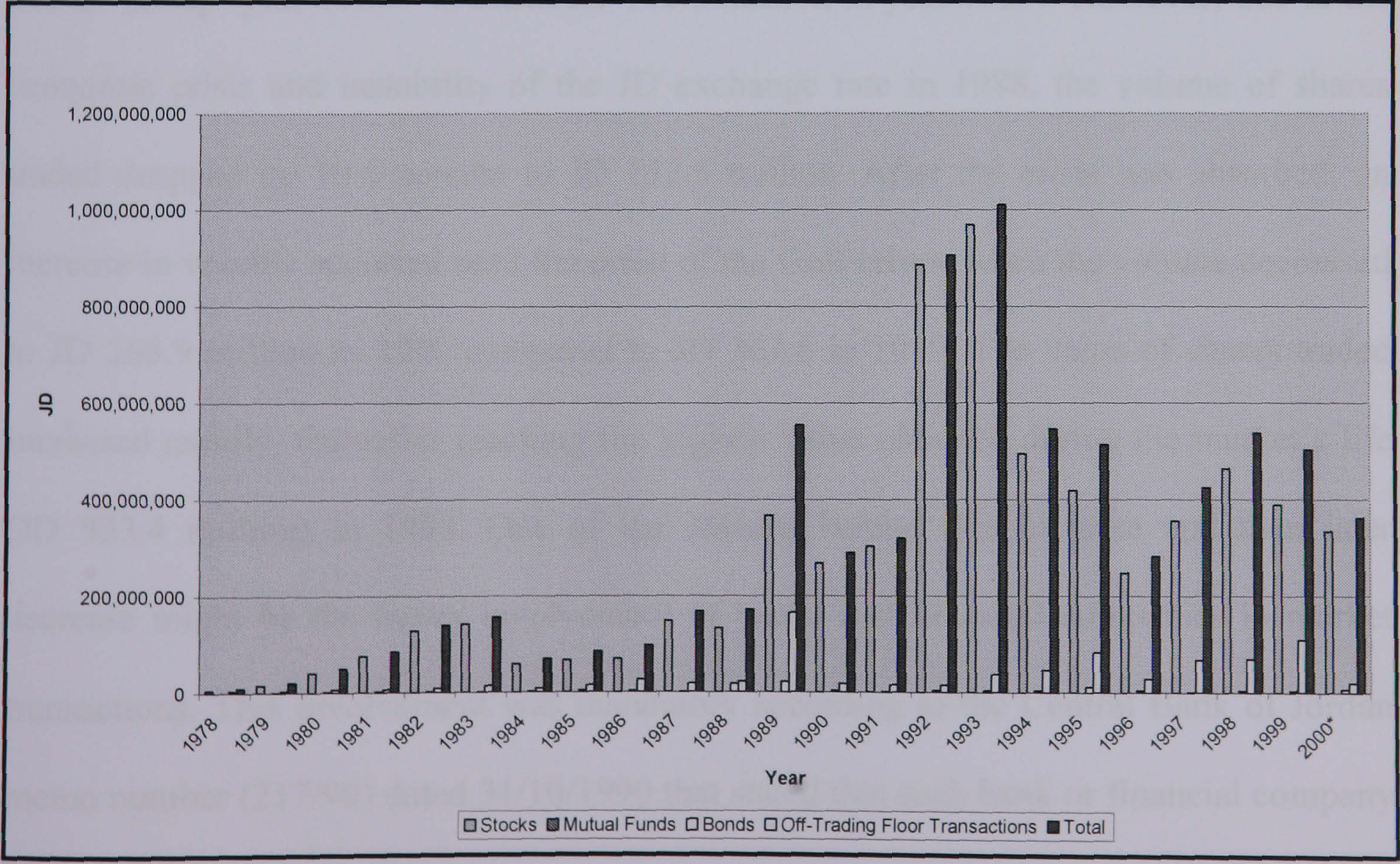
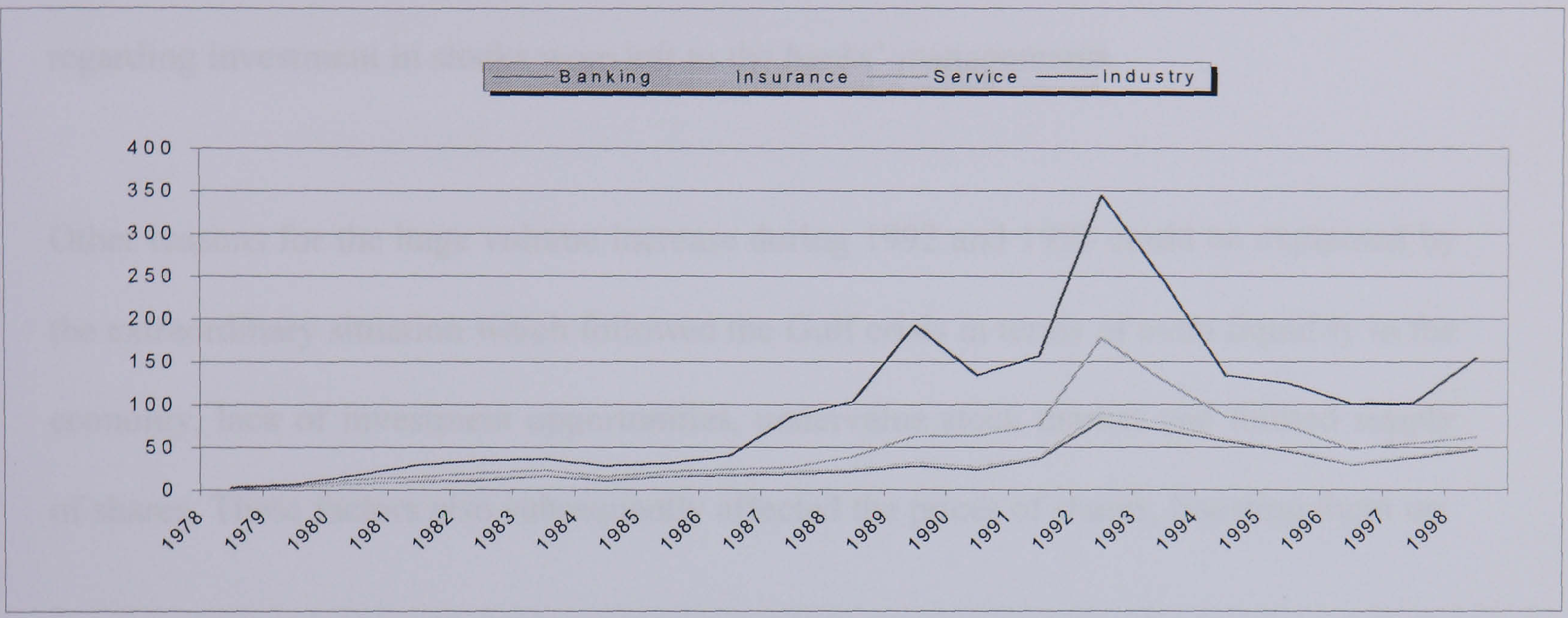


Figure 3-7: Number of Share Traded in the Organised Market by Sector



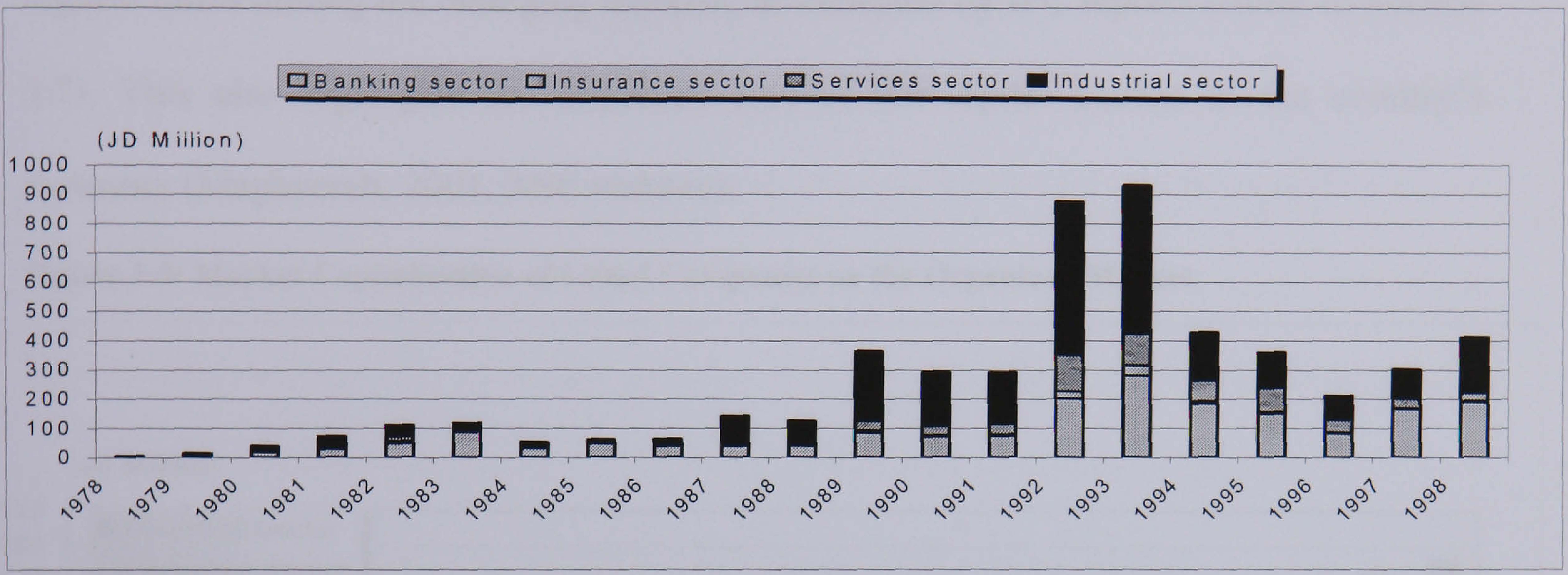
Source: Amman Stock Exchange, The Annual Report, Various years

The increase in the total number of shares traded has been accompanied by an increase in the trading volume and market capitalization. In 1978, the value of traded shares was approximately JD 5.6 million, it increased in general during the next nine years (1978-1987) –except year 1984- to reach JD 142.6 million in year 1987. However, due to the economic crisis and instability of the JD exchange rate in 1988, the volume of shares traded dropped by 10.5 percent to JD 132.6 million. After the crisis was absorbed, an increase in volume occurred until the onset of the Gulf crises, when the volume decreased to JD 268.9 million in 1990 compared to JD 367.6 in 1989. The value of shares traded increased rapidly, thereafter reaching the highest value obtained during the market's life (JD 933.4 million) in 1993. One of the reasons behind this increase and then later decrease might be the heavy involvement of banks and financial companies in market transactions. This involvement was mandatory according to the Central Bank of Jordan memo number (217/90) dated 31/10/1990 that stated that each bank or financial company must invest in the stock market and in local listed companies a minimum of 20% of its capital and reserves. This clause was cancelled in 8/8/1993, after which decisions regarding investment in stocks were left to the banks' managements.

Other reasons for the huge volume increase during 1992 and 1993 could be explained by the extraordinary situation which followed the Gulf crisis in terms of extra liquidity in the economy, lack of investment opportunities, undervalue stock market and limited supply of shares. These factors also subsequently affected the prices of shares, boosting them up.

Sharp declines in the volume of shares traded were recorded in 1994, 1995, and 1996 to JD 495 million, JD 419 million and JD 248.6 million, respectively. Political uncertainty about the Middle East peace process, poor economic performance, and the policy of maintaining high interest rates to support the Jordanian dinar, were the major factors behind this declination. In 1997 and 1998, the share volume traded increased to JD 355.2 million and JD 464.4 million respectively, or an increase rate of 42.9 percent and 30.7 percent, respectively, and in 1999 the value slightly declined to JD 389.5 (16.1 percent decrease) (Refer to Table 3.3 and Figure 3.8) (Maghyereh, 2001, ASE Annual Report 1999).

Figure 3-8: Trading Volume in the Organised Market by Sector



Source: Amman Stock Exchange, The Annual Report, Various years

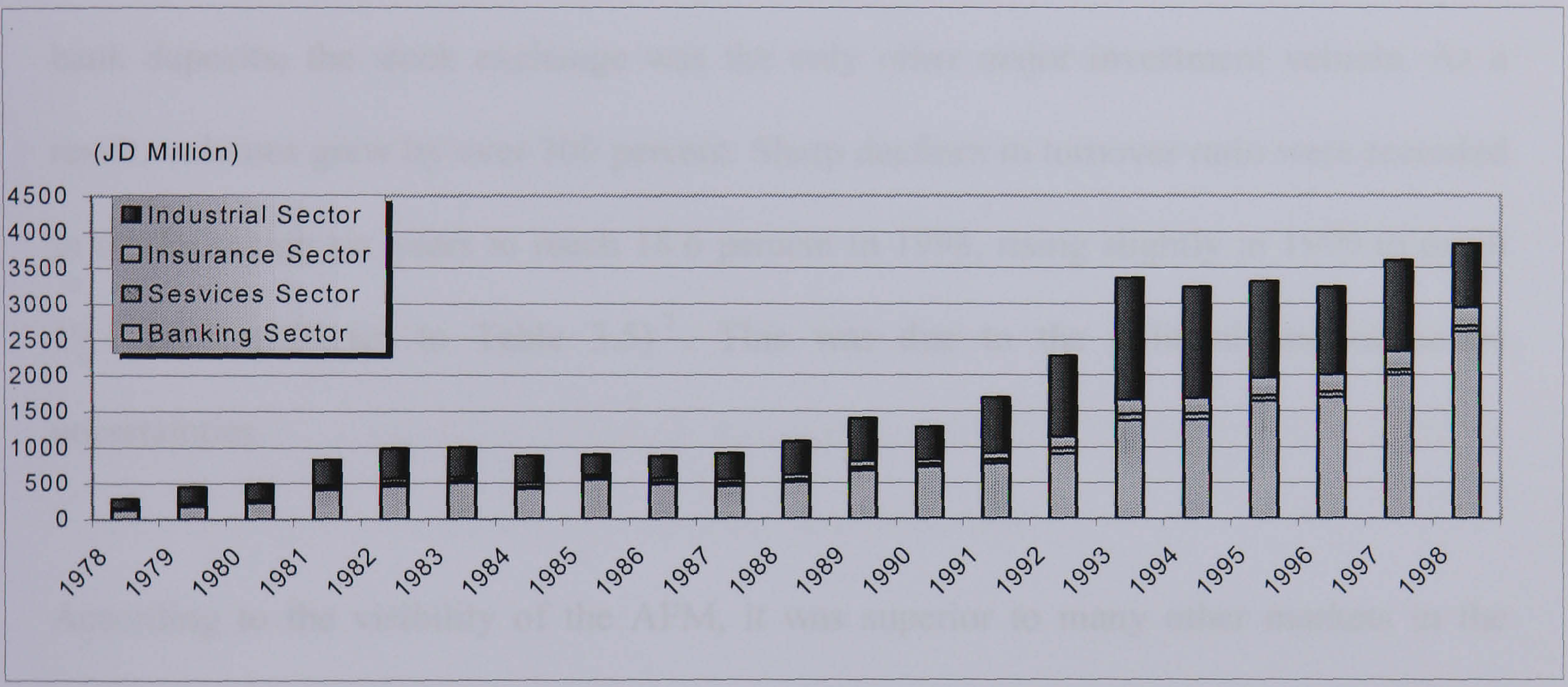
3.3.3.5 Market Capitalisation and Major Indicators for AFM

The market capitalisation at the AFM has grown in three phases[5]. It has enjoyed a steady, but rapid growth during the period 1978-83, from JD 286.1 million in 1978 to JD 1053.4 million in 1983. The following four years witnessed a decline in capitalisation, reaching JD 929.4 million in 1987. Real interest in the Jordanian capital market started taking place after the economic crisis of 1988 when market capitalisation began increasing at a faster rate, reaching about JD 3,495.4 million in 1995. Capitalisation dropped in 1996 to JD 3,461.2 million, and then increased to JD 3,862 million and JD 4,156.6 million, and JD 4,137.7 million in 1997, 1998, and 1999 respectively (Refer to Figure 3.9).

[5] The market capitalization is calculated by multiplying the current price of shares by the number of current listed shares.

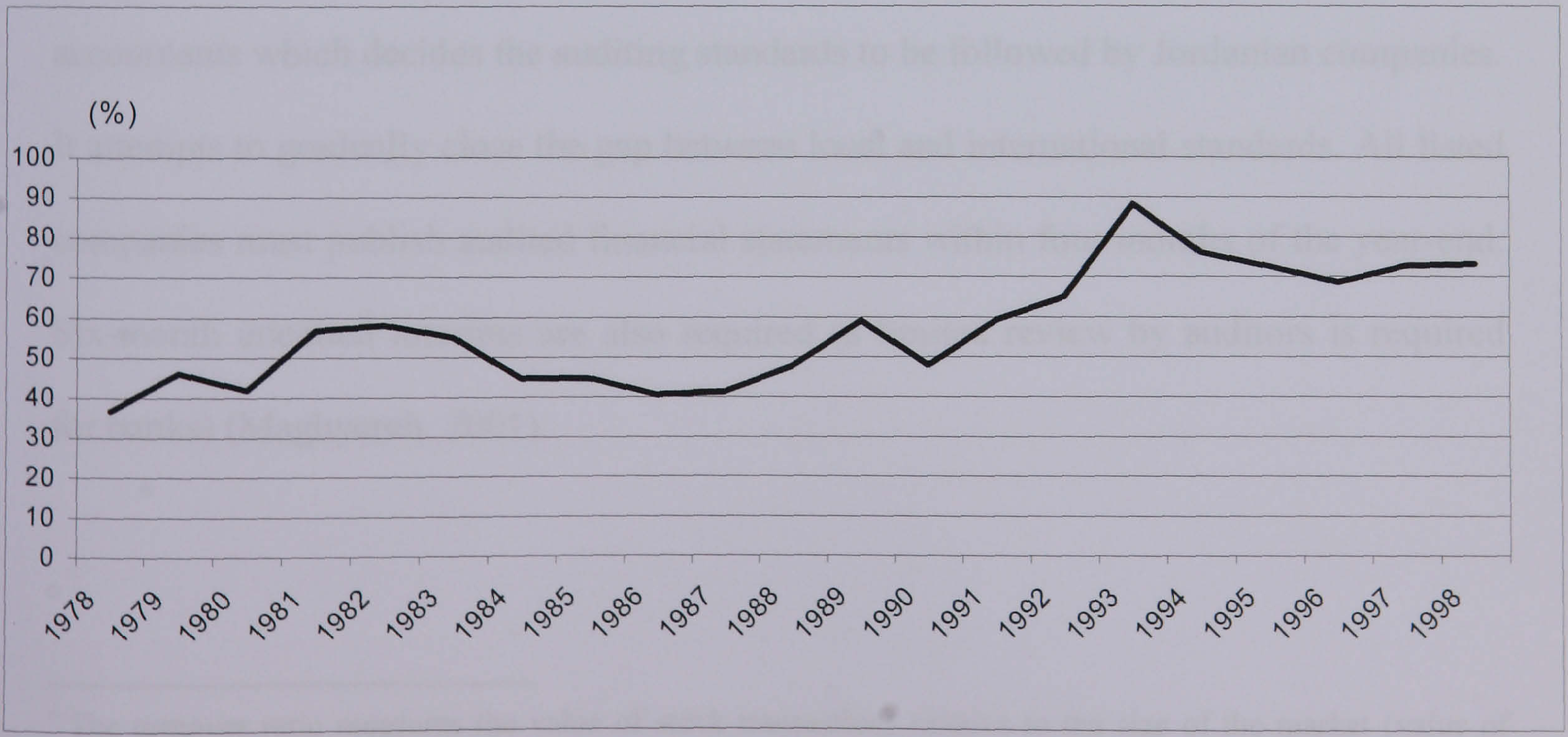
As a percentage of GDP, the market capitalisation increased from around 38.3 percent in 1978 to around 72.3 percent in 1999 (Refer to Figure 3.10). This is considered one of the highest ratios among the emerging markets, as indicated by IFC reports (Refer to Section 3.7). This also highlights the important role of the capital market in the country's economy (Maghyereh, 2001, ASE website).

Figure 3-9: Market Capitalisation of Listed Companies on the Organized Market



Source: Amman Stock Exchange, The Annual Report, Various years

Figure 3-10: Market Capitalisation as Percentage of GDP



Source: Amman Stock Exchange, The Annual Report, Various years

With respect to the turnover ratio[6], an indicator of market liquidity, it increased from 2.9 percent in 1978 to around 20.0 percent in 1981, before declining gradually in the following three years to reach 10.4 percent in 1984. Thereafter, this ratio rose to its highest historical level of 86.2 percent in 1992. The main reason for this large increase in turnover ratio could be explained by the high level of liquidity in the financial sector as 350,000 expatriates returned to Jordan, bringing with them their life savings. Apart from bank deposits, the stock exchange was the only other major investment vehicle. As a result, volumes grew by over 300 percent. Sharp declines in turnover ratio were recorded in the following six years to reach 18.6 percent in 1998, rising slightly in 1999 to reach 19.1 percent (Refer to Table 3.5)[7]. This was due to the political and economic uncertainties.

According to the visibility of the AFM, it was superior to many other markets in the region. Jordan is one of few countries in the Middle East to be represented on the Board of the International Accounting Standards Committee (IASC). Jordan has an institute of accountants which decides the auditing standards to be followed by Jordanian companies. It attempts to gradually close the gap between local and international standards. All listed companies must publish audited financial statements within four months of the year-end. Six-month unedited interims are also required (a limited review by auditors is required for banks) (Maghyereh, 2001).

[6] The turnover ratio measures the value of stock transactions relative to the size of the market (value of trades in year/ average market cap).
[7] Statistics after 1999 are presented in Section 3.3.4.6 under current market divisions.

Historically, the price-to-earnings (P/E) ratio at AFM has ranged between 7.2 times and 25.5 times. The P/E ratio increased from 10.8 times in 1978 to 25.5 times in 1984, before declining to 7.2 times in 1989 and thereafter continuously increasing to reach 24.1 times in 1993. The P/E ratio dropped to 19.5 times, 17.6 times and 17.5 times in 1994, 1995, and 1996, respectively. Thereafter, this ratio increased to 14.3 times and 16.3 times in 1997 and 1998, respectively. In 1999, it decreased slightly to 14.3 times. The price-to-book value increased from 1.2 times in 1978 to 1.8 times in 1981, before declining to 1.2 times in 1990. Thereafter this ratio rose to 2.2 times in 1993. By 1999, the price-to-book value ratio had declined to reach 1.44 times. Dividend yield ratio declined from 3.7 percent in 1978 to 2.7 percent in 1981 and then rising to 4.5 percent in 1990. The following years witnessed a decline in this ratio to reach 2.9 percent in 1999 (Refer to Table 3.5) (http://www.ase.com.jo/pages/hist_english9.htm).

Table 3-5: Major Indicators for the ASE

Year	P/E Ratio (times)	P/BV (times)	Dividend Yield Ratio (%)	EPS (JD)	Turnover Ratio (%)
1978	10.812	1.182	3.727	0.317	2.908
1979	12.385	1.429	3.260	0.308	5.520
1980	11.137	1.329	3.708	0.358	13.984
1981	15.799	1.849	2.710	0.361	19.985
1982	17.029	1.688	2.826	0.223	16.828
1983	20.900	1.554	2.595	0.119	14.475
1984	25.526	1.310	3.654	0.091	10.371
1985	18.690	1.740	3.397	0.136	10.202
1986	14.595	1.239	3.080	0.169	13.491
1987	15.183	1.247	3.464	0.164	26.597
1988	11.957	1.307	3.259	0.234	28.834
1989	7.182	1.480	3.109	0.494	49.547
1990	7.264	1.197	4.456	0.438	33.444
1991	11.098	1.425	3.811	0.359	37.753
1992	14.763	1.645	3.157	0.382	86.234
1993	24.143	2.190	2.246	0.271	51.121
1994	19.471	1.855	2.180	0.258	25.894
1995	17.631	1.683	2.249	0.237	20.981
1996	17.458	1.666	2.271	0.216	17.720
1997	14.300	1.630	2.310	0.203	17.800
1998	16.290	1.560	2.370	0.183	18.574
1999	14.300	1.440	2.880	0.172	19.134
2000	14.824	1.120	3.637	0.109	11.592
2001	15.338	1.381	2.703	0.056	20.317

Source: Amman Stock Exchange, The Annual Report, Various years

2.3.4 Current Secondary Market Division:

On June 15, 2000, ASE started implementing the Directives for Listing Securities on ASE for the year 2000, issued by virtue of the provisions of Article 26 (a) of the Securities Law no. 23 of 1997. The issuance of these Directives has ushered in new concepts in line with international standards regarding market divisions and listing requirements. Under these Directives, traded shares of public shareholding companies on ASE were divided according to various criteria, namely; paid-in capital, market value, per annum earned profits, distributed profits, shareholders' equity, turnover ratio and trading days (ASE Annual Report 2000). The current Secondary Market Segmentation is as follow:

3.3.4.1 First Market

That part of the Secondary Market through which trading takes place in securities, governed by special listing rules according to Directives for Listing Securities on Amman Stock Exchange. Companies whose shares are to be traded on the First Market must meet the following conditions:

1. The company's capital or market value must not be less than JD2 million,
2. The company's net shareholders' equity must not be less than its paid-in capital,
3. The company must have made net before tax profits for at least two of the last three fiscal years,
4. The company must have distributed profits or bonus shares at least once over the last three years,
5. Company's shares must have been listed on the Second Market for a full year at least.
6. The company's turnover ratio of shares over the last twelve months must not be less than 10%, and the company's trading days of shares must not be less than 15% of overall trading days for the same period.

(Article 5 from Directives for Listing Securities on Amman Stock Exchange/ Securities Market Issued by virtue of the provisions of Article 26 (a) of the Securities Law no. 23 of 1997).

3.3.4.2 Second Market

That part of the Secondary Market through which trading takes place in securities, governed by special listing rules according to Directives for Listing Securities on Amman Stock Exchange. The listing requirements for the Second Market state that the to-be-listed company's net shareholders' equity must not be less than 50% of its paid-in capital and one full year must have elapsed since it was granted the right to start business. (Article 3 from Directives for Listing Securities on Amman Stock Exchange/ Securities Market Issued by virtue of the provisions of Article 26 (a) of the Securities Law no. 23 of 1997).

3.3.4.3 Third Market

That part of the secondary Market through which trading takes place in securities that are not listed on ASE. The new Directives have introduced the concept of trading shares of un-listed companies through what is known as the "Third Market." Upon obtaining the right to start business, a company can file an application with the ASE to trade its shares through this market. The company shall not be listed on the ASE until it fulfills the listing requirements on the Second Market and submits an application for listing to ASE. Under this new concept, trading shares on ASE of newly established companies shall be permissible, upon completion of the set-up phase and initiation of business. This would provide a means for liquidizing the shares of such companies, including new IT companies, in an easy, smooth and fair-priced manner, since prices of shares would be determined by market supply and demand. The new Directives also include provisions on companies that were listed on both the Regular and the Parallel Markets at the time of transfer to the new markets. Companies listed on ASE at the time of enforcement of these Directives which do not fulfill the listing requirements on either the First or the Second Markets shall be considered as listed on the Second Market, provided that they adjust their conditions within the time period prescribed by the Board of Directors of ASE (two years).

Likewise, companies which are listed on the Regular Market and whose paid-in capital amounts to JD 20 million or more shall be considered as listed on the First Market, provided that they adjust their conditions according to these Directives within the time period prescribed by the Board of Directors of ASE (two years).

Furthermore, the Directives have given ASE some leniency in dealing with companies arising from privatization in a way commensurate with their performance and achievements. The Board of Directors of ASE has been granted the power to exempt recently privatized companies and companies which have been recently converted from limited liability companies and limited partnership in shares to public shareholding companies from the concept of gradual transfer from one market to another, and have allowed for their direct listing on the First or Second Markets. The rationale for this leniency is that most of these companies are relatively big and solvent.

3.3.4.4 Bonds Market

That part of the secondary market through which trading in development bonds and corporate bonds takes place. The new Directives cover matters relating to the listing requirements of bonds and investment funds, and regulate the listing of Jordanian securities on foreign exchanges and foreign securities' listings on ASE. Additional powers have been vested in ASE vis-à-vis its relation with public shareholding companies. The new Directives now obligate public shareholding companies to supply ASE with the same statements and information required by the Jordan Securities Commission (JSC) on financial statements and information and resolutions issued by the company that might affect the prices of its securities (ASE Annual Report 2000).

3.3.4.5 Transactions off the Trading Floor

That part of the secondary Market through which inheritance and inter-family transactions take place. Additionally, any off-the-trading-floor transfers (inheritance and family transfers) shall be done through the Securities Depository Center (SDC) as of the same date (ASE Annual report 2000, Newsletter, Issue no. 11, June 2000).

3.3.4.6 Market Capitalisation and Major Indicators for ASE

Indicators of the secondary market registered a considerable increase in their levels in 2001, compared to the year 2000. The secondary market volume was JD 727 million for the year 2001; an increase of 100.5%. The value of traded shares in the first, second and third markets constituted the major part of this volume: JD 668.7 million, with a rise of JD 334 million compared to the year 2000, or 99.8% (ASE annual report 2001).

The trading volume in the first and second market increased by 130.2%, JD 662.4 million during 2001, compared to JD 287.8 million in 2000 (ASE annual report 2001).

Out of 29 companies on the third market, 16 companies were traded in 2001. The trading volume was JD 6.3 million compared to JD 46.9 million for 2000. The number of traded shares reached 8.1 million, compared to 50 million for 2000. 2329 transactions took place compared to 221 during 2000 (ASE annual report 2001). The market value of traded bonds during this year reached JD 7.2 million, the same value for the year 2000. The number of traded bonds declined from 197.6 thousand in 2000, to 89 thousand in 2001. The market value of development bonds traded during 2001 amounted to JD 0.9 million, representing 12.5% of the total trading value of bonds. The market value of traded corporate bonds amounted to JD 6.3 million and represented 87.5% of total trading (ASE annual report 2001, ASE website).

Data indicate an increase in the value of the off-the-floor transactions (stocks and bonds) which reached JD 51.2 million in the year 2001, with an increase of 149.8% compared to the previous year. The number of transferred shares was 20.7 million, an increase of 91.7% compared to 2000. The value of inheritance transfers amounted to JD 31.2 million, or 60.9% of the total transfers, and family transfers at a value of JD 8.4 million, or 16.4% of the total transfers (ASE annual report 2001).

Regarding the mutual funds market, one mutual find was listed on the ASE by the end of 2001, with a trading volume of JD 168 in 2 investment units (ASE annual report 2001). Market capitalisation increased from JD 4,137.7 million in 1999 to JD 4,780.7 million in 2001. As a percentage of GDP, market capitalisation increased to 75.8% in 2002 (Refer to Table 3.3). Turnover ratio reached 20.3 % in 2001, and P/E ratio slightly decreased to 15.3 times. Price to book value declined to 1.4 times in 2001, while dividend ratio declined to 2.7% (Refer to Table 3.5) (ASE website).

3.4 Non-Jordanian Investment

As part of the efforts to modernize and improve the efficiency of the market, a new securities law was passed in 1997, as a part of the recent regulatory and legislative reforms aiming at creating an attractive and desirable local climate for foreign investment. Most importantly, the new law demolished the previous non-Jordanian ownership ceiling that was fixed at 50%, thereby allowing non-Jordanian investors to own up to 100% of any company in any sector, except in construction contracting, trading and trade services, and mining (Refer to: Regulation No. (54) for the year 2000 Regulating non- Jordanian Investments Regulation).

Further encouragement strategies for foreign investment included:

- Projects are exempted from income and social services taxes by 25%, 50%, or 75% for a ten year period, depending on the location of the project.
- Imported fixed assets are 100% exempted from customs duties and taxes.
- Imported spare parts for fixed assets can be exempted from fees and taxes.
- Additional exemption from customs duties and income tax is granted for the expansion, modernization, or development of existing projects.

- Hotels and hospitals may purchase furniture and supplies without customs duties once every seven years for renewal purposes.
- Income and social services tax exemptions for up to 10 years.
- Total customs exemptions on imported fixed assets.
- Ease of licensing and registration procedures.
- Revenues on exports are exempted from income taxes.
- Export industries are not subject to customs duties on imported raw material.
- Free repatriation of capital, profits and salaries (http://www.ase.com.jo/).

This change clearly represents an opportunity to attract foreign capital in order to finance economic growth. The rise in demand for shares on the stock market also reduces the cost of capital for local firms and adds to their incentives for going public. This in turn makes the market more liquid and efficient and increases market size. This increases local investors' opportunities for portfolio diversification, raising their incentive to invest in shares. Different reasons are provided regarding why stock market liberalization might cause a fall in the liberalizing country's cost of equity capital. First, stock market liberalization might increase net capital inflows and an increase in net capital inflow could reduce the risk free rate. Second, allowing foreigners to purchases domestic shares facilitates risk sharing between domestic and foreign investors and should reduce the equity premium. Finally, increased capital flows should increase stock market liquidity, and thereby, reduce equity premium.

Abolishing the ownership ceiling besides other legislative reforms had a direct effect on foreign investment in Jordan. The value of buy order in 2001 amounted to JD 104.5 million, compared to JD 26.4 million in 1996. The sell orders amounted to JD 212 million in 2001, compared with JD 17.9 million in 1996. As a consequence, the net investment for non-Jordanians in 2001 showed negative balance of JD 107.5 million, compared with JD 8.5 million in 1996. The main reason for this drop was the JD 68 million deal on 400,000 shares of the Arab Bank sold by Kuwaiti investors to Social Security Corporation/ Jordan. (Refer to Tables 3.6 and 3.7) (ASE annual report 2001).

The percentage of Non-Jordanian ownership of market capitalisation increased gradually from 31.1 percent in 1994 to reach 43.9 percent in 1998. By 2001, non-Jordanian ownership had slightly decreased to 38.5% (Refer to Table 3.7) (ASE annual reports).

Table 3-6: Trading of Non-Jordanian

			Buy			
	Individuals		**Companies**		**Total**	
Period	**Non - Arab**	**Arab**	**Non - Arab**	**Arab**		
1996	260,803	9,702,701	9,659,452	6,822,256	26,445,212	
1997	813,212	17,720,866	54,668,875	27,296,771	100,499,724	
1998	425,754	16,839,131	150,633,050	37,091,183	204,989,118	
1999	703,745	10,733,657	61,575,642	21,264,733	94,277,777	
2000	517,200	29,140,014	13,914,016	9,444,615	53,015,845	
2001	1,124,299	44,585,085	29,351,009	29,425,996	104,486,389	
			Sell			
	Individuals		**Companies**		**Total**	**Net**
Period	**Non - Arab**	**Arab**	**Non - Arab**	**Arab**		**Investment**
1996	361,713	10,009,572	4,716,222	2,836,087	17,923,594	8,521,618
1997	240,331	14,392,731	15,248,366	13,854,184	43,735,612	56,764,112
1998	457,246	10,823,666	46,002,404	25,099,356	82,382,672	122,606,446
1999	758,491	17,195,683	40,304,403	20,547,952	78,806,529	15,471,248
2000	800,828	28,346,339	28,418,588	7,283,165	64,848,920	(11,833,075)
2001	1,207,582	62,381,319	36,404,749	111,997,176	211,990,826	(107,504,437)

Source: Amman Stock Exchange, The Annual Report, Various years

Table 3-7: Percentage of the Non-Jordanian Ownership in the Shareholding Companies by Sector (1994-2001)

Year	Banks	Insurance	Services	Industry	Total
1994	46.7	16.0	2.9	23.6	31.1
1995	46.3	15.7	3.3	19.9	31.0
1996	47.7	16.5	7.3	21.8	32.8
1997	53.8	16.0	9.3	26.0	39.1
1998	56.4	15.1	11.6	28.1	43.9
1999	56.6	15.6	14.0	30.5	43.1
2000	55.2	17.9	21.3	30.2	41.7
2001	49.3	17.8	20.0	27.4	38.5

Source: Amman Stock Exchange, The Annual Report, Various years

3.5 Market Properties

This section deals with trading system, transaction costs, and available information in the market.

2.5.1 Trading System

As mentioned in Internal By-Law of the Amman Stock Exchange Securities Market Issued by virtue of Articles (25) and (73) of the Securities Law No [23] of the year 1997, Article 5:

a) Trading in listed securities shall take place by way of deals negotiated among financial brokers, each on behalf of his / her client or portfolio. Said deals shall be confirmed in entries in the Stock Exchange records.

b) Once sufficient and adequate precautions against any falsification of information and ensuring its validity are taken, registration of entries in, and keeping of the Stock Exchange records shall be either manual or electronically by computer. Unless otherwise proven, such entries together with any documents issued thereby shall be considered as legal evidence on trading in the securities designated therein, on the dates indicated on the records, accounts or documents.

Trading in ASE has to be executed through a licensed financial broker on the floor. Until the end of August 2002, there were 33 brokerage firms licensed by the ASE to trade in the market. Five brokerage firms are either suspended or not working. Of the remaining 28 firms, thirteen are public shareholding companies dealing in new shares as well as buying and selling securities for their own account and for their clients against a commission in the Secondary Market, and fifteen are private shareholding brokerage companies, buying and selling securities on behalf of their clients against a commission and sometimes for their own account. Their legal set-up and nature take the form of a limited liability company (ASE website). The new security law renders the trade confirmation available electronically and manually at least by the end of the day, which would increase the speed of transactions and registry and reduce the costs of intermediation. Applicable instructions provide for immediate cash settlements among brokers themselves and between brokers and their clients, in order to avoid any default by clients towards their brokers, which would in turn influence settlements among brokers, and ultimately create financial instability and confusion.

Settlement procedures require that the SDC enter trading data into its system via the Electronic Trading System (ETS) of the ASE on the same day of execution of sales and buys. On the following day (T+1) the SDC issues settlement records for brokers and cash settlements are undertaken amongst them. On (T+2) the SDC hands over the transfer of ownership contracts to the issuers. In turn, the issuers must transfer ownership of shares within three days of receipt of transfer contracts. Thus, all procedures of transfer of ownership of shares are completed within five days of execution of transactions (T+5) (Regulations on the Registration, Transfer of Ownership and Settlement of the Value of Securities Issued by virtue of Article (32) of the Securities Law No. (23) for the year 1997).

2.5.2 Transaction costs

In ASE, an individual can access the market directly by incurring a variable (fixed percentage) transaction cost for each contract, not like other markets where individuals can use the agent by paying a fixed fee.

The broker's commissions and market fees for ASE are as follows:

Brokers receive commissions calculated on the basis of the market value of both buying and selling transactions of the security, according to the following:

Security	Lower Limit (JD)	Upper Limit (JD)
Shares	JD 5.4 per thousand	JD 7.4 per thousand
Bonds	JD 0.8 per thousand	JD 1.0 per thousand
Investment Units	JD 2.0 per thousand	JD 2.2 per thousand

The fees for the market as indicated by Article 4 of Regulations for the Fees and Commissions of the Amman Stock Exchange Issued by virtue of the provisions of Articles 9 (J), 26 and 27 of the Securities Law No. 23 of 1997:

A. Subject to sub-paragraph B of this Article, the Stock Exchange shall collect, in return for trading in securities, a commission of 0.0006 (six per ten thousand) of the market value of traded securities from each contracting party.

B. In return for trading in bonds, the Stock Exchange shall collect a commission of 0.0001 (one per ten thousand) of the market value of traded bonds from each contracting

Market microstructure is a key determinant of transaction costs (trading costs), both directly through the institutional and competitive structure of the market, and more directly through any taxes or regulatory charges on market participants. The level of transaction costs may provide an indicator about the development of market microstructure e.g., regulatory regime, trading mechanisms, the type of information available to market participation and the manner in which incoming orders to buy and sell are matched.

Transaction costs include both the fixed costs associated with a trade, such as taxes and commissions, as well as the major costs that the market imposes: the bid/ask spread, which is the difference between the price one pays to pay and the price on receives for the sale. The spread that investors pay for accessing the market reflects a combination of factors, including the differences of opinion held by buyers and sellers, but also including microstructure features. In some markets, a market maker is responsible for quoting prices. He is responsible for ensuring market liquidity, but the risk associated with that activity is reflected in the bid/ask spread, which is the source of returns on the market makers inventory and for bearing risk. Alternatively, multiple market makers are possible and the competition this provides should reduce spreads. In other markets like in Jordan, no designated market maker exists, perhaps reducing spreads even further, but, with no individual responsible for making the market, investors are exposed to the possibility of reduced levels of liquidity.

Transaction costs may have several effects on markets performance; for example, one might expect that increased transaction costs would increase the average holding period of securities. However, the main effect of increased transaction costs is usually thought to be that they reduce the incentive to trade, and therefore produce a thinner market. Thin trading tends to induce or increase autocorrelation in share returns, and also affects volatility. Another important effect of transaction costs relates to market efficiency. In general, regulatory policy has a direct impact on stock market efficiency in that trading arrangements, costs and taxes may produce too little or too much trading, and thus causes inefficiency.

2.5.3 Available Information

The main information resources available for investors in ASE are company reports and ASE publications.

3.5.3.1 Company Report

Perhaps the most factual and direct source of information are company reports. All the listed companies are required by law to publish their annual reports during the first four months immediately following the end of the financial year. These include a profit and loss account and a balance sheet.

From a survey of annual reports, we can see that the main sections include notice of the annual general meeting, list of director, secretary and auditors, chairman's review, directors report, report of the auditors and the accounts. For the balance sheet, measures like loans, overdrafts and details of share capital, current and other assets including listed and unlisted investments, loans to directions, details of valuation of certain assets, additions to and disposal of fixed assets, arias of fixed cumulative and any change in the company's assets are included.

In the profit and loss account, charges for depreciation, interest on loans and overdrafts, charges in corporate tax, investment income, proposed and paid dividends, pension and compensation, auditor's remuneration and turnover are included. One of the conditions of entry into the listed stock market is that the company must be prepared to provide shareholders with sufficient information for its appraisal. To achieve this, companies are required to enter into a general agreement with the Stock Exchange for the provision of information. One of the provisions is to prepare a half-yearly report sent to the shareholders. In this report, half-year statements of profit and loss and comparative figures for the corresponding period are provided. Supplementary information may also be provided by the Chairman's Report.

3.5.3.2 Market Publications

In its various publications, the ASE has been active in providing information about the listed companies. These include:

3.5.3.2.1 Monthly Newsletter

It contains recent news about the ASE and ASE's performance indicators such as trading value , average daily trading value, number of traded shares, number of contracts, number of bonds traded, value of bonds traded, and market capitalisation. Additionally, some statistics are provided such as top ten performers and lowest ten performers. The general assembly meetings for listed companies and its resolutions are also mentioned.

3.5.3.2.2 Monthly Statistical Bulletin

A monthly statistical bulletin is published by the ASE. It contains valuable data and financial ratios of the listed companies. The bulletin includes cumulative market data, sectoral data, as well as individual company data.

3.5.3.2.3 Annual Report

The ASE publishes an annual report about the market's activities during the year, which can include the number of shares traded, their market value, the number of transactions made, companies which offered new issues, companies authorised capital and other similar information are included. The report also lists all the licensed brokers, and the achievement of the market and the chairman's view regarding future plans.

3.5.3.2.4 Companies' Guide

ASE publishes the Jordanian shareholding companies' guide on an annual basis to provide interested parties with a reference that contains important information. The guide includes valuable data and financial ratios of listing companies, in addition to information about the number of shareholders, ownership ratios, the number of employees in each company and their balance sheets and profit and cost account for the past five years. In addition, the rules and regulation of the market, Companies Law, Banks Law, and Insurance Law are also published.

3.5.3.2.5 Daily Official List

Prices of traded shares are quoted on a daily and weekly basis through the local Arabic and English newspapers, in addition to reports on the total number of traded shares, their market value, the number of transactions executed, the closing price, and the nominal value of the quoted shares. A short daily price quotation is broadcast on Jordanian television. The closing prices of Jordanian shares listed and traded on the regular market are also quoted and transmitted also via Reuters Monitor Network worldwide. In addition to Reuters, private companies began participating in the disclosure process by facilitating access to information on the market via computer modem and telephone services.

3.5.3.2.6 The Daily Stock Price Indices

ASE indices are used to portray the pattern of stock price movement, and to measure the performance of the ASE in terms of return. Back in 1980, the Amman Financial Market (AFM) constructed an Unweighted Price Index (General index) supplemented by sub-indices for the four sectors: Banking and Finance Companies, Insurance, Services and Industrial. At that time 38 stocks were covered and a base value of 100 was stipulated on the opening session of January 1st 1980 for the Unweighted Price Index.

As a result of a long statistical study, the ASE began in 1992 to calculate a Market Capitalisation Weighted Price Index (General index) covering 50, stocks increased to 60 stocks in 1994, and by 2001 the number increased to cover 70 stocks. A base value of 100 points on December 31st, 1991 was stipulated for the Weighted Price Index.

ASE indices are calculated using the latest closing prices and published on a daily basis. ASE indices are composed of number of companies listed at the Regular Market; the selection of these companies is based on the following five criteria which represent the companies' size and liquidity: market capitalisation, days traded, turnover ratio, value traded and the number of shares traded. Regarding the General index, the sector representation is also considered when selecting these companies.

ASE indices are adjusted to maintain their continuity and to safeguard them from exceptional events. These adjustments allow the indices to perfectly mirror the market trend. The constituents of the ASE indices are reviewed and adjusted every year. Non-periodic adjustments can be made for stocks whose trading will be halted for a long time or permanently (www.ammanstockex.com).

Unweighted Price Index

In the ASE unweighted index, all stocks carry equal weight. There is no consideration of the market capitalisation, and the price level does not have an impact because the index formula deals with percentage changes only. Such an index can be used by an investor who invests equal amounts of money in each stock in his/her portfolio. This index has been introduced in 1980 with the opening session of January 1st 1980 set at 100 points. In 1992, the ASE introduced some modifications to the index, of which was the changing of the base period to December 31st 1991. The unweighted index is supplemented by sub-indices for the four sectors: Banking and Finance Companies, Insurance, Services and Industrial.

Methodology

The general and sectoral indices are calculated using the following method:

$$Index(t) = Exp(Ln(10) * S) * 100$$

where,

$$S = \left(\sum_{i=1}^{n} Log(P_{i,t} / P_{i,o}) \right) / n$$

n : sample size

t : time period

Exp : Exponential function to the base (e)

Ln : Natural Logarithm to the base (e)

Log : Logarithm to the base (10)

Index (t) : Index value at time t

$P_{i,t}$: Closing price of the ith stock at time t

$P_{i,o}$: Closing price of the ith stock at the base period

The unweighted index uses the logarithmic function to smooth extreme price fluctuations. The above formula is similar to using the geometric average of the percent changes of the stock prices of the index constituents.

Adjustments are made to the prices when stock splits or stock dividends occur. Additions or deletions of stocks can be adjusted by computing an adjustment factor C which is equal to the value of the index after addition or deletion takes place, divided by the value of the index before. After that, the index will be multiplied by the factor C, i.e.

C = (Index after the addition or deletion)/(Index before the addition or deletion)

$$Index(t) = C * Exp(Ln(10) * S) * 100$$

Note that the factor C will be used on the day of the adjustment and thereafter. The adjustment factor C is calculated in such a way that, at constant stock prices, the value of the index before and after the addition or deletion remains exactly the same (www.ammanstockex.com)

Weighted Price Index

The ASE Market Capitalisation Weighted Index is presently made up of the most liquid 70 companies from the Regular Market[8]. The company's weight in the index is determined by its relative percentage of the aggregate market capitalisation of the 70 companies. A base value of 100 points on December 31st, 1991 was stipulated for the ASE weighted index. The stocks included in the index represent around 90% of the aggregate market capitalisation of the listed companies at the Regular Market. The ASE weighted price index is supplemented by sub-indices for the four sectors: Banking and Finance Companies, Insurance, Services and Industrial sector. The ASE weighted index provides a comprehensive measure of the market trend to investors or institutions who may be interested in general market price movement.

Methodology

The ASE index is a Paasche Index[9]. The general formula for the index (t) is:

At $t = 1$, Index = 100

B1 = M1, or market capitalisation = base value of the index

At $t > 1$, $Index(t) = (M_t / B_t) * 100$

$B_t = B_{t-1} * (M_t / Mad)$

---

[8] Refer to Appendix 1 for the index sample for 2003.

[9] Paasche Index: index developed by German economist Hermann Paasche for measuring current price or quantity levels relative to those of a selected base period. It differs from the Laspeyres index in that it uses current-period weighting. The Laspeyres index measures the relative costs of maintaining base-period standards in the base period and in period n; the Paasche index measures the relative costs of maintaining period n standards in the base period and in period n, in other words, Laspeyres price index for period *t* shows the extent of price changes since period 0 on the assumption that the expenditure pattern was the same in period *t* as in period 0 and Paasche index shows the change assuming the expenditure pattern was the same in period 0 as in period *t*. (Kenney and Keeping, 1962).

$$Mad = M_t - I_t - N_t + Q_{t-1}$$

where,

t : time period

Index (t) : Index at time t

B_t: base value of index

M_t: market capitalisation of constituents at time t (the sum of the market capitalisation of all stocks included in the index)

Mad : adjusted market capitalisation at time t. The adjustments are done for new issues of shares, and the addition or deletion of constituents

I_t: market capitalisation of new shares issued by a company included in the index and listed at time t

N_t: market capitalisation of the company added to the index at time t

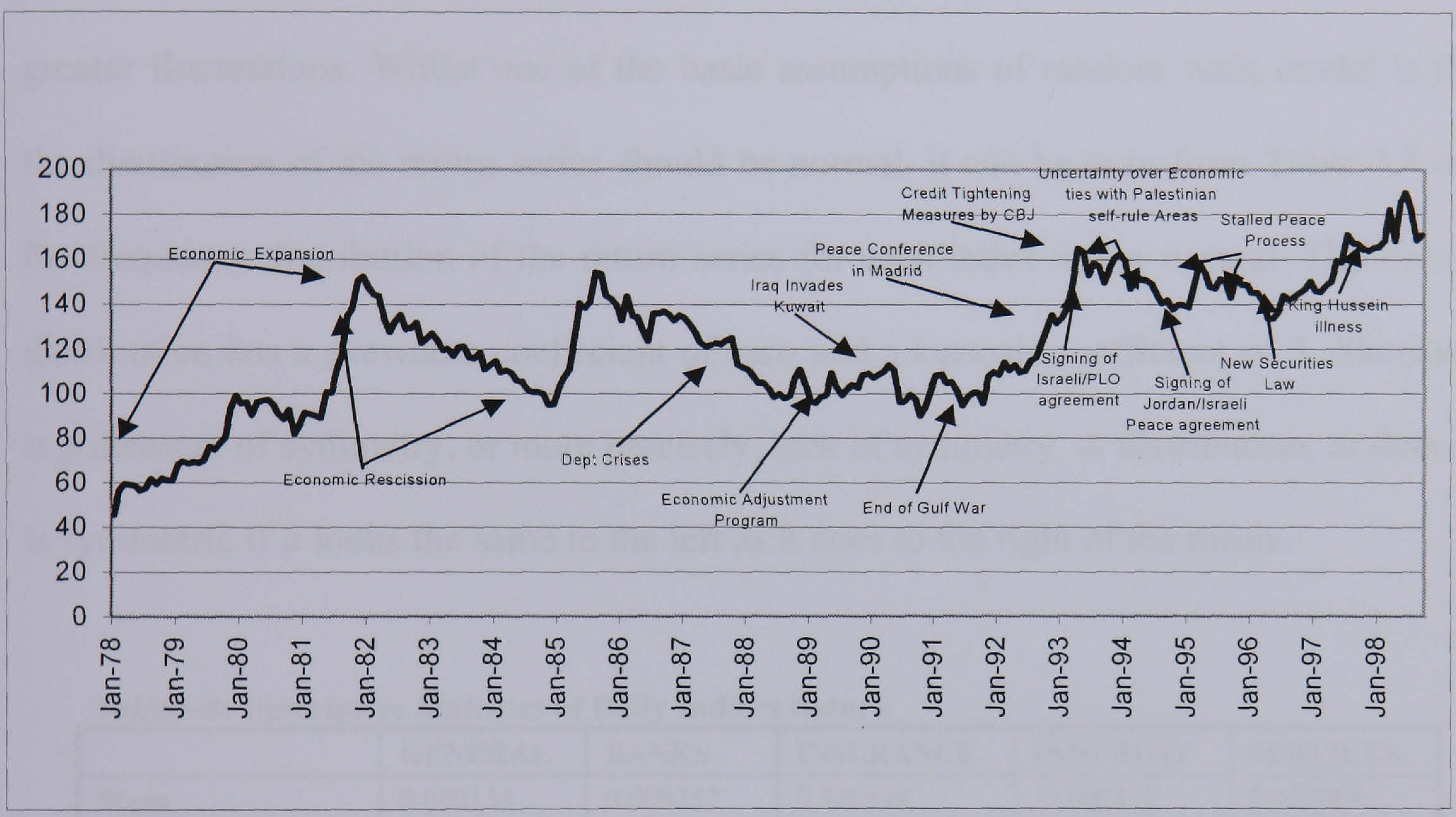
Q_{t-1}: market capitalisation of the company at time (t-1) which deleted of the index at time t.

The base value B_t is an adjusted base (market capitalisation) which is not the real market capitalisation at the base period.

No adjustment is made, however, in case of a stock split, bonus shares (stock dividend) and a decrease in paid-in capital, since such corporate actions do not affect the current market capitalisation. Thus, adjustments are done for any changes in index sample or any corporate action affecting the market capitalisation on index stocks. This can be achieved by using the adjustment factor Mad.

Without any adjustments, such changes would cause sudden and sharp movements of the index value which would not reflect the market's actual behavior (www.ammanstockex.com).

Figure 3-11: General Price Index



Source: Amman Financial Market Database

Figure (3.11) shows the developments in the prices based on the above measured price index from 1978 to 1998. The share price index of the AFM clearly establishes the strong correlation of the stock market with economic activity and the political situation.

The daily prices of the five indices in ASE from 1st January 1992 to 30th June 2001 are used for upcoming tests throughout the thesis. To ensure inter-temporal consistency, the period of the study commenced at 1/1/1992 as at this date, the Amman Stock Exchange (ASE) changed the form of calculation for the Price Index (from unweighted to market capitalization weighted). A base value of 100 points on December 31st, 1991 was stipulated for the new Weighted Price Index. Of the five indices, the bank index has the highest average return of 0.00035 over the time period 1992-2001, while the industry index has the lowest and the only negative mean daily average return of (-0.00014). In terms of standard deviation of stock returns, the bank and industry sectors have the greater fluctuations. Whilst one of the basic assumptions of random walk model is that the distribution of the return series should be normal, it can be seen from Table 3.8 that the frequency distribution of the return series for each index is not normal. The normal distribution has a skewness coefficient of zero and a kurtosis coefficient of 3. Skewness is a measure of symmetry, or more precisely, lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left as it does to the right of the mean.

Table3-8: Descriptive Statistics of Daily Indices Return

	GENERAL	BANKS	INSURANCE	INDUSTRY	SERVICES
Mean	0.000154	0.000352	0.000148	-0.000139	0.000008
Median	-0.000309	-0.000254	0.000000	-0.000564	-0.000274
Maximum	0.047449	0.048855	0.039177	0.047816	0.044548
Minimum	-0.043102	-0.048470	-0.045597	-0.045998	-0.044349
Std. Dev.	0.006831	0.008228	0.005949	0.008348	0.008101
Skewness[a] *(S)*	0.422	0.676	0.408	0.334	0.324
***t-statistics*[b]**	8.344	13.371	8.075	6.612	6.417
Kurtosis[c] *(K)*	8.778	8.613	14.358	7.905	7.256
***t-statistics*[d]**	57.116	55.491	112.271	48.486	42.073
Jarque-Bera *(JB)*	3331.90	3258.12	12670.03	2394.63	1811.33
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	2345	2345	2345	2345	2345

[a] For normal distribution the value of skewness is zero

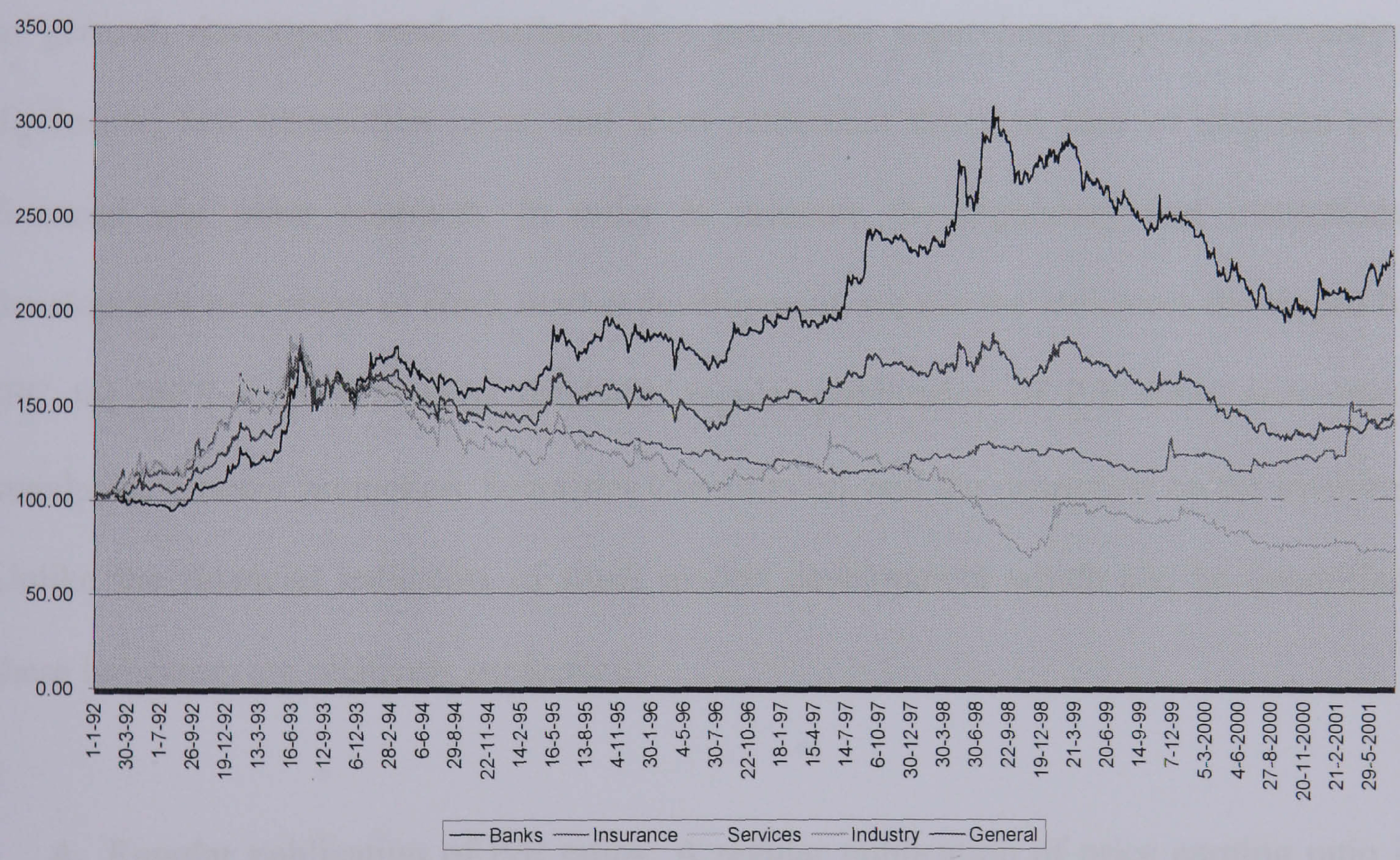
[b] The *t*-values indicate that the values of the skewness coefficient are statistically different than zero at 1% level of significance. The *t-statistic* is calculated as S/(sqrt(6/2345)).

[c] For normal distribution the value of Kurtosis is three.

[d] The *t*-value indicates that the values of the Kurtosis coefficient are statistically different than three at 1% level of significance. The *t-statistic* is calculated as (K-3)/(squr(24/2345)).

However, and from the plotting of the five price indices into a diagram and as shown in Figure 3-12, it is clear that the indices have different trends. As the bank index has upward trend through time, the industry index has a downward trend, implying that the sectors of economy are affected by different factors. This suggests that when differencing the price series of the indices, there will be a lower chance of finding shared trends or comovements between indices. This issue will be investigated thoroughly in Chapter 7.

Figure 3-12: The Price Series for the Five ASE Indices from1992 to 2001



3.6 Profession and Legislation Environment

Different aspects indicate the extent of stock market development. These aspects include legal and tax framework, accounting standards and also provision of a regulatory mechanism. King and Levine (1993), La Porta, Lopez-de-Silanes, Shleifer, and Vishny

(1997), Rajan and Zingales (1998), Henry (2000), and a number of others have analyzed the legal foundations of financial markets, the relationship of financial market development with macroeconomic variables, financial reform, and other country factors, and the relationships among the development of the various parts of a financial system. The general finding is that financial markets tend to develop as financial reform progresses. Stock market development specifically has been shown to depend on a good legal system, particularly minority rights that are being enforced.

In general, developed stock markets have prudential supervisory bodies, information disclosure, low transaction costs, and short settlement times in case of disputes over financial and other contracts. In order to measure the regulatory and institutional development as a proxy of stock market development, we use the indicators developed by IFC for its Emerging Markets database: regular publication of P/E ratio, accounting standards, investor protection, Securities Commission, and the restriction on the investors. Unlike the financial indicators of stock market development which can be quantified, these indicators are relatively subjective.

A. Regular publication of P/E ratios: A regular publication of price earning ratio is useful for investors to evaluate the company's performance. IFC classified the stock market regarding the publishing price-earning information in two groups: markets publishing this information internationally and comprehensively, and ones that are not, Jordan falls in the first category.

B. Accounting standards: The adoption of accounting standards which govern the preparation of financial statements is essential for efficient markets. It achieves the comparability and reliability among the financial data of companies. If foreign investment is to be encouraged, accounting practices need to be in line with internationally accepted accounting standards. IFC classified the countries to three groups: countries having good accounting standards, countries having adequate accounting standards, and others having poor accounting standards. Jordan adopted the international accounting standards; hence, it is classified as a country of good accounting standards.

C. Investment protection: The law protection for the shareholders rights, creditors, insiders (directors and corporate officers), investors, and other issues is an important characteristic for the development of a stock market. IFC classified the countries according to the quality of investment protection laws: countries that have good protection laws (and Jordan belongs to this group), countries that have adequate protection laws and others that have poor protection laws.

D. Restrictions on foreign investors: In order to attract foreign investments into financial markets, the restrictions on repatriation of dividend income, capital and entry/exit to the market must be minimized. The integration and globalization of financial markets require free trade in financial services as well as financial assets. While the scale of capital flows to and from developing countries is substantial, some developing countries` financial markets are closed, while others continue to restrict outward capital flows in an attempt to direct more domestic funds to domestic investments. The restrictions on the foreign portfolio investors take many forms such as the degree of foreign participation permitted in the market, the rules governing hard currency repatriation of profits and capital by foreigners, the tax bias against equity finance where a large percentage of capital gains and dividend income are withheld as taxes. IFC classified stock markets according to the treatment of the foreign portfolio investment into: A)- Free entry markets, where no significant restriction on trading, B)- Relatively free entry markets, where some restriction procedures are required to insure repatriation rights, C)- Special classes of share market where foreigners are restricted to certain classes of stocks designated for foreign investors, D)- Authorised investor only where only approved foreign investors may buy stocks, and E)- Closed market in which access is severely restricted (e.g., for non-resident nationals only). IFC also covers the foreign investment ceiling for listed stocks in emerging markets. According to the repatriation of profits or income, IFC covers withholding taxes of interest, dividends, and long-term capital gains on listed shares. As is evident from institutional development indicators, Jordan appears to have a more developed stock market compared to most emerging markets; the price-earnings information is published internationally and comprehensively, accounting standards are good and internationally accepted, investor protection laws are adequate, listed stocks are freely available to foreign investors, income and capital are freely repatriated, and that is no tax on capital gains and dividends (See Table 3.9 which compares the legislations in Middle East and Africa Emerging Markets).

Table 3-9: Legislations in Middle East and Africa Emerging Markets

		Entry	Exit				
			Repatriation of		Withholding Taxes		
	Foreign Investment Ceiling	Are listed Stocks Freely Available to Foreign Investors	Income	Capital	Interest (%)	Dividends (%)	Capital Gains (%)
Bahrain	Up to 49% foreign ownership if company approves; some companies are 100% open to foreign ownership; 100% for GCC* nationals	Free	Free	Free	0	0	0
Botswana	55% for institutional, 10% for private	Free	Free	Free	15	15	0
Cote d'lvoire	100% in general	Free	Free	Free	0	10	0
Egypt	100% in general	Free	Free	Free	0	0	0
Ghana	74% in general	Free	Free	Free	0	10	0
Jordan	100% in general; 50% for construction, retail trade and mining sectors	Free	Free	Free	0	10	0
Kenya	40% in general	Relatively Free	Free	Free	15	10	0
Lebanon	100% in general	Free	Free	Free	0	10	0
Mauritius	100% in general; 15% for sugar companies	Relatively Free	Free	Free	0	0	0
Morocco	100% in general	Free	Free	Free	0	10	0
Namibia	100% in general	Free	Free	Free	0	10	0
Nigeria	100% in general	Relatively Free	Free	Free	10	10	0
Oman	Up to 49% foreign ownership if company approves; 100% for GCC nationals	Free	Free	Free	0	0	0
Saudi Arabia	25% for GCC nationals, other foreign investors may access market via mutual funds	Closed	Some Restrictions	Some Restrictions	0	0	0
South Africa	100% in general	Free	Free	Free	0	0	0
Tunisia	49.9% in general	Free	Free	Free	-	0	0
Zimbabwe	40% in general	Relatively Free	Free	Free	30	15	10
Source: Emerging Stock Markets Factbook 2001							
*Gulf Cooperative Council							

3.7 Comparison of Amman Stock Exchange with other Markets in the Region

The Middle Eastern region has attracted a disproportionately small share of recent international flows to developing countries. The Arab countries received only about US$ 0.2 billion out of the total sum US$ 52 billion that flowed into developing country equity markets in 1993 (Bates,1994)

In order to investigate the status of ASE among other markets, a number of market activity indicators, calculated in the Emerging Markets Factbook 2001, are applied. Based on Standard & Poor's Emerging Markets Data Base (EMDB), Jordan is classified as an emerging market belonging to the Middle East and North Africa region. EMDB classifies a stock market as "emerging" if it meets at least one of two general criteria:

- It is located in a low-or middle- income economy as defined by the World Bank,

or

- Its investable market capitalisation is low relative to its most recent GNI figures. (Emerging Stock Markets Factbook, 2001).

Regarding the number of listed companies in the region's markets and as Table 3.10 and Figure 3.13 show, Jordan stands almost in the middle of the group, and the increasing number of listed companies in ASE matches the trend of the group. Tables 3.11, 3.12, and 3.13 display, for the region's stock markets, market capitalisation, GDP, and market capitalisation as a ratio to GDP throughout the last ten years[10]. Figure 3.14 plots market

[10] It is worth mentioning that the comparability of such indicators between countries may be limited by conceptual and statistical weaknesses, such as inaccurate reporting and differences in accounting standards.

capitalisation as a ratio to GDP. Whilst market capitalisation increased gradually -in general - for the group, which reflects generally higher prices for existing stocks, as well as increased listings, Jordan has the highest market capitalisation as a ratio to GDP till 1998, although the (Market Cap/GDP) ratio declined from 0.878 in 1993 to reach 0.722 in 1998.

The ratio of market capitalisation to GDP shows the portion of the stock market on the total national product of an economy. However, when considering activity of the market measured by the value traded, Jordan's increase in value traded stopped in 1993, and decreased sharply till 1996, after which it gradually increased, while for the group, trading values increased gradually through time. The turnover ratio (Table 3.15 and Figure 3.15) is calculated as $TR_t = \frac{VT_t}{0.5(MC_{t-1} + MC_t)}$, where TR_t is the turnover ratio at time t, VT_t is the value traded at time t, and MC_t is the market capitalisation at time t of time. Turnover ratio is considered to be one of the commonly used measures of liquidity, liquidity generally refers to the ability to easily buy and sell securities. Savers are very often unwilling to place their savings in financial instruments for long periods. However, though a reasonable level of liquidity is important, an excessively liquid market could be as bad as a market characterized by thinness. Greater stock market liquidity may reduce the rate of savings. It may also seriously reduce an investor's incentive to monitor management and firm's performance as they can quickly sell their stake (Derminguç – Kunt and Levine (1996)).

Jordan has one of the lower ratios especially in the latest years, indicating shallow market liquidity. Several factors could account for that. The market is highly concentrated. For Jan. 2003, the top ten companies in ASE, by trading value, comprise 66.5% of the total value traded in ASE. And the top ten companies, by market capitalisation, comprise 68.8% of the total market capitalisation, which indicates the high degree of concentration for ASE (Amman Stock Exchange Monthly Statistical Bulletin, February 2003). A related argument could be that the shareholders are not willing to part with their shares for fear that they will have to purchase them later at a higher price. The buy and hold strategy rather than a speculative strategy predominates.

Tables 3.16, 3.17, and 3.18 and Figures 3.16, 3.17, and 3.18 illustrate the profitability of the markets. The valuation of market profits is dependent on dividend payout ratio, potential profit growth, and risk of return. All these factors are included into the P/E, P/BV, and Dividend Yield ratios. In general, Jordan falls in the middle of the group.

Table 3-10: Number of Listed Company in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	101	627	67	58	59	15	97	134	126
1992	103	656	62	60	60	17	118	145	129
1993	101	674	65	62	65	19	124	152	143
1994	95	700	51	67	68	21	147	176	216
1995	97	746	44	80	69	26	169	205	212
1996	98	649	47	94	70	30	220	229	224
1997	139	654	49	114	70	34	258	257	230
1998	150	861	53	131	74	38	275	277	244
1999	152	1033	55	140	73	44	292	285	281
2000	163	1076	53	131	75	44	304	315	329

Source: Emerging Stock Markets Factbook, 2001

Table 3-11: Market Capitalisation (Millions US $) in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	2512	2651	1528		48213	712	34282	15703	13118
1992	3365	3259	1909	1061	54960	814	33663	9931	9489
1993	4891	3814	2651	1088	52773	956	1304	37496	12319
1994	4594	4263	4376	1705	38686	2561	2770	21605	14921
1995	4670	8088	5951	1978	40907	3927	6552	20772	17060
1996	4551	14173	8705	2662	45861	4263	17024	30020	24178
1997	5446	50830	12177	7108	59386	2321	15160	61090	34164
1998	5838	24381	15676	4392	42563	2268	14882	33646	79992
1999	5827	32838	13695	4302	60440	2706	21858	100000	204213
2000	4943	28741	10899	3463	67171	2828	34041	69659	110839
Source: Emerging Stock Markets Factbook, 2001									

Table 3-12: Gross Domestic Product (GDP)(Millions US $) in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	4193	36971	27836	10188	118035	13075	NA	150978	89048
1992	5203	41856	28451	11308	123204	15497	NA	160263	98446
1993	5569	47197	26801	11168	118515	14609	NA	180213	92195
1994	6078	51898	30351	11310	120168	15626	NA	129702	98859
1995	6508	60159	32986	12102	127824	17987	NA	170047	116046
1996	6721	67651	36639	15319	141335	19587	NA	181682	123375
1997	6976	75605	33415	15665	146489	18899	116331	190664	119946
1998	7393	82710	35546	14962	128892	19956	112772	198844	120724
1999	8073	89148	34998	_	139383	20944	110792	185691	125088
2000	_	_	_	_	_	_	_	_	_
Source: Emerging Stock Markets Factbook, 2001									

Table 3-13: Market Cap/GDP in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	0.599	0.0717	0.0549		0.4085	0.054	NA	0.104	0.1473
1992	0.647	0.0779	0.0671	0.0938	0.4461	0.053	NA	0.062	0.0964
1993	0.878	0.0808	0.0989	0.0974	0.4453	0.065	NA	0.208	0.1336
1994	0.756	0.0821	0.1442	0.1508	0.3219	0.164	NA	0.167	0.1509
1995	0.718	0.1344	0.1804	0.1634	0.32	0.218	NA	0.122	0.147
1996	0.677	0.2095	0.2376	0.1738	0.3245	0.218	NA	0.165	0.196
1997	0.781	0.6723	0.3644	0.4538	0.4054	0.123	0.1303	0.32	0.2848
1998	0.79	0.2948	0.441	0.2935	0.3302	0.114	0.132	0.169	0.6626
1999	0.722	0.3684	0.3913		0.4336	0.129	0.1973	0.607	1.6326
2000									
Source: Emerging Stock Markets Factbook, 2001									

Table 3-14: Trading Value (Millions US $) in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	432	139	49		2274	30	5217	8571	2443
1992	1317	195	70	102	3653	33	6995	8191	1605
1993	1377	170	498	108	4629	46	311	23242	2713
1994	626	757	788	242	6632	296	424	21692	5145
1995	517	677	2426	211	6194	663	741	51392	6091
1996	297	2463	432	545	6773	281	2617	36831	8283
1997	504	5859	1048	3880	16549	260	1213.7	59105	21031
1998	653	5028	1390	1943	13713	188	1389	68459	45835
1999	548	9.38	2530	529	14816	420	2270	81277	188722
2000	416	11120	1094	553	17313	626	4998	200000	95106
Source: Emerging Stock Markets Factbook, 2001									

Table 3-15: Turnover ratio (%) in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	19.6	6.2	4.2	NA	0	5.3		52.9	18.8
1992	44.4	6.1	4.1	NA	7.1	4.2		68.2	14.1
1993	33.1	4.8	21.7	NA	8.6	5.2	17.4	80.9	24.4
1994	13	18.7	22.1	NA	14.5	17	20.8	94.2	37.5
1995	11.1	10.9	45.9	NA	15.6	19.8	15.9	226	37
1996	6.4	22.2	5.9	NA	15.6	6.8	22.2	133.3	39.9
1997	10	33.5	10.2	NA	31.4	8.3	7.5	113.5	73.8
1998	11.6	22.3	101	NA	26.9	8.3	9.2	154.9	86.5
1999	9.4	31.6	17.6	NA	28.8	17.2	12.4	102.8	131.1
2000	7.7	34.7	9.2	NA	27.1	23.3	17.9	206.2	63.7
Source: Emerging Stock Markets Factbook, 2001									

Table 3-16: P/E ratio in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	10	NA	NA	NA	NA	NA	NA	13.7	10.7
1992	14.5	NA	NA	NA	NA	NA	NA	6.9	6.9
1993	17.9	NA	NA	NA	NA	NA	4	36.3	10.2
1994	20.8	NA	NA	NA	NA	NA	NA	31	10.4
1995	18.2	NA	NA	NA	NA	NA	NA	8.4	10.5
1996	16.9	11.3	13.8	NA	NA	25.8	8.4	10.9	10.4
1997	14.4	11.5	18.3	NA	NA	13.1	4.9	20.1	17.6
1998	15.9	8.7	21.2	NA	12.2	10.5	NA	7.8	33.6
1999	14.1	16.7	18.4	NA	22.4	12.4	9.3	34.6	55.6
2000	13.9	7.6	11.9	NA	17.2	14.3	4.7	15.4	19.2
Source: Emerging Stock Markets Factbook, 2001									

Table 3-17: P/BV ratio in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	1.4	NA	NA	NA	NA	NA	NA	2.3	2.3
1992	1.6	NA	NA	NA	NA	NA	NA	1.3	1.7
1993	2	NA	NA	NA	NA	NA	5.7	7.2	1.9
1994	1.7	NA	NA	NA	NA	NA	NA	6.3	1.9
1995	1.9	NA	NA	NA	NA	NA	NA	2.7	1.8
1996	1.7	3.2	2.5	NA	NA	3.1	NA	4	2
1997	1.8	3.9	3.5	NA	NA	1.7	NA	6.8	3.1
1998	1.8	2.6	3.6	NA	1.6	1.3	NA	2.7	4.8
1999	1.5	3.6	3	NA	2.3	1.7	NA	8.9	9.4
2000	1.2	1.7	2.2	NA	2.4	1.8	0.3	3.1	4
Source: Emerging Stock Markets Factbook, 2001									

Table 3-18: Dividend Yield (%) in the Region's Stock Markets

	Jordan	Egypt	Morocco	Oman	Saudi Arabia	Tunisia	Iran	Turkey	Greece
1991	8.7	NA	NA	NA	NA	NA	NA	4.4	3.8
1992	2.5	NA	NA	NA	NA	NA	NA	8.1	11
1993	2.7	NA	NA	NA	NA	NA	22.8	2.4	74.8
1994	2.4	NA	NA	NA	NA	NA	NA	3.6	4.6
1995	1.9	NA	NA	NA	NA	NA	NA	4.4	4.5
1996	2.3	4.9	2.1	NA	NA	2.2	NA	3.3	3.7
1997	2.1	3.4	1.5	NA	NA	2.2	NA	1.6	2.9
1998	1.8	7.4	1.8	NA	8.6	4.7	NA	4.3	1.6
1999	2.7	3.7	2.2	NA	3.5	3.2	18.5	1.1	1.1
2000	3.4	5.3	3.2	NA	3.2	2.8	18.2	1.1	2
Source: Emerging Stock Markets Factbook, 2001									

Figure 3-13: Number of Listed Companies in the Region's Stock Markets

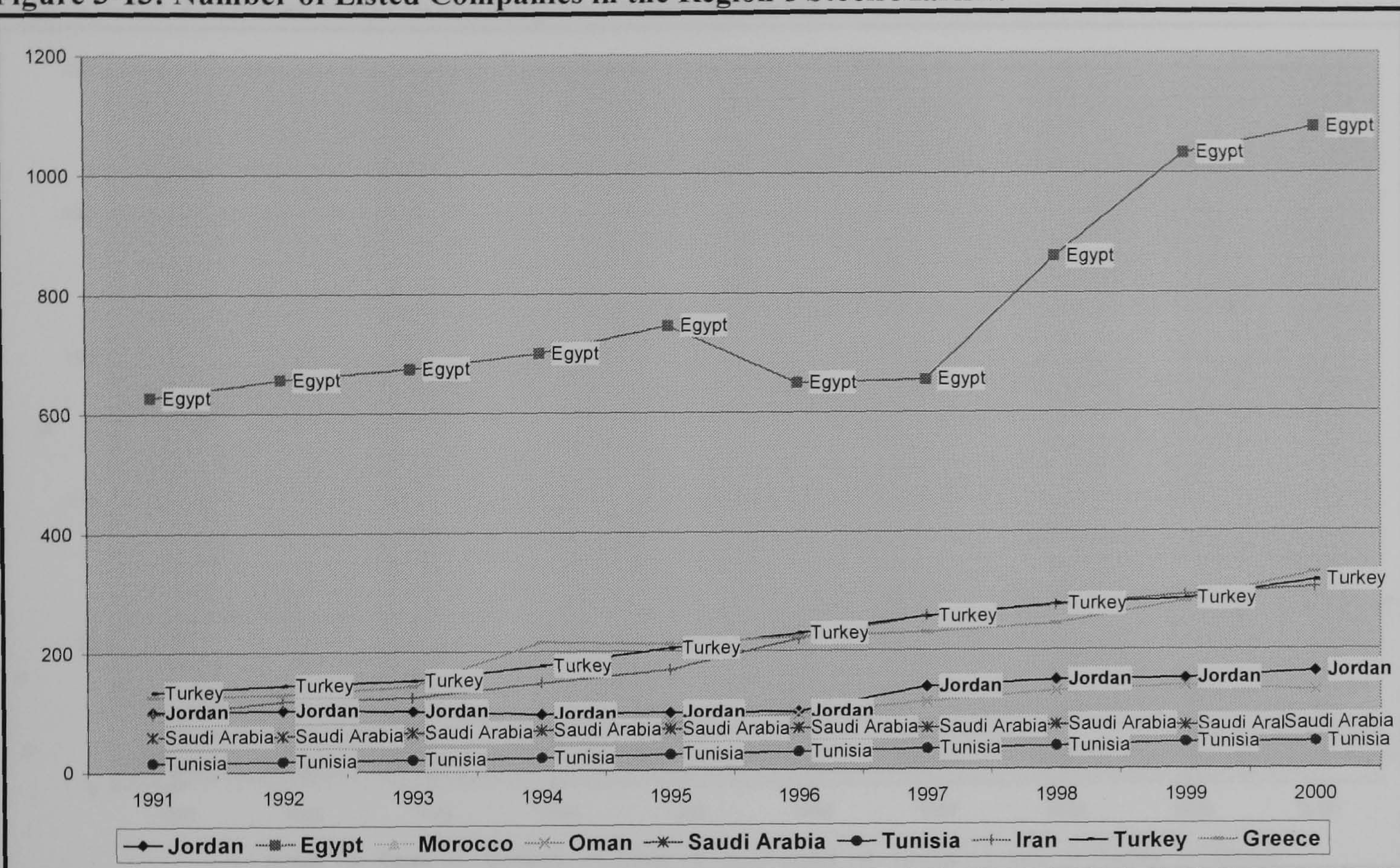


Figure 3-14: Market Cap as Percentage of GDP in the Region's Stock Markets

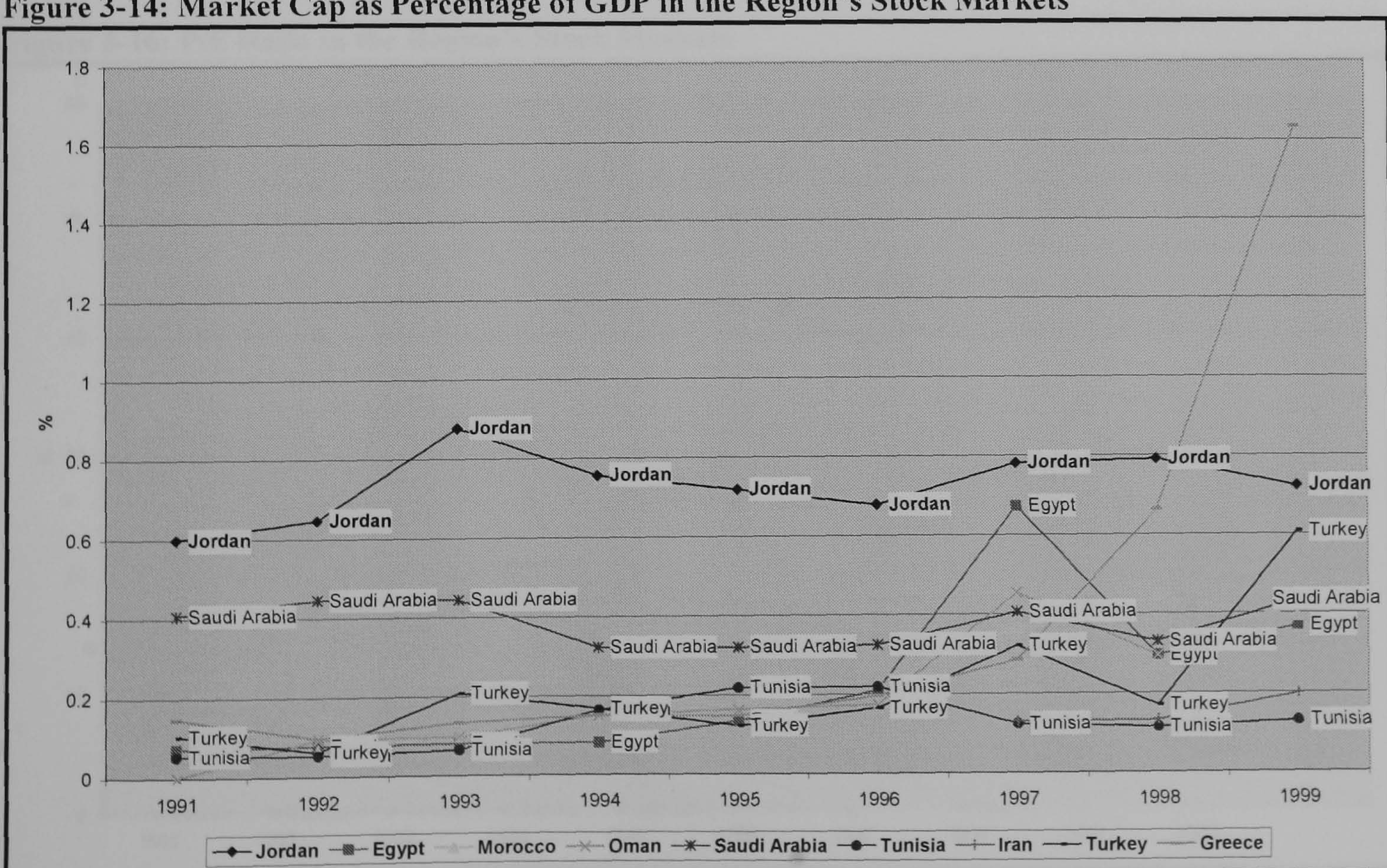


Figure 3-15: Turnover Ratio in the Region's Stock Markets

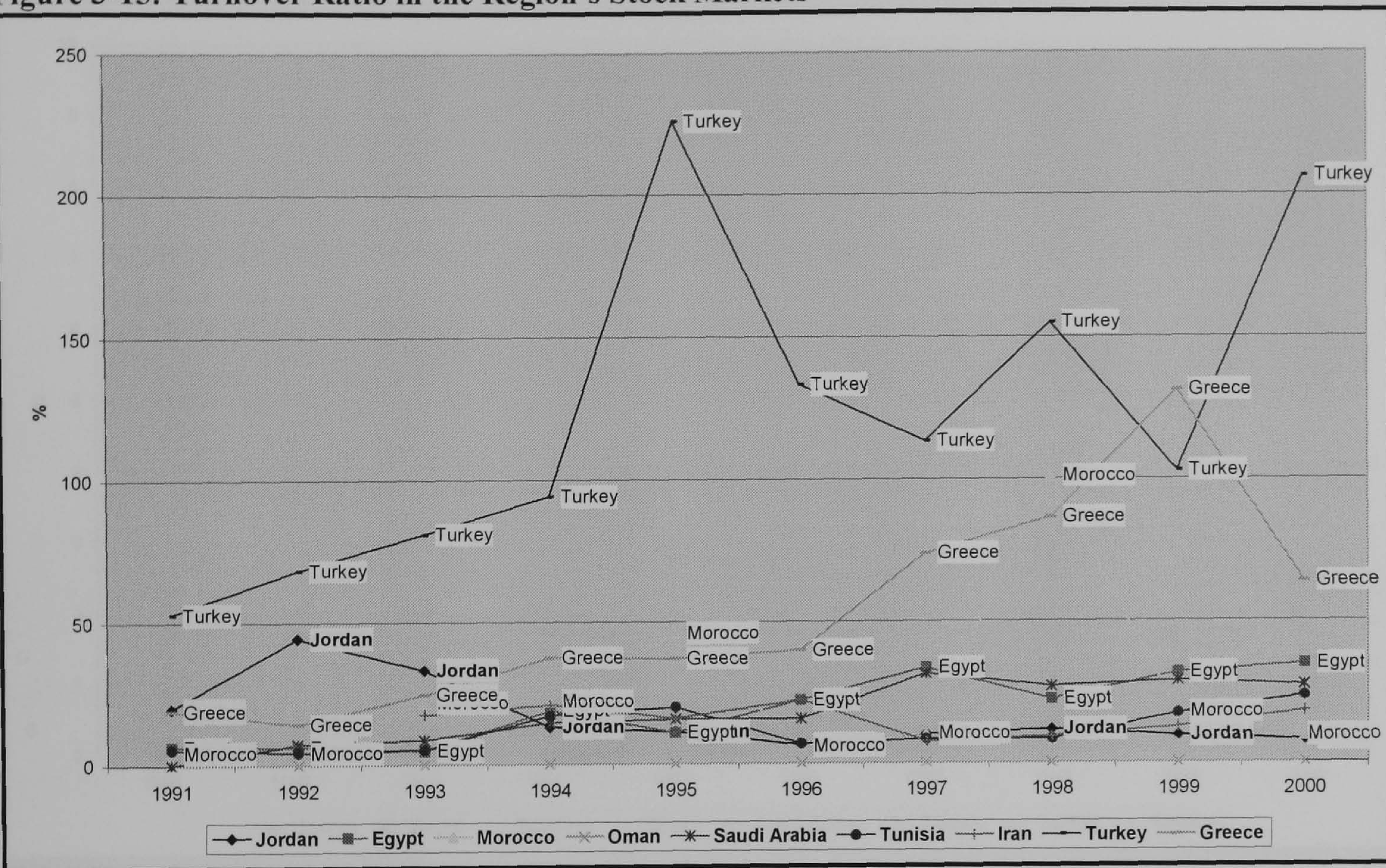


Figure 3-16: P/E Ratio in the Region's Stock Markets

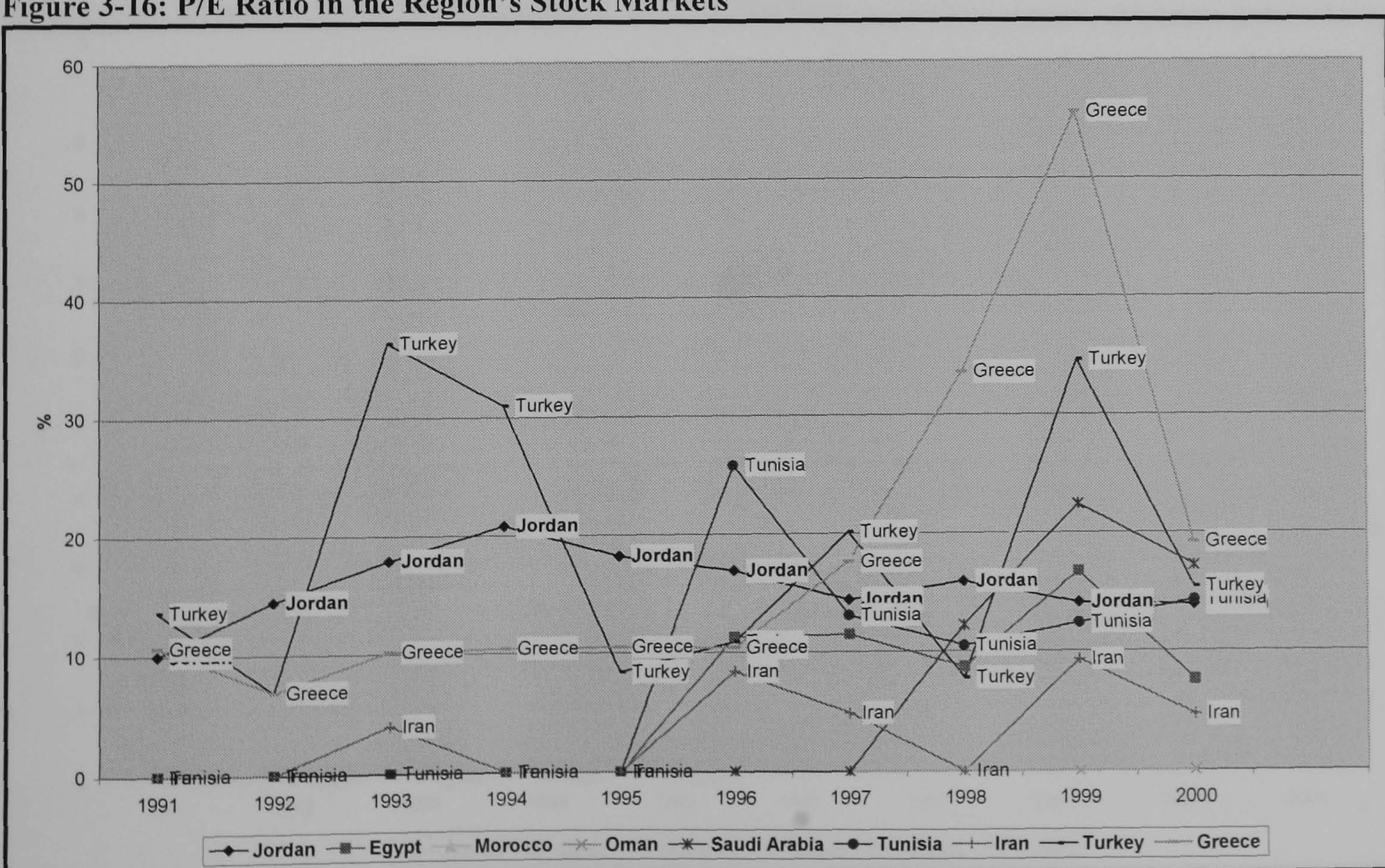


Figure 3-1712: P/BV Ratio in the Region's Stock Markets

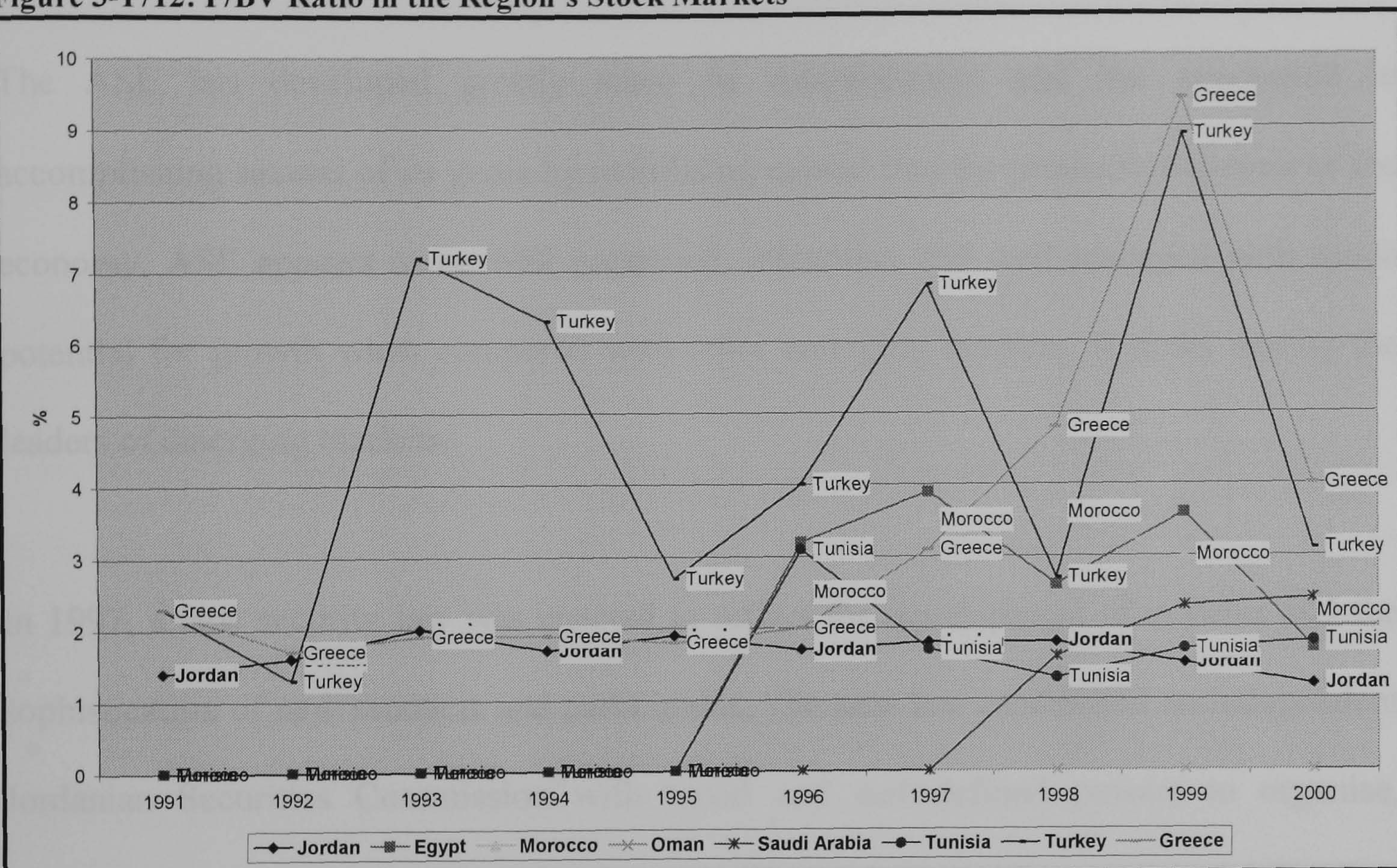
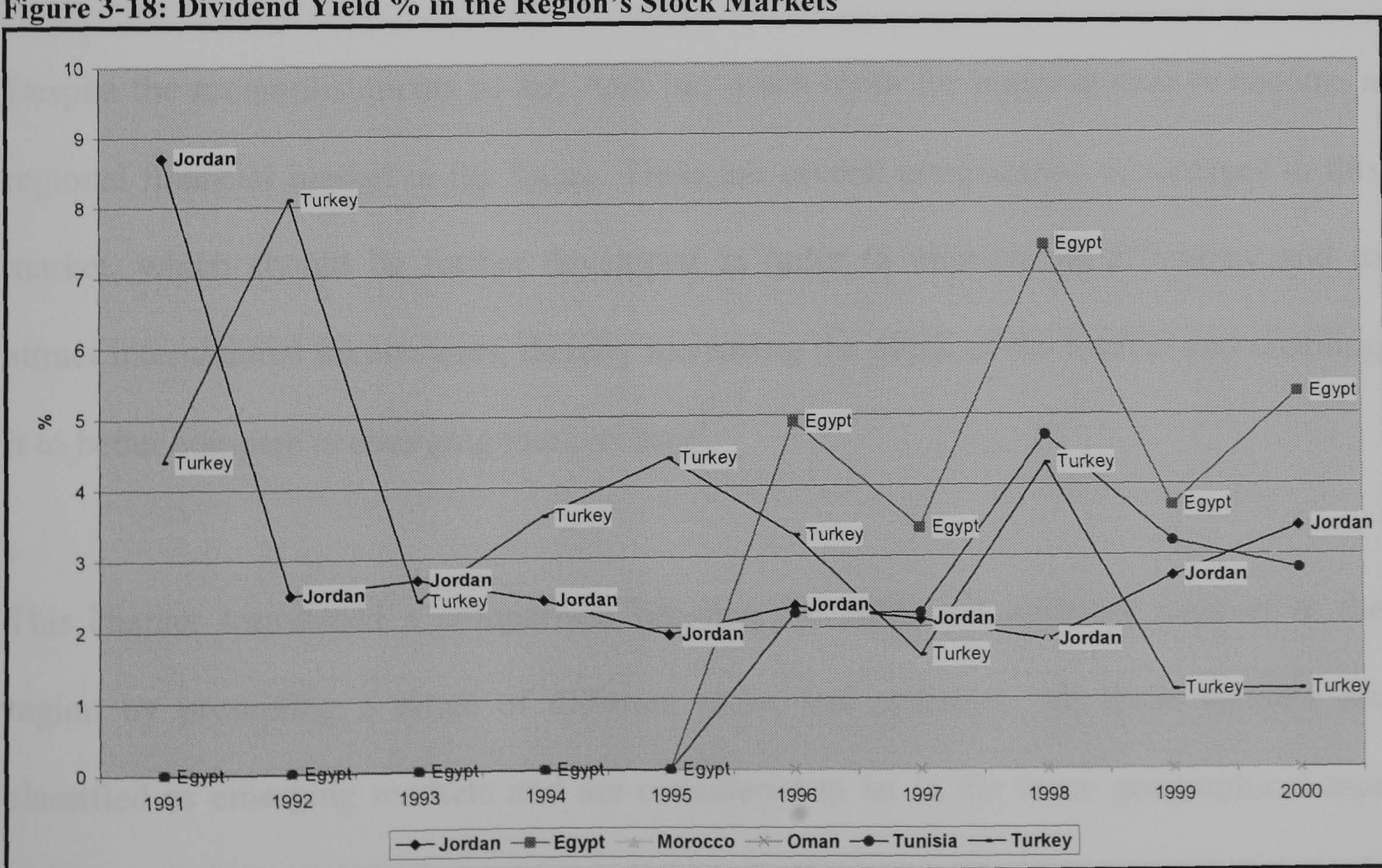


Figure 3-18: Dividend Yield % in the Region's Stock Markets



3.8 Conclusion

The ASE has developed greatly since its establishment and has succeeded in accomplishing several of its goals by mobilising capital into the productive sectors of the economy. ASE appears to be well organised, attractive, and well managed with much potential for growth when compared with other emerging markets. It ranks among the leaders of emerging markets.

In 1997, a new security law was enacted to reflect the development of systems and the sophistication of new products and participants. The new law established an independent Jordanian Securities Commission with broad and well-defined powers to organise, develop, and monitor the securities market. The new law also established other key institutions, participants, and practices.

Despite the accomplishments so far, ASE has much room for improvement to become a regional financial market in the future. There are several comparative advantages in this market, which should be further developed in order to improve its efficiency and to attract international investments, thereby increasing the depth of the market and enabling it to better compete at emerging markets level.

This chapter introduced a comparison between the ASE and different markets in the region by presenting a range of different ratios and statistics. All these markets are classified as emerging markets and are considered to be in the same geographical area which makes the comparison more reliable. Furthermore, the last part of the thesis

(Chapter 7) tests the comovement and cointegration among these markets and investigates the shared trends exhibited by these markets. Although the comparison of ASE with the region's other markets is important, it is of interest to compare the emerging ASE with the US and UK markets as developed markets as a benchmark.

When comparing the ASE with the markets in the region in terms of turnover ratio, the results are close among these markets as most of the emerging markets are characterized by thin trading and high concentration[11]. However, when comparing the ASE with the US and UK, the difference is much higher especially in the last five years. Table 3-19 shows the big difference in turnover ratio between ASE, and US and UK markets. This result which indicates that the ASE market is illiquid and suffers from thin trading may have an impact on investors and market performance. A body of literature has found that investors demand a premium for less liquid stocks, so that expected returns should be negatively related to the level of liquidity. Additionally, several other studies have investigated the effect of trading activity on spread and stock return volatility. In general, the results of these studies indicate that there is a positive relationship between trading volume and variance of returns, and a negative relationship between trading volume and bid-ask spread.

On the other hand, and from international market integration point of view, the importance of trading activity in achieving international integration is recognised. The law of one price is expected to hold to a greater degree for stocks that are heavily traded

[11] In February, 2003, the top ten companies in ASE, by market capitalisation, comprise 68.8% of the total market capitalisation.

over several markets, because each market offers sufficient liquidity to facilitate price–equalizing trades.Hence, with more actively traded stocks, stronger cointegration is expected and thinner markets are expected to display deviations from the law of one price.

Table 3-19: Turnover ratio (%) for ASE compared with US&UK markets

	Jordan	US	UK
1991	19.6	53.4	31.9
1992	44.4	48.5	40.0
1993	33.1	69.7	40.7
1994	13	69.8	39.3
1995	11.1	85.6	39.0
1996	6.4	92.8	36.8
1997	10	103.2	44.4
1998	11.6	106.2	53.4
1999	9.4	123.4	51.9
2000	7.7	200.7	66.6

Source: Emerging Stock Markets Factbook, 2001

Another interesting ratio presented in this chapter is the dividend yield ratio. In certain cases, cash dividends can impact the prices of companies, and the variation in stock prices can be attributed to changes in expected future dividend growth and discount rates. Unfortunately a performance index over the considered period is not available for the ASE. The price index used for upcoming tests of market efficiency thus does not account of dividends. However, although the cash dividends can affect stock prices, the industry norm is not to make any adjustment for dividends in the price index. Since the dividend yield is relatively low in ASE (in average it is never higher than 4% over the period except for the extraordinary 1993 year) and as the value-weighted index is used, it is expected that the effects of individual dividend payments on the index are diluted and therefore the results should be reliable.

Another ratio which could affect the upcoming tests of market efficiency is the ratio of market to book value. For Jordan, this ratio is considered low, compared to other markets in the region. It is well documented that firms of small size and low market-to-book (or high book-to-market) ratio ceteris paribus earn higher rate of returns (Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994)). The market-to-book ratio reveals future prospects and potential, and it is important when calculating long-run abnormal returns.

CHAPTER 4

Conventional Tests of Random Walk (Autocorrelation and Runs Tests)

Contents:

Summary

This chapter applies the autocorrelation and runs test - runs up and down, distributions of runs by length, and runs above and below -to examine whether ASE is weak form efficient. The empirical results obtained in this chapter suggest that the price behaviour in ASE does not follow the random walk model over time. However, this does not necessarily imply a violation of weak form efficiency (vice versa is not correct). Further tests are applied in the next chapters to further investigate the efficiency of ASE.

4.1 Introduction

As mentioned in Chapter 2, the theory of market efficiency involves defining an efficient market as one in which trading on available information fails to provide an abnormal profit. Three levels of market efficiency have been defined; firstly, the weak form of the efficient market hypothesis which claims that prices fully reflect the information implicit in the sequence of past prices. Secondly, the semi-strong form of the efficient market hypothesis which asserts that prices reflect not only past prices but all relevant information that is publicly available. Researchers have tested this by looking at specific items of news such as announcements of earnings and dividends, forecasts of company earrings, changes in accounting practices, and mergers. Thirdly, the strong form of the efficient market hypothesis which asserts information that is known to any participant is reflected in market prices; hence, prices reflect not just public information but all the information that can be acquired by painstaking fundamental analysis of the company and the economy. In such a case, prices would always be fair and no investor would be able to make consistently superior forecasts of stock prices. Most tests of this view have involved an analysis of the performance of professionally managed portfolios.

The efficient market hypothesis yields a variety of testable predictions about the behaviour of financial asset prices and returns. The following are examples of these predictions (Beechey, Gruen, and Vickery 2000):

- Asset prices move as random walks over time, which test the weak form level (a test regarding this will be conducted in this chapter)

- Technical analysis should provide no useful information; also test the weak form level (this will be conducted in Chapter 5).
- New information is rapidly incorporated into asset prices, and currently available public information cannot help in achieving abnormal returns, which tests the semi-strong level by using the event study.
- Fund managers cannot outperform the market, testing the strong form level.
- The actual asset price at any point in time will be a good estimate of its fundamental value, testing also the strong form level.

In order to investigate whether asset prices move as random walk over time, the hypothesis that successive price changes are independent must be tested. Different approaches have been utilised in literature. One is an approach that relies primarily on common statistical tools, such as serial correlation coefficients and the runs test which determines whether successive price changes are independent, and consequently, whether the market is weak-form efficient. This approach has been used excessively and produced evidence of important independence in series of successive price changes in developed markets. Serial correlation is the most important test to investigate the correlation between two observations of the same series at different dates. The serial correlation coefficient measures the relationship between the values of a random variable at time t and its value in the previous period. It is expected to have zero autocorrelation coefficients of the first differences at different lags if the series is a random walk.

The non-parametric runs test determines whether successive price changes are independent, but unlike its parametric equivalent serial correlation test, the runs test does not require returns to be normally distributed (Levene, 1952)[1].

The remainder of this chapter is structured as follows: Section 4.2 gives a review of the empirical studies for serial correlation and runs tests. Many of the studies previously performed undertook both tests, and the tests usually produced similar and consistent results. Section 4.2 starts with studies conducted in developed markets, followed by studies conducted in developing markets, in order to investigate whether differences exist, and ends with studies conducted in ASE. Section 4.3 describes the data, the descriptive statistics of the index return series, and examines the normality assumption. Section 4.4 presents the serial correlation and runs test (runs up and down, distributions of runs by length, and runs above and below), and the empirical results and its interpretation. The summary and conclusion are in Section 4.5.

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[1]Parametric and nonparametric statistical procedures test hypotheses involving different assumptions. Nonparametric tests are often used in place of their parametric counterparts when certain assumptions about the underlying population are questionable
Parametric statistics test hypotheses based on the assumption that the samples come from populations that are normally distributed. Also, parametric statistical tests assume that there is homogeneity of variance (variances within groups are the same). The level of measurement for parametric tests is assumed to be interval or at least ordinal. On the other hand, nonparametric statistical procedures test hypotheses that do not require normal distribution or variance assumptions about the populations from which the samples were drawn and are designed for ordinal or nominal data.
The main weakness of nonparametric tests is that they are less powerful than parametric tests. They are less likely to reject the null hypothesis when it is false. When the assumptions of parametric tests can be met, parametric tests should be used because they are the most powerful tests available.
There are, however, certain advantages of nonparametric techniques such as the underlying populations need not be normal. Furthermore, they are less sensitive to measurement error because they use only signs or ranks. Another unique value of nonparametric procedures is that they can be used to treat data which have been measured on nominal (classificatory) scales. Such data cannot, on any logical basis, be ordered numerically, hence there is no possibility of using parametric statistical tests which require numerical data (Conover, 1980; Siegel, 1965).

4.2 Review of Empirical Studies

This section presents a review of the empirical studies for serial correlation and runs tests. It starts with studies conducted in developed financial markets and follows this with a review of studies conducted in emerging markets, then a review of studies conducted in the ASE .

4.2.1 Developed markets

The early studies testing for weak form efficiency started on developed markets and applied serial correlation and runs tests[2]. Generally, these studies supported the weak-form efficiency of the market, where it found a low degree of serial correlation or an insignificant difference between the expected and observed number of runs, hence, the null hypothesis that the daily returns are random couldn't be rejected. Kendall (1953) stated that "an analysis of stock-exchange movements revealed little serial correlation within series and little lag correlation between series. Unless individual stocks behave differently from the average of similar stocks, there is no hope of being able to predict movements in the exchange for a week ahead without extraneous information". Similar conclusions have also been reached by Fama (1965). This study used the daily prices for the thirty stocks of Dow-Jones Industrial Average over the period 1957-1962 to test the empirical validity of the independent hypothesis of the random walk model. Serial correlation and runs tests (in addition to other technical tests) were applied to daily, four-day, nine-day, and sixteen-day price changes. The

[2] The runs test dates at least to Wolfowitz (1943) and David (1947). It has been applied extensively in quality control engineering (for example, Grant and Leavenworth (1988)). and it can be viewed as an application of categorical data analysis (for example, Andersen (1994)). It can also apply to test market efficiency

results showed little evidence, either of serial correlations or, from the various runs tests, of any large degree of dependence in price changes. Hence, dependency in price changes can not explain the departures from normality that has been observed in the empirical distribution of price changes. Cooper (1982) studied world stock markets using monthly, weekly and daily data for 36 countries. He examined the validity of the random walk hypothesis by employing correlation analysis, runs tests and spectral analysis. With respect to the USA and the UK, the evidence supported the random walk hypothesis.

Several other studies support the results that price changes are random and past changes are not useful in forecasting future price changes (Working, 1934; Kendall, 1943, Cootner, 1962; Osborne, 1962). On the other hand, there are some studies conducted in developed markets reporting high autocorrelation, indicating predictability of share price changes. Poterba and Summers (1988) investigated transitory components in stock prices, using data from the United States and 17 other countries. The results showed a positive autocorrelation in returns over short horizons and a negative autocorrelation over longer horizons, although random-walk price behaviour could not be rejected at conventional statistical significance levels. They suggest that noise trading, that is, trading by investors whose demand for shares is determined by factors other than their expected returns[3], provides a plausible explanation for the transitory component in stock prices. They also suggest that

[3] For example, Barber and Odean (2001) analyse the asymmetry in the buying and selling decisions of investors and suggest that attention generated by market-wide news events may be an important determinant of buying decisions of individual investors. Hirshleifer, Myers, Myers, and Teoh (2002) analyse whether individual investors are the main drivers of the post-earnings announcement drift and find evidence to the contrary. Other studies examined the investor trading behavior and suggest that investors may systematically condition their trading behavior on past return patterns (Goetzmann and Massa 2000, Grinblatt and Keloharju 2001, Dhar and Kumar 2001).

constructing and testing theories of noise trading as well as theories of changing risk factors could account for the characteristics of the stock returns auto-correlogram they observed. Additionally, Fama and French (1988) investigated the autocorrelations for returns, using 1-month returns for all (NYSE) stocks for the 1926-1985 period. Large negative autocorrelations for return horizons beyond a year suggested that predictable price variation due to mean reversion accounts for large fractions of 3-5 year return variances. It was suggested that these observed auto-correlations may reflect market inefficiency or time-varying equilibrium expected returns generated by rational investor behaviour.

In general, most empirical studies conducted in developed markets have tended to uphold weak form efficiency and thus no abnormal return would occur by using past prices.

4.2.2 Emerging markets

Although it is generally believed that emerging markets are less efficient than developed markets, the research findings on emerging markets are actually quite mixed. There are different studies in favour of weak-form efficiency in developing markets which applied serial correlation and runs tests techniques. Branes (1986) tested the applicability of the random walk hypothesis to the Kuala Lumpur Stock Exchange, using the traditional statistical techniques: serial correlation, runs, and spectral analysis. The Kuala Lumpur Stock Exchange exhibits a high degree of weak-form efficiency. Dickinson and Muragu (1994) used weekly prices over ten years of the 30 most actively traded equities on the Nairobi Stock Exchange. They failed to find evidence inconsistent with weak-form efficiency in the stock exchange by means of both runs tests and Q-test statistics, but suggested that a number of studies must be carried out on any market using a variety of methodologies to draw firm conclusions about weak-form efficiency.

Olowe (1999) also came out with similar conclusions. He carried out tests using monthly data on 59 randomly selected securities from 1981-92 on the Nigerian Stock Exchange. The Nigerian market was found to conform to weak-form efficiency in joint Q-tests of partial autocorrelation coefficients for ten lags in the return data, though he argues that poor informational flows and inefficient communication systems cast doubts on the ability of the market to pass a higher hurdle of efficiency.

Urrutia (1995) tests showed opposite results. He used variance-ratio tests and runs tests to investigate random walk and weak-form market efficiency in four Latin American emerging stock markets: Argentina, Brazil, Chile, and Mexico. Results from the variance-ratio estimates obtained, assuming homoskedasticity, reject the random walk hypothesis for the four Latin American markets. However, the runs tests indicate that the four Latin American markets are weak-form efficient. Urrutia suggested that investors might not be able to detect patterns in stock prices and develop trading strategies that would allow them to earn abnormal returns, as one interpretation for these results.

However, other studies contradict the previous results; Claessens, Dasgupta and Glen (1995) found a significant first-order autocorrelation in stock market returns from 19 emerging markets and suggest that stock prices in emerging markets violates weak-form EMH. Similar findings are reported by Harvey (1995a) for most emerging markets. He states that "In contrast to the developed markets, the first-order serial correlation coefficients are higher for the emerging markets. Twelve of the 20 emerging markets have serial correlation coefficients greater than 10 percent and 8 of the markets have coefficients above 20 percent. The first-order autocorrelation in Colombia is an astonishing 49 percent."

El-Erian and Kumar (1995) also found some departures from weak-form efficiency in Middle Eastern stock markets, but emphasise the serial dependence is sufficiently weak that it likely has little value in predicting future prices. Their finding is consistent with that of Butler and Malaikah (1992), who found statistically significant autocorrelation in the stock markets of Kuwait and Saudi Arabia. Nourrrendine Kababa (1998) has also examined the behavior of stock prices in the Saudi Financial Market, seeking evidence for weak-form efficiency, but found that the market is not weak-form efficient. Poshakwale (1996) investigated the weak form efficiency and the day of week effect in the Bombay Stock Exchange using runs test and serial correlation coefficient tests. The results of runs test and serial correlation coefficient tests indicate a nonrandom nature of the series and, therefore, violation of weak form efficiency in the BSE. The other null hypothesis that there is no difference between the returns achieved on different days of the week is also rejected as there is clear evidence that the average returns are different on each day of the week. Mobarek (2000) examined the weak-form efficiency in Dhaka Stock Exchange using the daily price indices of all the listed securities on the DSE for the period 1988 to 1997. The results of both non-parametric tests (Kolmogrov –Smirnov normality test and run test) and parametric tests (Auto-correlation test, Auto-regression, ARIMA model) provided evidence that the share return series do not follow the random walk model. and the significant autocorrelation co-efficient at different lags reject the null hypothesis of weak-form efficiency.

Briefly, the previous studies cannot support or contradict the weak form efficiency in emerging markets. Much work must be conducted to investigate price dynamics in emerging markets. It is interesting to find if ASE is weak-form efficient and to what extent, and to explore the return generating process by using serial correlation and runs tests.

4.2.3 ASE

Few studies investigated the weak form efficiency of ASE by using the conventional tests. El-Erian and Kumar (1994) analyzed the development of equity markets in selected Middle Eastern countries, and evaluated their informational efficiency. The analysis focused on a sample of six countries consisting of: relatively active markets, (Jordan and Turkey), an established but less active market (Eygpt), and more recently established markets (Iran, Morocco, and Tunisia). A range of quantitative indicators, including market capitalization and concentration, price earnings ratios, price volatility, and the extent of correlation with industrial country markers, are applied. A quantitative analysis of the efficiency of selected markets in the region, and a comparison of the efficiency of these markets with a number of other emerging markets, are also undertaken. The results show that there are significant differences across these countries in the importance and characteristics of equity markets. For example, the study measured the volatility of the Jordanian and Turkish markets[4] and compared it with other emerging[5] and developed markets[6]. The emerging markets have been found to be more volatile than the developed markets. Nevertheless, the Jordanian market exhibits the lowest volatility among the emerging markets. The paper also examined the degree to which emerging equity markets are efficient in pricing stocks, through assessing whether stock prices display any systematic patterns or whether they are indistinguishable from random walk. The empirical evidence is based on the serial correlation, for the first ten lags, and the non-parametric runs technique. Daily and weekly data were used[7]. For the daily series for Jordan, the results indicate that the first order serial correlation (0.194) is highly significant, and hence, the random walk model does not hold. For the higher order coefficients, the 3rd, 4th, and 6th are significant. In the case of the weekly data, the pattern is different: the serial correlation coefficients are not statistically significant only for the 4th lag and at the 10% level.

The runs test is performed by comparing the actual number of runs (defined as a sequence of price changes of the same sign preceded and followed by price changes of different signs) with the expected number of runs on the assumption that price changes are independent. If the observed runs are not significantly different from the expected number of runs, then the inference is that successive price changes are

[4] The volatility is measured by the standard deviation of the percentage change in equity prices (at end-month) in domestic currency for the period 1983-1993.

[5] These markets are: Chile, Colombia, Hong Kong, India, Korea, Mexico, Pakistan, Thailand, and Zimbabwe.

[6] These markets are: Japan, United Kingdom, and United States.

[7] The daily data for the indices is from September 1992 to March 1994. For Jordan, data consisted of 167 observations for the first lag, 166 for the second lag, and so on. Only three observations are provided each week. This is because while the ASE is open for business from Saturday to Wednesday, Bloomberg, the information source provider, does not provide data for trading on Saturday and Sunday. The weekly data is from December 1988 to April 1993; there are 225 observations for first lag, 224 for the second lag, and so on.

independent. The results of the runs analysis for both the daily and weekly data indicate that the null hypothesis of independence could be rejected at the 1% level[8].

Another study for Karemera, Ojah, and Cole (1999) reported different interesting results. They used the runs test and the single and multiple variance-ratio tests to examine the stochastic properties of local currency –and US dollar- based equity returns in 15 emerging capital markets. The results indicate that the majority of the emerging equity series analysed are consistent with the RWH and weak form efficient when both local currency-based data and exchange rate-adjusted data are used. The data comprises monthly national stock price indices expressed in both domestic (local) currency and US dollars from 1987:12 to 1997:5, and obtained from Morgan Stanley Capital Information (MSCI) files for emerging markets. The study also provides some descriptive statistics on returns of the stock indices.

According to Karemera, Ojah, and Cole (1999), and ss El-Erian and Kumar (1994) results, Jordan is found to have the lowest standard deviation (a measure of asset's risk) among the emerging markets covered in the study. However, according to the runs test statistics[9], the hypothesis of independence can not be rejected at the 5% level for the Jordanian equity return series, and also for most of the emerging markets covered in the study, for both US dollar-based data and local currency-based data. Hence, the Jordanian market and most of the emerging markets covered in the study are weak-form efficient.

[8] The actual and expected runs for Jordan are as follows:

	Actual No. of Runs				Expected No. of Runs
	Positive	Negative	Zero	Total	
Daily data	20	29	2	51	85.8
Weekly data	47	46	3	96	115.6

[9] The data comprises of monthly equity market returns (not prices), and all statistics are computed according to the SPSS program specifications

Karemera, Ojah, and Cole present different possible reasons for the presence of a positive and/or negative serial correlation when a market is, at the same time, documented to be weak-form efficient. For example, infrequent or nonsynchronous trading patterns can yield a positively autocorrelated stock price series behaviour. When small-capitalized firms trade less frequently than large-capitalized firms, information is impounded first into large-capitalized firms' prices, and then small-capitalized firms', with a lag; and this lag induces a positive serial correlation in the index series that contain these distinct capitalized groups of stocks. Given the market concentration of the top large companies whose stocks dominate the emerging market indices[10], this explanation is not far-fetched. The effects of government interventions can also be another reason for the positive autocorrelation in emerging equity markets' series. Furthermore, they reported that RWH seems to be sensitive to the test observation intervals of the series, and the testing methodology used. On the other hand, the results of variance ratio tests suggest that the Jordanian market does not follow a random walk for either US dollar-based data or local currency-based data for all intervals, given that the observation intervals q=2, 4,8,16 months, with a base of one month, variance ratio estimates are computed for two-month, four-month, eight-month, and sixteen month observation intervals.

Omet (1990) examined the Jordanian market in its beginings, by using the daily prices for most active sixteen shares, and covered the period from 1st Jan. 1979 to 31st Dec. 1986. He applied the serial correlation model, runs analysis, distribution of runs by length, and filter technique. The price time series of each of the sixteen shares are

[10] For Jan. 2003, the top ten companies in ASE, by trading value, comprise 66.5% of the total value traded in ASE. And the top ten companies, by market capitalization, comprise 68.8% of the total market capitalization, which indicate the high degree of concentration for ASE (Amman Stock Exchange Monthly Statistical Bulletin, February 2003).

used to calculate the sample correlation coefficients for daily changes in log prices for the first five lags. For the first lag, the coefficients for all shares are significant and range from +0.269 to -0.061. For the other lags, the correlation coefficients are close to zero and most of them are statistically insignificant. Hence, results suggest that the price changes reflect some degree of significant positive dependency patterns. The runs test was performed for the sixteen shares for the 1-day and 2-day price changes. The number of actual runs for the 1-day price change was found to be less than the number of expected for all shares, thirteen of these differences are significant. However, regarding the 2-day price changes, fifteen shares were found to have actual runs less than expected, but these differences are not significant. Omet concluded that the 1-day price changes reflect positive dependency patterns, which is in agreement with the serial correlation model's results.

It is noticeable that the above studies covered different periods and used different frequencies and methods, and the results produced are mixed. In this chapter, the daily data for five indices, covering almost the last ten years, will be used to examine the weak form efficiency for ASE by applying serial correlation and runs tests.

4.3 Data and Descriptive Statistics

4.3.1 Data

Data tested comprised of the daily prices of the five indices in ASE from 1st January 1992 to 30th June 2001 (excluding dividend yields)[11]. To ensure inter-temporal

[11] Many researchers confirm that their conclusions remain unchanged whether they adjust their data for dividend or not (for example, Lakonishok and Smidt, 1988; Fishe, Gosnell and Lasser, 1993).

consistency, the period of the study commenced at 1/1/1992 as at this date, the Amman Stock Exchange (ASE) changed the form of calculation for the Price Index (from unweighted to market capitalization weighted). A base value of 100 points on December 31st, 1991 was stipulated for the new Weighted Price Index (refer to section 3.5.3.2.6). Indices are good proxies for the market, as they reflect a broad base and are composed of relatively actively traded stocks, thereby eliminating thin trading or specific firm effects. The five indices calculated in ASE are General, Banks, Insurance, Industry, and Service indices.

4.3.2 Descriptive Statistics

Summary statistics for the ASE indices are presented in Table 4.1. The daily return for each index is calculated as: $\ln(p_t) - \ln(p_{t-1})$ where $\ln(p_t)$ is the natural logarithm of the index at time (day) t. Dividends are assumed away (Campbell *et al.*, 1997). Of the five indices, the bank index has the highest average return of 0.00035 over the time period 1992-2001, while the industry index has the lowest and the only negative mean daily average return of (-0.00014). In case of standard deviation of stock returns, the bank and industry sectors have the greater fluctuations. Whilst one of the basic assumptions of random walk model is that the distribution of the return series should be normal, it can be seen from Table 4.1 that the frequency distribution of the return series for each index is not normal. The normal distribution has a skewness coefficient of zero and a kurtosis coefficient of 3. Skewness is a measure of symmetry, or more precisely, lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left as it does to the right of the centre point. The formula for the Skewness is:

$$S = \frac{\frac{1}{T}\sum_{t=1}^{T}(y_t - \bar{y})^3}{\sigma^3} \quad \textbf{(4-1)}$$

where $\bar{y}$ is the mean, σ is the standard deviation, and T is the number of observations. Negative values for skewness indicate data that are skewed left, and positive values for skewness indicate data that are skewed right. By skewed left, we mean that the left tail is heavier than the right tail. Similarly, skewed right means that the right tail is heavier than the left tail. Some measurements have a lower bound and are skewed right. For example, in reliability studies, failure times cannot be negative.

Regarding ASE indices, the skewness coefficient is positive for all indices. These lie in the opposite direction to that commonly manifested by most stock markets (see, for example, Harvey and Siddique, 1999; Peiró, 1999; and Premaratne and Bera, 2001).

Kurtosis is a measure of whether the data is peaked or flat, relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. The formula for Kurtosis is:

$$K = \frac{\frac{1}{T}\sum_{t=1}^{T}(y_t - \bar{y})^4}{\sigma^4} \quad \textbf{(4-2)}$$

where $\bar{y}$ is the mean, σ is the standard deviation, and T is the number of observations.

The kurtosis of a normal distribution is 3. If the distribution has thicker tails than does the normal distribution, its kurtosis will exceed three. A positive kurtosis indicates a peaked distribution, while a negative kurtosis indicates a flat distribution.

The kurtosis coefficient is higher than 3 for all indices, indicating a leptokurtic distribution. A kurtosis higher than 3 indicates a leptokurtic distribution, while one lower than 3 indicates a playkurtic distribution (Parkinson, 1987). Hence, skewness and kurtosis values for the ASE indices return series deviated from the normal distribution both on skewness and kurtosis values and at 1% significant level, indicating that the distribution of indices return series are not normal. In light of the previous results, and to assess the extent of non-normality in the distributions of the indices return series, the Jarque-Bera statistic is used to test whether each series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from a normal distribution.

Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as χ^2 with 2 degrees of freedom. The reported probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis; a small probability value leads to the rejection of the null hypothesis of a normal distribution. The formula for Jarque-Bera is:

$$JB = \frac{T-k}{6}\left[S^2 + \frac{1}{4}(K-3)^2\right] \qquad \textbf{(4-3)}$$

where T is the number of observations, k is zero for an ordinary series and the number of regressors when examining residuals to regression equation, S is skewness and K is kurtosis (Bera, 1981). As shown in Table 4.1, the probabilities, for the *JB* test, for the indices return series are all less than 0.0001, which is statistically significant at 1% level and confirms that the distribution of the daily price indices of the ASE is not normal.

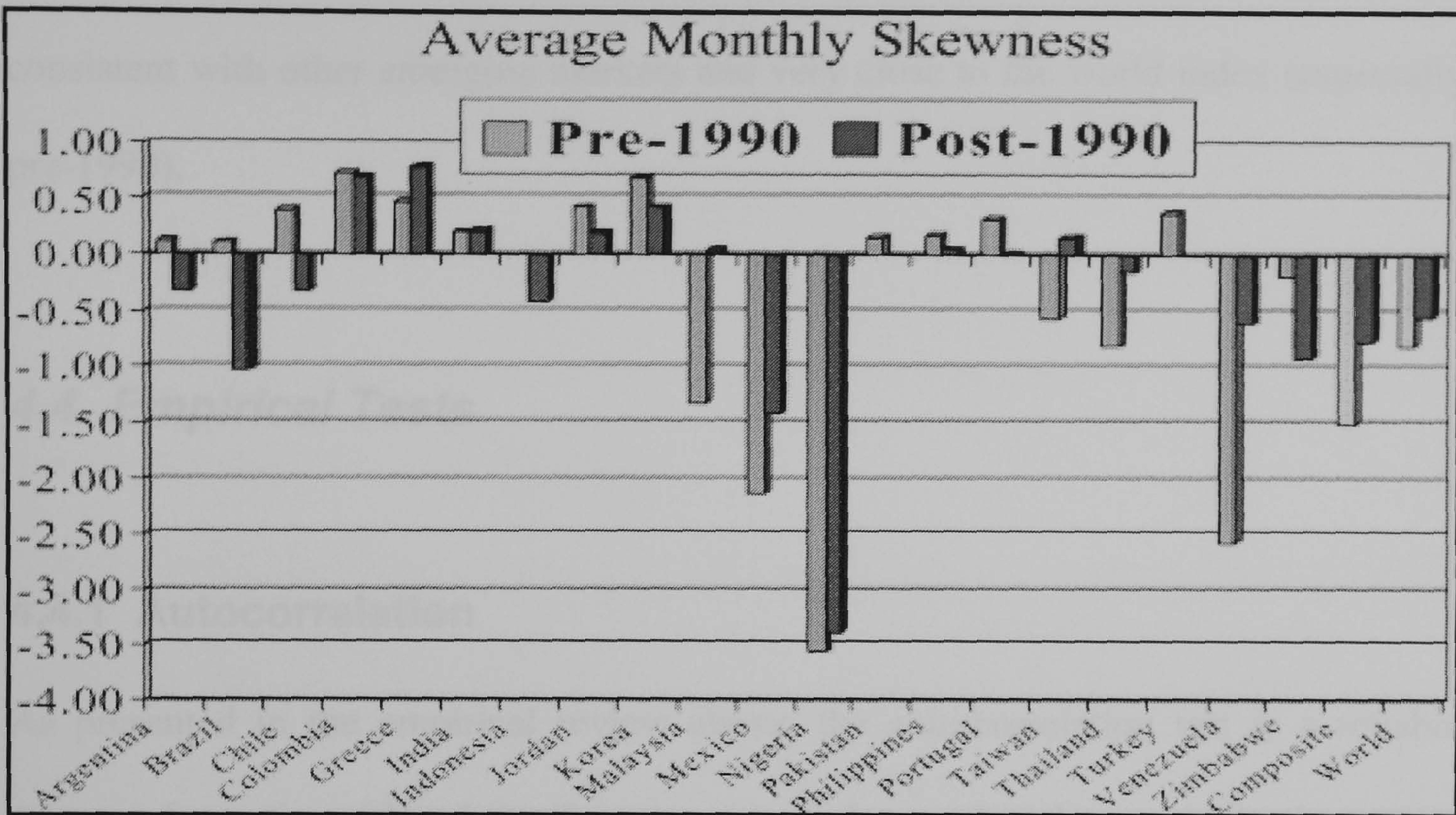
Table 4-1: Descriptive Statistics of Daily Indices Return

	GENERAL	BANKS	INSURANCE	INDUSTRY	SERVICES
Mean	0.000154	0.000352	0.000148	-0.000139	0.000008
Median	-0.000309	-0.000254	0.000000	-0.000564	-0.000274
Maximum	0.047449	0.048855	0.039177	0.047816	0.044548
Minimum	-0.043102	-0.048470	-0.045597	-0.045998	-0.044349
Std. Dev.	0.006831	0.008228	0.005949	0.008348	0.008101
Skewness[a] *(S)*	0.422	0.676	0.408	0.334	0.324
***t-statistics*[b]**	8.344	13.371	8.075	6.612	6.417
Kurtosis[c] *(K)*	8.778	8.613	14.358	7.905	7.256
***t-statistics*[d]**	57.116	55.491	112.271	48.486	42.073
Jarque-Bera *(JB)*	3331.90	3258.12	12670.03	2394.63	1811.33
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	2345	2345	2345	2345	2345

[a] For normal distribution the value of skewness is zero
[b] The *t*-values indicate that the values of the skewness coefficient are statistically different than zero at 1% level of significance. The *t-statistic* is calculated as S/(sqrt(6/2345)).
[c] For normal distribution the value of Kurtosis is three.
[d] The *t*-value indicates that the values of the Kurtosis coefficient are statistically different than three at 1% level of significance. The *t-statistic* is calculated as (K-3)/(squr(24/2345)).

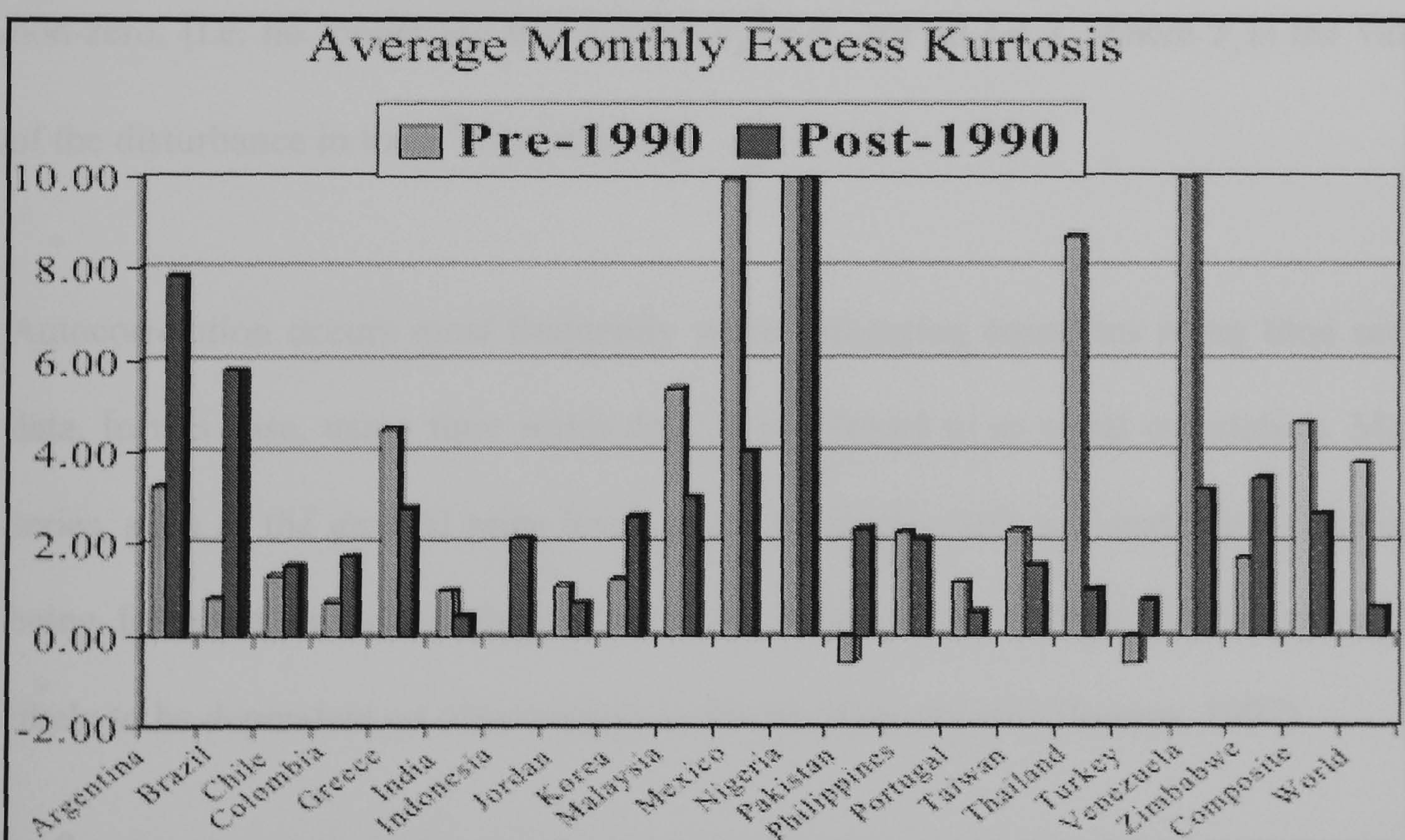
This result supports earlier findings that the emerging market returns are not normally distributed (Harvey, 1995). Recently, Bekaert and Harvey (2002) reported the skewness and excess kurtosis (Figs. 4.1 and 4.2) of twenty emerging markets, including Jordan, with the longest history in the EMDB, the IFC composite portfolio and the MSCI world market portfolio (pre-1990 and post-1990).

Figure 4-1: Average Monthly Skewness. Data through April 2002



Source: Bekaert and Harvey (2002)

Figure 4-2: Average Monthly Excess Kurtosis. Data through April 2002



Source: Bekaert and Harvey (2002)

It is noticeable that the return series of the ASE has a positive skewness, which contradicts the IFC composite portfolio and the MSCI world market portfolio as well as most of other emerging markets[12]. The average monthly excess of kurtosis is consistent with other emerging markets and very close to the world index (especially pre-1990).

4.4 Empirical Tests

4.4.1 Autocorrelation

As presented in the empirical review above, the auto-correlation test is a reliable measure for testing either dependence or independence of random variables in a series. It has been used extensively to test random walk hypothesis. Autocorrelation occurs when the covariances and correlations between different disturbances are no longer all non-zero, [i.e. no longer are that $Cov(\varepsilon_i, \varepsilon_j) = \sigma_{ij}$ for all $i \neq j$, where ε_i is the value of the disturbance in the i^{th} observation]

Autocorrelation occurs most frequently when estimating equations using time series data. In this case, using time series data, it is referred to as serial correlation. Many series, such as the general price level, move cyclically with self-sustaining upswings being followed by downswings. When this occurs, observations in one period are likely to be dependent on observations in the previous period (Thomas, 1997).

The order of autoregressive process: A first-order autoregressive process is designated by the model

[12] Risk-averse investors prefer positively skewed distributions to negatively skewed distributions (Harvey and Siddique, 2000). In an asset pricing context, assets that decrease a portfolio's skewness (i.e. make the portfolio returns more left skewed) should command higher expected returns (e.g., Harvey and Siddique (1999)).

$$\varepsilon_t = \rho\varepsilon_{t-1} + u_t \tag{4-4}$$

where ρ is the first-order autocorrelation coefficient lying between 1 and -1 and can be interpreted as the correlation between successive disturbances, and u_t is a further disturbance that is normally distributed.[13]

The first order autoregressive process contains values of ε_t lagged by just one period, indicating that the disturbance in period t is influenced by the disturbance in the previous period, ε_{t-1}. A second order process contains values of ε_t lagged by two periods, indicating that the disturbance in period t is influenced by the disturbance in the past two periods; ε_{t-1}, ε_{t-2}. That is,

$$\varepsilon_t = \rho_1\varepsilon_{t-1} + \rho_2\varepsilon_{t-2} + u_t \tag{4-5}$$

Referring to the first-order process (4.4), three cases can be distinguished regarding the ρ parameter:

- Positive autocorrelation (ρ>0): In this case, positive values of ε_{t-1} tend to be followed by positive values of ε_t, and negative values of ε_{t-1} tend to be followed by negative values of ε_t. Hence, there may be a tendency for random disturbances to spill over from one time period to the next. In other words, 'runs' over time of positive disturbances are followed by 'runs' of negative disturbances.

[13] When dealing with autocorrelation, it is customary to replace i subscripts by t subscripts, since autocorrelation is normally associated with time series data.

- Negative autocorrelation (ρ<0): Positive values of ε_{t-1} tend to be followed by negative values of ε_t and negative values of ε_{t-1} tend to be followed by positive values of ε_t. Hence, successive disturbances tend to alternate in sign over time.
- No autocorrelation (ρ=0): In this case $\varepsilon_t = u_t$, meaning that there is no relationship between ε_t and ε_{t-1}.

Autocorrelation tests whether the correlation coefficients are significantly different from zero. The null hypothesis is that ρ=0. This would imply a random walk process and hence weak form efficiency. The Ljung-Box Q statistic tests for serial correlation. It is given by:

$$Q_{LB} = n(n+2)\sum_{j=1}^{m}\left(\rho_j^{\,2}/(n-j)\right) \qquad \textbf{(4-6)}$$

where ρ_j is the *j-th* autocorrelation and *n* is the number of observations.

For a large sample, the Ljung—Box statistic follows the chi-square distribution with *m* degrees of freedom. Ljung-Box Q statistic can be used to test the hypothesis that all of the autocorrelations are zero; that is, that the series is white noise. (Box and Pierce, 1970)

4.4.1.1 Empirical Results for Autocorrelation

A: Daily Returns

As shown in Table 4.2, the autocorrelation functions of the price changes for all indices have been computed for 20 lags. The first order autocorrelation for all indices is significant, massively high and positive (ranging from 0.20 to 0.27), indicating that stock returns are indeed to an extent predictable on the basis of past price history. It is noticeable that there are some significant positive autocorrelation coefficients in addition to the first order autocorrelation for the general index at the 11th, 14th, and 17th lag, for the bank index at the 14th, and 17th lag, for the industry index at the 11th, 14th, and 18th lag, for the insurance index at the 3rd, and 4th lag, and for the service index at 2nd, 14th, and negative autocorrelation coefficient at the 19th lag. The fourteenth order autocorrelation is significant for all the indices except the insurance index.[14]. These results of significant nonzero autocorrelation, combined with the Q_{LB} statistic, reject the random walk process, since the Q_{LB} statistic at each lag is significantly higher than the critical values, and the probability that these autocorrelations would be generated by a random walk is less than 1 percent. Accordingly, the weak form market efficiency is rejected (in Chapter 6 other models, which may better describe the return moves, will be investigated).

From the viewpoint of the investment strategy, serial correlations can be exploited to earn excess returns through a mechanical form of technical analysis.

[14] This suggests that not only successive price changes are related but distant lagged changes also exhibit some association, however for longer lags the coefficients are relatively small, and there is very little pattern in the signs of serial correlations.

• A positive serial correlation could be exploited by a strategy of buying after periods with positive returns and selling after periods with negative returns.

• A negative serial correlation would suggest a strategy of buying after periods with negative returns and selling after periods with positive returns (this will be studied in chapter 5). Though these results suggest positive autocorrelation and market inefficiency, the simple linear relationships that underlie this model are much too simplistic to pick up the complicated patterns that the chartist sees in stock prices. Non-trading in some of the components of the index can also create a carry-over effect from the prior time period, and this can result in positive serial correlation in the index returns.

Table 4-2: The Autocorrelation and Ljung-Box Statistics from Lag 1 to Lag 20 for the Indices Daily Return

	General Index		Bank Index		Industry Index		Insurance Index		Service Index	
Lag	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics
1	(0.266)**	(166.66)**	(0.227)**	(121.48)**	(0.259)**	(157.88)**	(0.196)**	(90.49)**	(0.220)**	(113.19)**
2	0.013	(167.05)**	0.018	(122.26)**	0.022	(159.04)**	0.029	(92.46)**	(0.054)**	(120.15)**
3	-0.02	(167.99)**	-0.01	(122.47)**	-0.039	(162.60)**	(0.058)**	(100.32)**	0.024	(121.48)**
4	-0.028	(169.84)**	-0.023	(123.68)**	-0.037	(165.74)**	(0.044)*	(104.84)**	0.004	(121.52)**
5	-0.019	(170.65)**	-0.025	(125.15)**	0.001	(165.75)**	-0.015	(105.37)**	-0.031	(123.73)**
6	0.01	(170.88)**	0.013	(125.54)**	0.023	(167.02)**	-0.023	(106.63)**	-0.01	(123.99)**
7	-0.012	(171.24)**	-0.022	(126.73)**	0.025	(168.50)**	0.004	(106.66)**	-0.029	(125.94)**
8	-0.015	(171.74)**	-0.024	(128.13)**	0.002	(168.51)**	0.016	(107.28)**	-0.002	(125.96)**
9	-0.006	(171.83)**	-0.019	(128.93)**	0.014	(168.97)**	-0.005	(107.34)**	-0.022	(127.13)**
10	0.024	(173.17)**	0.002	(128.94)**	0.038	(172.41)**	0.005	(107.39)**	0.003	(127.15)**
11	(0.049)*	(178.80)**	0.036	(131.95)**	(0.051)*	(178.65)**	-0.009	(107.57)**	-0.003	(127.17)**
12	-0.017	(179.47)**	-0.023	(133.23)**	-0.01	(178.88)**	-0.03	(109.72)**	0.018	(127.90)**
13	-0.01	(179.70)**	-0.018	(134.00)**	0.021	(179.92)**	-0.018	(110.45)**	-0.011	(128.19)**
14	(0.055)**	(186.80)**	(0.049)*	(139.77)**	(0.044)*	(184.52)**	0.014	(110.93)**	(0.045)*	(133.04)**
15	0.032	(189.24)**	0.032	(142.16)**	0.015	(185.07)**	0.033	(113.48)**	0.032	(135.50)**
16	0.016	(189.83)**	0.022	(143.28)**	0.008	(185.22)**	0.035	(116.36)**	0.005	(135.56)**
17	(0.045)*	(194.70)**	(0.059)**	(151.40)**	0.03	(187.33)**	0.035	(119.29)**	0.014	(136.05)**
18	0.033	(197.22)**	0.028	(153.22)**	(0.052)*	(193.85)**	-0.008	(119.46)**	0.007	(136.15)**
19	0.015	(197.73)**	0.017	(153.89)**	0.008	(194.00)**	0.022	(120.60)**	(-0.05)*	(142.06)**
20	-0.017	(198.42)**	-0.003	(153.92)**	-0.027	(195.69)**	-0.003	(120.61)**	-0.029	(144.01)**

** Significant at 1% level,
* Significant at 5% level

B: Weekly Returns:

The autocorrelation test is also performed using weekly returns for the indices. The ASE is characterised by a thin trading[15] market, as are most of the other emerging markets. Although the indices are made up of the most liquid companies, and the selection of these companies is based on market capitalization, days traded, turnover ratio, value traded and the number of shares traded, the market is highly concentrated[16] and the nontrading effect may still present in the indices.

The nontrading effect arises when asset prices are taken to be recorded at time intervals of one length when in fact they are recorded at time intervals of other, possibly irregular, lengths. The nontrading effect induces potentially serious biases in the autocorrelation coefficients. Suppose that the returns to stocks A and B are temporally independent but A trades less frequently than B and both are included in the index. If news arrives in a certain moment, it is more likely that B's end-of-day price will reflect this information than A's, simply because A may not trade after the news arrives. A will respond to this information eventually with a lag which induces spurious cross-autocorrelation between the daily returns of A and B when calculated with closing prices. This lagged response will also induce spurious own-autocorrelation in the daily returns of A: During periods of nontrading, A's observed

[15] Thin trading is when there is little activity in the market and few shares are bought and sold and the securities are traded infrequently.
[16] For example, for Jan. 2003, the top ten companies in ASE, by trading value, comprised 66.5% of the total value traded in ASE.

return is zero and when A does trade, its observed return reverts to the cumulated mean return, and this produces a serial correlation in A's returns (Campbell. 1997).

The use of weekly returns should alleviate the nontrading effects. Low frequent data would reduce the number of nontrading consecutive intervals, and hence the probability that the information is reflected in prices without lag is higher.

The autocorrelation results for weekly data, as shown in Table 4.3, are overwhelming when compared to daily autocorrelation results. The autocorrelation coefficients for the first lag of the weekly return are not significant for 3 indices (bank, insurance and service) and significant at the 5% level for the other 2 indices (general and industry), whilst, the autocorrelation coefficients for the first lag of the daily return are significant for all indices at the 1% level. On the other hand, and for the significant autocorrelation coefficients, the autocorrelation coefficients dropped from 0.266 to 0.102 and form 0.259 to 0.101 for the general and industry indices respectively when using the weekly return. It is obvious that the biases associated with nontrading and asynchronous prices are troublesome for the daily data, and the weekly sampling minimizes the biases inherent in daily data.

These results agree with statistics presented in Chapter 3 indicating low turnover ratios in ASE and that the market is highly concentrated and suffers thin trading.

Table 4-3: The Autocorrelation and Ljung-Box Statistics from Lag 1 to Lag 20 for the Indices Weekly Return

	General Index		Bank Index		Industry Index		Insurance Index		Service Index	
Lag	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics	Auto-correlation	Ljung-Box Statistics
1	(0.101)*	(4.89)*	0.089	3.755	(0.101)*	(4.831)*	0.060	1.5113	0.027	0.3545
2	-0.034	5.42	-0.059	5.384	-0.001	4.831	0.036	2.1219	-0.013	0.4344
3	(0.113)*	(11.45)*	(0.099)*	(10.034)*	(0.134)**	(13.275)**	0.029	2.5077	0.023	0.6904
4	0.051	(12.67)*	0.063	(11.874)*	0.018	(13.423)**	0.064	4.4498	0.017	0.8327
5	-0.026	(12.99)*	-0.055	(13.279)*	0.032	(13.916)*	-0.043	5.3019	-0.026	1.1631
6	-0.022	(13.21)*	-0.002	(13.281)*	0.074	(16.511)*	-0.070	7.6194	-0.061	2.9340
7	-0.046	(14.19)*	-0.004	13.288	0.003	(16.516)*	0.058	9.2130	0.036	3.5668
8	-0.043	15.08	0.021	13.502	-0.063	(18.420)*	-0.050	10.415	(-0.126)*	11.104
9	-0.026	15.40	-0.041	14.294	0.014	(18.514)*	0.016	10.525	0.001	11.104
10	-0.071	17.79	-0.028	14.657	-0.036	(19.136)*	0.033	11.022	-0.040	11.874
11	-0.045	18.73	-0.001	14.657	(-0.104)*	(24.305)*	-0.021	11.225	-0.027	12.214
12	0.021	18.94	0.042	15.473	-0.001	(24.306)*	-0.015	11.335	-0.002	12.216
13	0.048	20.05	0.064	17.392	0.044	(25.226)*	0.046	12.318	0.081	15.444
14	-0.059	21.67	-0.069	19.648	-0.013	(25.302)*	(0.098)*	16.588	-0.056	16.941
15	0.026	21.99	0.011	19.700	0.040	(26.052)*	-0.051	17.668	-0.025	17.236
16	0.086	25.49	0.083	22.973	0.065	(28.032)*	0.087	20.563	0.010	17.290
17	0.013	25.57	-0.011	23.025	-0.023	(28.297)*	0.071	22.317	0.009	17.327
18	-0.069	27.85	-0.061	24.796	-0.079	(31.244)*	0.039	22.835	0.010	17.376
19	0.013	27.93	-0.001	24.796	-0.030	(31.677)*	-0.050	23.692	(0.091)*	21.434
20	(0.127)**	(35.65)*	(0.109)*	30.346	0.076	(34.458)*	0.086	26.292	0.015	21.549

**** Significant at 1% level,**
*** Significant at 5% level**

C: Autocorrelation Tests for Two Subperiods

The years 1992 and 1993 witnessed an abnormal trading volume as shown in Table 3-13. The reason for the huge volume increase could be explained by the extraordinary situation following the Gulf crisis, which produced high liquidity in the Jordanian economy and an elevated trading volume[17]. In order to test the stability of the autocorrelation coefficients during the sample period, the autocorrelation coefficients are applied on two subperiods of the whole period. The first subperiod is the period of 1992 and 1993 which recognized the unusual trading activity in the ASE, and the second subperiod is the remaining period where the trading returns to normal. The Chow test for structural difference is also applied.

The Chow test involves of breaking the sample into the two or more postulated structures, then comparing the sums of squared errors from the separate equations with that from the equation estimated using all data. The purpose of breaking the sample is to test whether the coefficient vector may be regarded as constant over the subsets (Chow, 1960).

[17] In August, 1990, Iraq invaded Kuwait and at that time, there were around 400 thousands of Jordanian workers and investors in Kuwait. After war, most of the Jordanian returned to Jordan with their life savings and investments. High percent of these investments were directed to the ASE which raised the trading volume and liquidity.

Table 4-4: The Autocorrelation and Chow Test for the Whole and Subperiods of the Indices Daily Return

Autocorrelation Coefficient	General	Bank	Industry	Insurance	Service
1992-1993	(0.244)**	(0.208)**	(0.256)**	(0.172)**	(0.204)**
1994-2001	(0.275)**	(0.235)**	(0.256)**	(0.217)**	(0.230)**
1992-2001	(0.266)**	(0.227)**	(0.259)**	(0.196)**	(0.220)**
Chow Test					
F-statistics	(2.55)*	1.43	(2.56)*	(4.40)**	1.61

** Significant at 5% level,
 * Significant at 10% level

Table 4-4 presents the autocorrelation coefficients and Chow test results for the two subperiods for the indices daily returns. The first notable observation is that the autocorrelation coefficients for the first subperiod are lower than the second subperiod for all indices. This support the previous results that one of the causes of the autocorrelation is attributed to thin trading, as the first subperiod experienced a high trading volume, it produced lower autocorrelation coefficients. However, the autocorrelation coefficients are still significant and high for both subperiods. According to Chow test results, the null hypothesis that the coefficient is regarded as constant over the subsets is accepted for the bank and services indices. However, the null hypothesis is rejected at the 10% level for the general and industry indices and rejected at the 5% level for the insurance index. The high trading volume in 1992 and 1993 affected the autocorrelation coefficients slightly but couldn't be considered as a structural difference for most of the indices. It is worth mentioning that the high liquidity in the market in 1992 and 1993 was absorbed in the following years by issuing new subscriptions. For example, and as shown in Figure 3-4, the numbers of listed and waiting-to-be listed companies in 1992 was 117 while the numbers raised to 216 in year 1998.

However, the results reported above for the ASM are consistent with studies conducted on different emerging markets and on the ASE. For example, Harvey (1995a), reported that eight economies in emerging market (Chile, Colombia, Mexico, Pakistan, the Philippines, Portugal, Turkey, and Venezuela) had significant first order auto-correlations greater than 0.20 (Colombia had ρ=0.49). Furthermore, Poshokwale (1996) recognized significant autocorrelation at various lags of the return series for India, Philippines, Malaysia, and Thailand, indicating interdependence in returns.

4.4.2 Non-Parametric Runs Test

The runs test is another approach to determine whether successive price changes are independent; the normality assumption of distribution is ignored by this test, unlike the autocorrelation test. The null hypothesis for the runs test is that the observed series is a random series. A run is defined by Siegel (Siegel, 1956) as: "a succession of identical symbols which are followed or preceded by different symbols or no symbol at all". For the purpose of this test, runs up and down, distribution of runs by length, and runs above and below are applied.

4.4.2.1 Runs Up and Down

A run is counted every time the price series changes its sign. There are three possible changes: positive (+), negative (-), and zero changes (0). A run of length i is defined as i consecutive + or – or 0. In other words, a plus run of length i is a sequence of i consecutive positive price changes preceded and followed by either negative or zero changes. For example, the sequence of daily prices of (166.05, 166.38, 165.78, 165.20, 164.57, 164.01, 163.97, 164.03, 164.86, 164.86, 164.28, 163.79, 164.47, 164.54) has 6 runs (+, -, +, 0, -, +) with lengths of (1, 6, 2, 1, 1, 2) respectively (Excel software is used to perform this test as shown in Appendix 2).

This test examines if the direction of one observation influences the direction taken in later observations. The run's test compares the observed number of runs with the expected number of runs, which are computed under the assumption that prices fluctuate randomly and independently (Fama, 1965):

$$Expected\ Runs = \left[N(N+1) - \sum_{i=1}^{3} n_i^2 \right] \Big/ N \qquad \textbf{(4-7)}$$

where N is the total number of return observations, and n_i is the number of price changes of each sign.

The standard error of the series (σ) of runs can be shown to be (Fama, 1965):

$$\textbf{\textit{Standard Error}} = \left(\frac{\sum_{i=1}^{3} n_i^2 \left[\sum_{i=1}^{3} n_i^2 + N(N+1) \right] - 2N \sum_{i=1}^{3} n_i^3 - N^3}{N^2 (N-1)} \right)^{\frac{1}{2}} \qquad \textbf{(4-8)}$$

The difference between the actual number of runs and the expected number of runs is examined for significance. Thus the difference between the actual number of runs, R, and the expected number, m, can be expressed by means of the usual standardized variable,

$$Z = \frac{\left(R + \frac{1}{2} \right) - m}{\sigma_m} \qquad \textbf{(4-9)}$$

where the half in the numerator is a discontinuity adjustment. For large samples, Z will be approximately normal with a mean (0) and a variance (1). When the difference is found to be significant, this means that daily returns are not random and that there is an opportunity to make abnormal returns. If the actual number of runs are significantly less than the expected value, this indicates the market's overreaction to information, while a higher number of runs reflects a lagged response to information (Poshokwale, 1996)[18](refer to Appendix 2).

[18] The non randomness in stock prices can be exploited through simple trading rules to make abnormal returns. Technical Analysis and different trading rules are studied in Chapter 6.

4.4.2.2 Empirical Results

The non-parametric runs test is considered more appropriate than a parametric serial correlation test as the returns data does not conform to the normal distribution (Jarque-Bera test statistic is reported in Table 4.1). The standard normal Z-statistic can be used to test whether the actual number of runs is consistent with the independence hypothesis. If the Z value is greater than or equal to ±1.96, the null hypothesis at the 5% level of significance is rejected (Sharma and Kennedy, 1977).

When the actual number of runs exceeds (falls below) expected runs, a positive (negative) Z value is obtained. A positive (negative) Z value indicates negative (positive) serial correlation in the return series. As can be seen from Table 4.5, the Z statistics of the daily market return is greater than ±2.64 and negative for all indices. This means that the observed number of runs is significantly fewer than the expected number of runs at the 1% level of significance. Therefore, the null hypothesis that the return series of the indices follow a random walk can be rejected for all series.

Even though the empirical results rejected the random walk, runs tests are not considered a sophisticated method for identifying movements, since the termination of the movement is simply predicted when the price level has temporarily changed direction, regardless of the size of the price change that caused the change in sign. Nevertheless, this result is consistent with the serial correlation test of the previous section (section 4.4.1.1). It is also consistent with other emerging market studies. For example, Poshokwale (1996) reported that the daily return series in the Indian, Philippine, Malaysian, and Thailand market produced an actual number of runs significantly lower than the expected number of runs. El-Erian and Kumar (1994) and Omet (1990) reported similar results for the Jordanian market, even though the study periods were different.

Table 4-5 The Results for the Runs Up and Down Test

Index	Actual Runs	Expected Runs	Standard Error	Z-statistic
General	929	1171.9	24.10	(-10.09)**
Bank	990	1175.1	24.07	(-7.71)**
Industry	942	1168.3	24.00	(-9.45)**
Insurance	1294	1540.6	22.72	(-10.88)**
Service	1042	1192.2	23.95	(-6.29)**

** Significant at 1% level

The next step is to analyze the difference between the actual and expected number of runs using the distribution of runs by length (number of days), in other words, by examining the differences-in length-between the actual and expected number of each sign.

4.4.2.3 Distribution of Runs by Length

When the differences between the actual and expected number of runs is significant, the distribution of runs by length analysis provides a more detailed description and answers the following question: given the total actual number of runs of each sign, how would we expect the totals to be distributed among runs of different lengths, and what is the actual distribution? In other words, if the signs of the price changes are generated by an independent process with their respective probabilities of P(+), P(-) and P(0), we are required to examine the differences (in length) between the actual and expected runs of each sign (TSP software is used to perform this test as shown in Appendix 2).

Depending on the actual number of positive price changes (NP(+)) , negative price changes (NP(-)), and zero price changes (NP(0)), the probability of positive price change [P (+)] to occur would be: (Fama, 1965)[19]

$$P(+) = NP(+) / \left[NP(+) + NP(-) + (NP(0)\right] \quad \textbf{(4-10)}$$

and P (-), P (0) would be

$$P(-) = NP(-) / \left[NP(+) + NP(-) + (NP(0)\right] \quad \textbf{(4-11)}$$

$$P(0) = NP(0) / \left[NP(+) + NP(-) + (NP(0)\right] \quad \textbf{(4-12)}$$

---

[19] Since the differences between the actual and expected numbers of runs are significant, using the total expected number of runs to calculate the expected distribution by length of each sign would be misleading. Instead, the expected distribution by length of the total "actual" numbers of runs of each sign should be considered.

The expected proportion of positive runs of length i (where i =1,2,3,…, α) would be $P(+)^{i-1}[1-P(+)]$ (Fama, 1965). In other words, given that a positive run has occurred, this proportion is equivalent to the conditional probability of positive runs of length i(the sum of the conditional probabilities for positive runs of all length will be one). Similarly, this is applied for negative and zero runs to get the expected distributions by length of the total actual number of runs of each sign: $P(-)^{i-1}[1-P(-)]$ and $P(0)^{i-1}[1-P(0)]$respectively. The expected distributions, by length, of the total actual number of runs of each sign could be calculated by using (4.10), (4.11), and (4.12). The expected numbers of positive, negative, and zero runs of length i (where i =1,2,3,…, α) are calculated as: (Fama, 1965)

$$\overline{R}_i(+) = R(+)P(+)^{i-1}[1-P(+)] \quad \textbf{(4-13)}$$

$$\overline{R}_i(-) = R(-)P(-)^{i-1}[1-P(-)] \quad \textbf{(4-14)}$$

$$\overline{R}_i(0) = R(0)P(0)^{i-1}[1-P(0)] \quad \textbf{(4-15)}$$

where $\overline{R}_i(+)$, $\overline{R}_i(-)$ and $\overline{R}_i(0)$are the expected numbers of positive, negative and zero runs of length i and $R(+)$, $R(-)$and $R(0)$are the total actual numbers of positive, negative and zero runs (refer to Appendix 2).

4.4.2.4 Empirical results

Table 4.6 reports, for each type of run, the probability of a run of each length, the expected number of runs of each length, and the actual number of runs of each length for the five indices. It is noticeable that all indices produced similar results, and that there are very few long runs. The most interesting point is that, for the runs of length 1 day, the actual number of runs is predominantly less than the expected number of runs. However, for runs of length 4 or more days, the actual number is mostly greater than the expected number. These results support the Omet (1990) results and previous runs test analyses, and suggest that the indices price series could not be characterised as random walk. The next chapter will investigate whether these short term trends of similar price changes could be utilized by a trader to increase the expected profit, by applying the filter techniques.

Table 4-6: Distribution of Runs by Length for the Actual and Expected Runs of each Sign

General Index

(+)ve Runs				(-)ve Runs				(0) Runs			
Length	**Proba.**	**Expected**	**Actual**	**Length**	**Proba.**	**Expected**	**Actual**	**Length**	**Proba.**	**Expected**	**Actual**
1	0.503	193.5	168	**1**	0.501	193.5	139	**1**	0.997	2.0	2
2	0.250	96.5	80	**2**	0.250	96.5	101	**2**	0.003	0.0	0
3	0.125	48.1	56	**3**	0.125	48.1	41	**3**	0.000	0.0	0
4	0.062	24.0	34	**4**	0.062	24.0	42	**4**	0.000	0.0	0
5	0.031	12.0	18	**5**	0.031	12.0	21	**5**	0.000	0.0	0
6	0.015	6.0	12	**6**	0.015	6.0	16	**6**	0.000	0.0	0
7	0.008	3.0	7	**7**	0.008	3.0	13	**7**	0.000	0.0	0
8	0.004	1.5	4	**8**	0.004	1.5	4	**8**	0.000	0.0	0
Other	0.002	0.7	7	**Other**	0.002	0.7	9	**Other**	0.000	0.0	0
Total	0.998	385.3	386	**Total**	0.998	385.3	386	**Total**	1.000	2.0	2

Bank Index

(+)ve Runs				(-)ve Runs				(0) Runs			
Length	**Proba.**	**Expected**	**Actual**	**Length**	**Proba.**	**Expected**	**Actual**	**Length**	**Proba.**	**Expected**	**Actual**
1	0.504	205.7	194	**1**	0.503	205.7	163	**1**	0.993	6.0	6
2	0.250	102.0	75	**2**	0.250	102.2	91	**2**	0.007	0.0	0
3	0.124	50.6	57	**3**	0.124	50.8	64	**3**	0.000	0.0	0
4	0.061	25.1	44	**4**	0.062	25.3	27	**4**	0.000	0.0	0
5	0.030	12.4	17	**5**	0.031	12.5	25	**5**	0.000	0.0	0
6	0.015	6.2	8	**6**	0.015	6.2	17	**6**	0.000	0.0	0
7	0.007	3.1	6	**7**	0.008	3.1	8	**7**	0.000	0.0	0
8	0.004	1.5	3	**8**	0.004	1.5	8	**8**	0.000	0.0	0
Other	0.002	0.8	4	**Other**	0.002	0.8	6	**Other**	0.000	0.0	0
Total	0.998	407.3	408	**Total**	0.998	408.2	409	**Total**	1.000	6.0	6

Table 4-6: Continued

Industry Index											
(+)ve Runs				(-)ve Runs				(0) Runs			
Length	Proba.	Expected	Actual	Length	Proba.	Expected	Actual	Length	Proba.	Expected	Actual
1	0.503	194.2	167	1	0.501	194.2	141	1	0.996	3.0	3
2	0.250	96.5	85	2	0.250	97.0	93	2	0.004	0.0	0
3	0.124	47.9	57	3	0.125	48.4	50	3	0.000	0.0	0
4	0.062	23.8	33	4	0.062	24.2	41	4	0.000	0.0	0
5	0.031	11.8	15	5	0.031	12.1	19	5	0.000	0.0	0
6	0.015	5.9	10	6	0.016	6.0	18	6	0.000	0.0	0
7	0.008	2.9	10	7	0.008	3.0	11	7	0.000	0.0	0
8	0.004	1.5	3	8	0.004	1.5	5	8	0.000	0.0	0
Other	0.002	0.7	6	Other	0.002	0.8	10	Other	0.000	0.0	0
Total	0.998	385.3	386	Total	0.998	387.3	388	Total	1.000	3.0	3

Insurance Index											
(+)ve Runs				(-)ve Runs				(0) Runs			
Length	Proba.	Expected	Actual	Length	Proba.	Expected	Actual	Length	Proba.	Expected	Actual
1	0.638	253.3	243	1	0.607	261.7	232	1	0.755	203.0	161
2	0.231	91.7	85	2	0.239	102.8	96	2	0.185	49.8	66
3	0.084	33.2	34	3	0.094	40.4	62	3	0.045	12.2	18
4	0.030	12.0	10	4	0.037	15.9	20	4	0.011	3.0	12
5	0.011	4.3	12	5	0.014	6.2	11	5	0.003	0.7	5
6	0.004	1.6	8	6	0.006	2.4	4	6	0.001	0.2	4
7	0.001	0.6	1	7	0.002	1.0	2	7	0.000	0.0	3
8	0.001	0.2	2	8	0.001	0.4	0	8	0.000	0.0	0
Other	0.000	0.1	2	Other	0.000	0.1	4	Other	0.000	0.0	0
Total	1.000	397.0	397	Total	1.000	430.9	431	Total	1.000	269.0	269

Table 4-6: Continued

Service Index											
(+)ve Runs				(-)ve Runs				(0) Runs			
Length	**Proba.**	**Expected**	**Actual**	**Length**	**Proba.**	**Expected**	**Actual**	**Length**	**Proba.**	**Expected**	**Actual**
1	0.510	215.2	216	**1**	0.504	215.2	167	**1**	0.986	11.8	12
2	0.250	105.5	85	**2**	0.250	106.7	121	**2**	0.014	0.2	0
3	0.122	51.7	50	**3**	0.124	52.9	50	**3**	0.000	0.0	0
4	0.060	25.3	27	**4**	0.061	26.3	28	**4**	0.000	0.0	0
5	0.029	12.4	14	**5**	0.030	13.0	27	**5**	0.000	0.0	0
6	0.014	6.1	16	**6**	0.015	6.5	13	**6**	0.000	0.0	0
7	0.007	3.0	6	**7**	0.007	3.2	9	**7**	0.000	0.0	0
8	0.003	1.5	2	**8**	0.004	1.6	6	**8**	0.000	0.0	0
Other	0.002	0.7	6	**Other**	0.002	0.8	6	**Other**	0.000	0.0	0
Total	0.998	421.3	422	**Total**	0.998	426.2	427	**Total**	1.000	12.0	12

4.4.2.5 Runs Above and Below

A run is counted every time the price series rises above or falls below a cut point measure (which may be the mean, median, mode, or any other chosen value). Each price observation is classified with either a + or - to indicate whether the price is above or below the cut point (theoretically, an observation could equal the cut point, and in this case according to SPSS package, the observation is classified as +). After classifying the observations, they are investigated for "runs". Unlike the runs before, the runs sought this time are of consecutive numbers that share the property of being above or below the cut point. Then, the number of numbers above the cut point is counted, as well as the number of numbers below the cut point. Lastly, the total number of runs is counted. The computation of the cutting point, number of runs, and significance level, are as follows: (according to the SPSS guide as this package is the used to perform the test).

Computation of Cutting Point

The cutting point which is used to dichotomize the data can be specified as a particular number, or the value of a statistic which is to be calculated. The possible statistics are:

$$Mean = \sum_{i=1}^{N} X_i / N \qquad \textbf{(4-16)}$$

$$Median = \begin{cases} \left(X_{(N/2+1)} + X_{(N/2)}\right)/2 & \text{if } N \text{ is even} \\ X_{((N+1)/2)} & \text{if } N \text{ is odd} \end{cases} \tag{4-17}$$

where the data are sorted in an ascending order from $X_{(1)}$, the smallest, to $X_{(N)}$, the largest. The mode is the most frequently occurring value. If there are multiple modes, the one largest in value is selected.

Numbers of runs:

For each observation, the difference between the observation and the cut point is computed,

$$D_t = X_t - Cutpoint \tag{4-18}$$

If $D_t \geq 0$, the difference is considered positive. Otherwise it is negative. The number of times the sign changes, that is, $D_t \geq 0$ and $D_{t+1} < 0$, or $D_t < 0$ and $D_{t+1} \geq 0$, as well as the number of positive (n_p) and negative (n_a) signs, are determined. The number of runs *(R)* is the number of sign changes plus one.

Significance Level:

The sampling distribution of the number of runs *(R)* is approximately normal with

$$\mu_r = \frac{2n_p n_a}{n_p + n_a} + 1 \tag{4-19}$$

$$\sigma_r = \sqrt{\frac{2n_p n_a (2n_p n_a - n_a - n_p)}{(n_p + n_a)^2 (n_p + n_a - 1)}} \tag{4-20}$$

The two-sided significance level is based on

$$z = \frac{R - \mu_r}{\sigma_r} \tag{4-21}$$

4.4.2.6 Empirical results

The observed mean, median, and mode are used as cut points. Cases with values less than the cut point are assigned to one group, and cases with values greater than or equal to the cut point are assigned to another group. One test is performed for each cut point chosen.

Tables 4.7, 4.8, and 4.9 present the results for the five series of indices daily prices for the period from 1st January 1992 to 30th June 2001, considering the mean, median, and mode of the daily prices as cut points.

Table 4-7: Runs Above and Below the Median Test

	General	Banks	Insurance	Industry	Services
Test Value	152.8	190.4	124.6	115.9	114.0
Cases < Test Value	1172	1172	1171	1172	1172
Cases >= Test Value	1173	1173	1174	1173	1173
Total Cases	2345	2345	2345	2345	2345
Number of Runs	55	12	22	39	35
Z	-46.2**	-47.9**	-47.5**	-46.8**	-47.0**

** Significant at 1% level

Table 4-8: Runs Above and Below the Mean Test

	General	Banks	Insurance	Industry	Services
Test Value	150.3	192.9	129.8	113.5	121.4
Cases < Test Value	1030	1223	1501	1056	1385
Cases >= Test Value	1315	1122	844	1289	960
Total Cases	2345	2345	2345	2345	2345
Number of Runs	39	20	14	23	17
Z	-46.8**	-47.6**	-47.8**	-47.5**	-47.7**

** Significant at 1% level

Table 4-9: Runs Above and Below the Mode(1) Test

	General	Banks	Insurance	Industry	Services
Test Value	160.7	216.7	122.8	117.0	100.2
Cases < Test Value	1597	1618	990	1257	172
Cases >= Test Value	748	727	1355	1088	2173
Total Cases	2345	2345	2345	2345	2345
Number of Runs	41	22	44	45	39
Z	-46.5**	-47.4**	-46.6**	-46.6**	-42.7**

** Significant at 1% level

(1)There are multiple modes. The mode with the largest data value is used.

The "Test Value" in each output table corresponds to the statistic value used as the cut point. Referring to the Z statistics reported by the above tables, all the tests show that the null hypothesis of randomness can not be rejected. Hence, runs tests using all three measures of central tendency (median, mean, and mode) are consistent with previous results demonstrated in this chapter. On the other hand, these results contradict the findings of Karemera, Ojah, and Cole (1999); they reported that the hypothesis of independence can not be rejected at the 5% level for the Jordanian equity return series[20]. However, the other tests used in their study, simple and multiple

[20] In order to compare results of this section with Karemera, Ojah, and Cole (1999), the runs tests are reproduced for both the daily and monthly returns and prices series for the five indices from 1/1/1992 to 30/7/2001, since they used the monthly returns, for the period 1987:12 to 1997:5. The results for both daily prices and returns and monthly prices and returns are similar in rejecting the null hypothesis

variance ratio tests, suggest that the Jordanian market is not weak-form efficient. In The study of Karemera, Ojah, and Cole (1999) consisted of 114 monthly observations of the returns covering the period from 1987:12 to 1997:5. The returns series is used to perform the runs test

4.5 Conclusion

Empirical literature suggests that the price behaviour in developed markets can be characterized as random walk. However, it is still controversial in the case of developing countries. The empirical results obtained in this chapter for the ASE suggests that it is not weak-form efficient. The ASE reflects a high degree of positive temporal dependency patterns, violating the assumption of random walk model.

However, this does not necessarily imply a violation of weak form efficiency. As Ko and Lee (1991) state that if the random walk hypothesis holds, the weak-form of the

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that the return series of the indices follow a random walk. Furthermore the runs test above and below the median is conducted for the monthly prices and returns series from 31/1/1978 to 31/12/2002, which cover the period from inception up to date, the data is obtained from Morgan Stanley Capital Information (MSCI). The results supported the rejection for randomness at 1% level when using price series, however, the results could not support the rejection for randomness at 1 % level when using return series.

It is worth mentioning that the daily data for Jordan index obtained from (MSCI) is not reliable, Friday in Jordan is a holiday and there is no trading, nevertheless, MSCI insert the observation of Thursday twice on Thursday and Friday (see the following sample).

Monday	06/01/2003	173.01
Tuesday	07/01/2003	173.19
Wednesday	08/01/2003	172.04
Thursday	**09/01/2003**	**172.27**
Friday	**10/01/2003**	**172.27**
Monday	13/01/2003	173.75
Tuesday	14/01/2003	174.41
Wednesday	15/01/2003	175.82
Thursday	**16/01/2003**	**175.52**
Friday	**17/01/2003**	**175.52**

efficient market hypothesis must hold, but not vice versa. Thus, evidence supporting the random walk model is evidence of market efficiency. But violation of the random walk model need not be evidence of market inefficiency in the weak form. Hence, the autocorrelation found in the ASE in the return series does not necessarily mean that the returns are predictable[21]. More tests are applied in the next chapters to investigate the models that fit the generating process of the ASE data. In order to examine whether the predictive ability can enable investors to beat the market, trading rules are applied in the next chapter.

[21] For example, noise traders whose demand for stocks is determined by factors other than their expected returns could be an explanation for this autocorrelation (Uruttia, 1995). Government intervention policies also may case stock price changes to be positively correlated (Liu and He, 1991). Furthermore, stock index returns may show positive autocorrelation if some of the securities in the index trade infrequently (Poterba and Summers, 1988). They suggest that if small stocks trade less frequently than larger stocks, then new information is incorporated first into larger stock prices and then into smaller stock prices with a lag, this lag induces a positive serial correlation.

CHAPTER 5

Technical Analysis Rules

Contents:

Summary

The results in Chapter 4 reflected significant positive dependency patterns in stock prices. This chapter investigates whether these results could be exploited, through technical analysis, to outperform the simple buy-and-hold policy. Filter rules and moving average techniques are used; the results suggest that technical analysis helps predict stock price changes in the ASE. Furthermore, and for the results of moving average techniques, standard statistical testing is extended through the use of bootstrap techniques. According to the moving average rule, buy and sell signals are generated by two moving averages of the level of the index (long and short period averages). The conditional returns on buy or sell signals from actual data are compared to the conditional returns from simulated series generated by a range of models (random walk with a drift, AR (1), and GARCH-(M)).

5.1 Introduction

Technical analysis forecasts future price trends through the identification of recurring patterns in historical prices, and claims it is capable of exploiting the trends that it discovers. Hence, the general goal of technical analysis is to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data. The vast majority of professional traders use technical analysis; Allen and Taylor (1990) found that technical analysis is used by over 90 percent of foreign exchange dealers in the London market to inform their forecasts one to four weeks ahead. However, most academics, until recently, had not recognized the validity of these methods (Lo, Mamaysky, and Wang, 2000).

Technical analysis attempts to predict and exploit the trends occurring in price movements. Hence, price movement is affected by the changing attitudes of investors towards many forces (economic, monetary, political, and psychological), and these forces are predictable (Pring, 1985). Although several trading rules exist, they generally all aim to identify the initiation of new trends. Filter rules and moving average intersections are two of the simpler rules. Such rules are not expected to generate excess profits in an efficient market, according to the weak-form of the efficient market hypothesis (EMH). As historical price information is already reflected in the present price, technical analysis is totally useless for predicting future price movements.

Since the seminal work of Friedman (1953) and Fama (1970), the role of technical analysis as a forecasting mechanism has been considered controversial in literature. Early work seemed to indicate weak form and probably semi strong form efficiency

(Alexander 1964; Fama and Blume; Jensen and Benington 1970). However, more recent work has established strong evidence that simple forms of technical analysis contain significant forecasting power (Pruitt and White, 1988; Neftci, 1991; Brock, Lakonishok, and LeBaron, 1992; Neely, Weller, and Dittmar, 1997; Neely and Weller, 1998; Chang and Osler, 1994; Osler and Chang, 1995; and Allen and Karjalainen, 1999).

In this chapter, the forecasting power of two simple trading rules, the filter and the moving average rules, will be investigated. The aim is to study, in this emerging market (ASE), the extent to which alternative filter rules and moving average trading rules forecast future prices and hence are profitable. Additionally, this chapter aims to study the performance of the trading rule under alternative specifications for the underlying generating process (namely, random walk, AR1, GARCH-M). In each case, the model is fitted to the original data – and the residuals from that model are used in a bootstrap methodology as developed by Efron (1979), Freedman and Peters (1984), Efron and Tibshirami (1986), and Brock, Lakonishok and Lebaron (1992). The bootstrap technique can be used to generate trading rule returns for any given model of the underlying generating process. The comparison between returns from simulated series and those for the actual series reveals that actual trading profits are consistent to a certain limit with those that would be generated using any of the three fitted models (random walk, an AR(1), or a GARCH-M model).

The remainder of this chapter is structured as follows: Section 5.2 gives a briefing about the technical analysis theory and how it is considered, by some researchers, as an alternative to the equilibrium theories and market efficiency. Section 5.3 reviews the empirical studies that have applied technical analysis in stock markets. Some studies have found technical analysis to be ineffective and to not outperform the simple buy-and-hold strategy, while others have found some value in it. Section 5.4 describes the filter rule technique, and how the rate of return for filter rules and for the buy-and-hold strategy is calculated. Afterwards, the empirical results of filter rules are compared with buy-and-hold strategies for the five indices. Additionally, the returns per filter are shown separately for long and short transactions. Section 5.5 presents the description of fourteen alternative moving average trading rules, followed by empirical results for the fourteen rules, including the number of buy and sell signals, the mean return for buy, sell, and buy-sell signals and their *t-statistic*. Section 5.6 explores, using the bootstrap methodology, the extent to which trading results are consistent with alternative specifications of the price generation process. The functional forms used for modeling the price generation process are RW, AR1, and GARCH-M. The summary and conclusion are then presented in Section 5.7.

5.2 Technical Analysis Theory

Technical analysis is considered by some researchers as a contradiction to the equilibrium theories of market efficiency (Rode, et al., 1995), e.g., if it is possible to earn abnormal returns using technical analysis, then this casts doubts on the equilibrium theories of market efficiency. Evidence against the notion that capital markets are efficient is now wide spread in empirical studies. Hawawini and Keim (1994) provide a comprehensive econometric analysis of international equity market inefficiencies, and Rode (1995) reviews the decision-theoretic literature on capital market efficiency (see also Vaga, 1990; Peters, 1991; Allen and Karjalainen, 1993;

Peters, 1994; and Vaga, 1994). Hence, markets – at the very least- are not perfectly efficient, and since capital market efficiency is almost always discussed in the context of investor rationality, rationality itself must also be questioned.

Various studies have found constraints imposed on investors that affect their decisions- such as time and memory (Newell and Simon, 1972; Simon, et al., 1987). The decision environment for investors usually compels investors to make decisions with incomplete and even unknown information and under time pressure. The flow of information exceeds investors' abilities to process it completely (floor traders have to make decisions immediately after new information is released), indicating that investors have bounded rationality[1]. There has been increasing interest in bounded rationality; early behavioural work suggested that individuals do not optimize, they satisfy and simplify complex decision problems through the use of, more or less, arbitrary rules of thumb (Dobbs, 2000). In such an environment, investors cannot make optimal decisions; instead, they will use heuristics, adapted over time, to make reasonably good decisions when faced with complex problems.

The equilibrium models –such as CAPM and APT- hold when investors behave rationally. However, if investors are quasi-rational[2], then the CAPM and APT cease to be correct determinates of market equilibrium because of the systematic error embedded in quasi-rational behaviour. As a conclusion, markets are inefficient

[1]Rational behavior, in economics, means that individuals maximize some target function under the constraints they face (e.g., their utility function) in pursuit of their self-interest (Savage, 1954). The term bounded rationality is used to designate rational choice that takes into account the cognitive limitations of both knowledge and cognitive capacity. The premise of the rational expectations hypothesis is that economic variables are generated by systematic processes. Over time, economic agents learn what the process determining a variable is and they will use this knowledge to form expectations of that variable (Muth, 1961).

[2] Quasi rationality goes beyond the conventional notions of rationality and irrationality. It denotes less than fully rational (Thaler, 1994).

because investors cannot behave optimally due to the constraints imposed by the task environment. Thus, investors use heuristic rules when making decisions, and as a result, the market deviate from efficiency in ways that traditional equilibrium models cannot begin to incorporate.

The concept of technical trading rule theory is that technical trading rules represent efficient heuristic rules which can help to make good investing decisions. In other words, technical analysis tries to predict a complex time series with one which is easier to calculate and forecast. Although such an analysis is extremely complicated, various works has been done on the predictive power of technical analysis and the results were found to be supportive of the technical rule approach (see for example, Naftci, 1991; Blume, Easeley, and O'Hara, 1994). Sears and Trennepohk (1993) interpreted why technical analysis might work and identified five principle factors:

- Security price is determined solely by its supply and demand.
- Prices tend to move in trends that persist for an appreciable time.
- Changes in trends depend on changes in supply and demand.
- The patterns of trends tend to repeat themselves over time.
- Supply and demand are governed by both rational and irrational factors.

According to the second factor, technical analysis differs from the market efficiency theory in that it considers trends in prices to be persistent, while the market efficiency theory proposes that such irregularities would disappear in the aggregate as irrational acts tend to cancel out one another.

The main problem of technical trading rules is that the forecasting ability of the rules seem to persist for only a short period, and therefore, must be changed over time. The mechanism of how to create metarules, which determine which technical rules are used in which environments, is beyond the scope of this study.

5.3 Review of Empirical Studies

Technical analysis is considered one of the original tools of investment analysis, and has been a part of financial practice since the 1800s. It attempts to forecast prices by detecting patterns in stock prices. It has been used to examine the efficient market hypothesis by investigating predictability of equity returns based on past returns. Some studies (e.g. Chopra, Lakonishok, and Ritter (1992) , and Fama and French (1986)) found negative serial correlations in returns of individual stocks and various portfolio, while other studies found negative serial correlations in first lags and positive correlations in longer lags (e.g. Jegadeesh (1990)). Predictability of stock returns, manifested in various forms of stock market anomaly (such as the size effect, the turn-of-the-year effect, the weekend effect, the earning/price (E/P) effect, and the momentum effect) was viewed in the early literature as evidence of stock market inefficiency.

More recently, the concept of market efficiency has been increasingly refined, and other explanations have been developed (for example, time-varying equilibrium returns, non-linear generating processes (see Neftci (1991), Hsieh (1991), Hsieh (1995), Antoniou, Ergul, and Holmes (1997), and Brorsen and Yang (1994)).

Several researchers have denied the forecasting power of analytical techniques, arguing that such techniques usually cannot produce better returns than a buy-and-hold (B-H) strategy. The filter trading rule was one of the most investigated trading rules in the finance literature. Many filter rules were tested on the US stock market and most of them conclude that filter rules do not only generate superior returns to B-H strategy, but the returns could even be negative when the cost of transactions is considered (Alexander 1964; Fama and Blume 1966; Jensen and Benington 1970). These results are consistent with the efficient market hypothesis in the way that the current price reflects all available information, and thus, investors cannot expect abnormal returns by using technical analysis.

However, market professionals tend to include technical analysis in forecasting the market and there is also a shift away from the fundamentals to technical analysis in the 1980's, according to a survey done by Euromoney (Frankel and Froot, 1990a). When there is information influencing the future economic prospects of the firm, such information could assist in developing a successful trading strategy. This is because whatever the fundamental reason for a change in the stock price, if the stock price is sluggish to adjust, the analyst can identify a trend that could be exploited during the adjustment period. Therefore, the key to successful technical analysis is a lazy response of stock prices to fundamental supply and demand phenomena. This condition is opposite to the notion of the efficient market.

Whilst early studies often found technical analysis to be ineffective, much of the later work has found some value in it. For example, Fama and Blume (1966) found no profits for the best (0.5 percent) filter rule after adjusting for transaction costs, utilizing the Dow 30 of the late 1950s) whilst the later study by Sweeny (1988). based on the same sample of stocks but for a later period, concluded that mechanical trading rules did have profit potential. Recent work has often found that technical analysis can be an effective means for extracting information from market prices (see for example Pruitt and White (1988), Neftci (1991), Brock, Lakonishok and LeBaron (1992), Neely, Weller, and Dittmar (1997), Neely and Weller (1999), Chang and Osler (1994), and Osler and Chang (1995)).

The moving average rules and the filter rules are two types of trading strategies which are used extensively. As a matter of fact, these two families of rules constitute only the very primitive level of the practical strategies normally conducted in the financial markets. The moving average form of technical analysis is extremely popular amongst practitioners and has been extensively studied in the academic literature (e.g. Neill (1931), Schabacker (1930), Gartley (1930), Caslow (1966), LeBaron (1990), Brock, Lakonishok and LeBaron (1992), Roberts (1959), Brealey (1969), Fama and Blume (1966) and Jensen and Benington (1970)).[3] Much of this work focussed on major stock markets such as the NYSM, but more recently there have been several studies on emerging markets. For example, Renter and Leal (1999) examined the potential profit of technical trading strategies among 10 emerging equity markets in Latin America and Asia. Technical trading strategies were found to be profitable for some markets, but not for others. Bessembinder and Chan (1995) investigated some trading rules by using the daily equity market indices of six Asian countries over the period 1975-1991. The results indicated different forecasting abilities among these markets.

[3] Whilst some forms of technical analysis can be viewed as 'art' or 'subjective judgement', the advent of computerised trading systems has led to great interest by practitioners in technical trading rules which can be programmed and hence automated - and this motivates the question of whether it is possible to earn abnormal profits by the use of such rules.

One might expect that technical analysis might well 'work' rather better in emerging markets than in developed markets - and there is some evidence that this is in fact the case. For example Harvey (1995) concluded that autocorrelation is much higher in emerging than in developed markets (see also Bekaert and Harvey (1995) Bekaert and Harvey (1997), Claessens, Dasgupta, and Glen (1995), Campbell (1996), Jochum, Kirchgassner and Platek (1999)). In view of this, one would expect technical trading rules to perform rather better in such emerging markets.

The aim of the present chapter is to investigate a further case study to this developing strand in literature by examining to what extent the ASE behaves in similar ways to these other markets. An interesting feature of the ASE, which differs from most other stock markets, lies in the extremely low level of transaction costs[4]. Early studies (such as Brock, Lakonishok and LeBaron (1992)) often ignored these costs when considering the performance of alternative forms of trading rules. Omet (1990) calculated the return of the filter technique, using 16 share prices from the ASE, before and after deducting transaction costs, and compared it with the buy-and-hold strategy. He concluded that the filter technique produced greater profits than the buy-and-hold strategy before and even after deducting transaction costs. It can be argued that these costs are so low in the case of the ASE, that there is, in practice, no need to make any adjustment for such costs. Of course, low transaction costs should, *ceteris paribus*, help to promote market efficiency.

[4] The broker commissions in ASE vary form 0.54% to 0.74% of the transaction value. Whilst, in other Arab countries, Lebanon for example, the commission charges may reach 4% of the transaction value (www.bse.com.lb/bse.htm)

5.4 Filter Rules

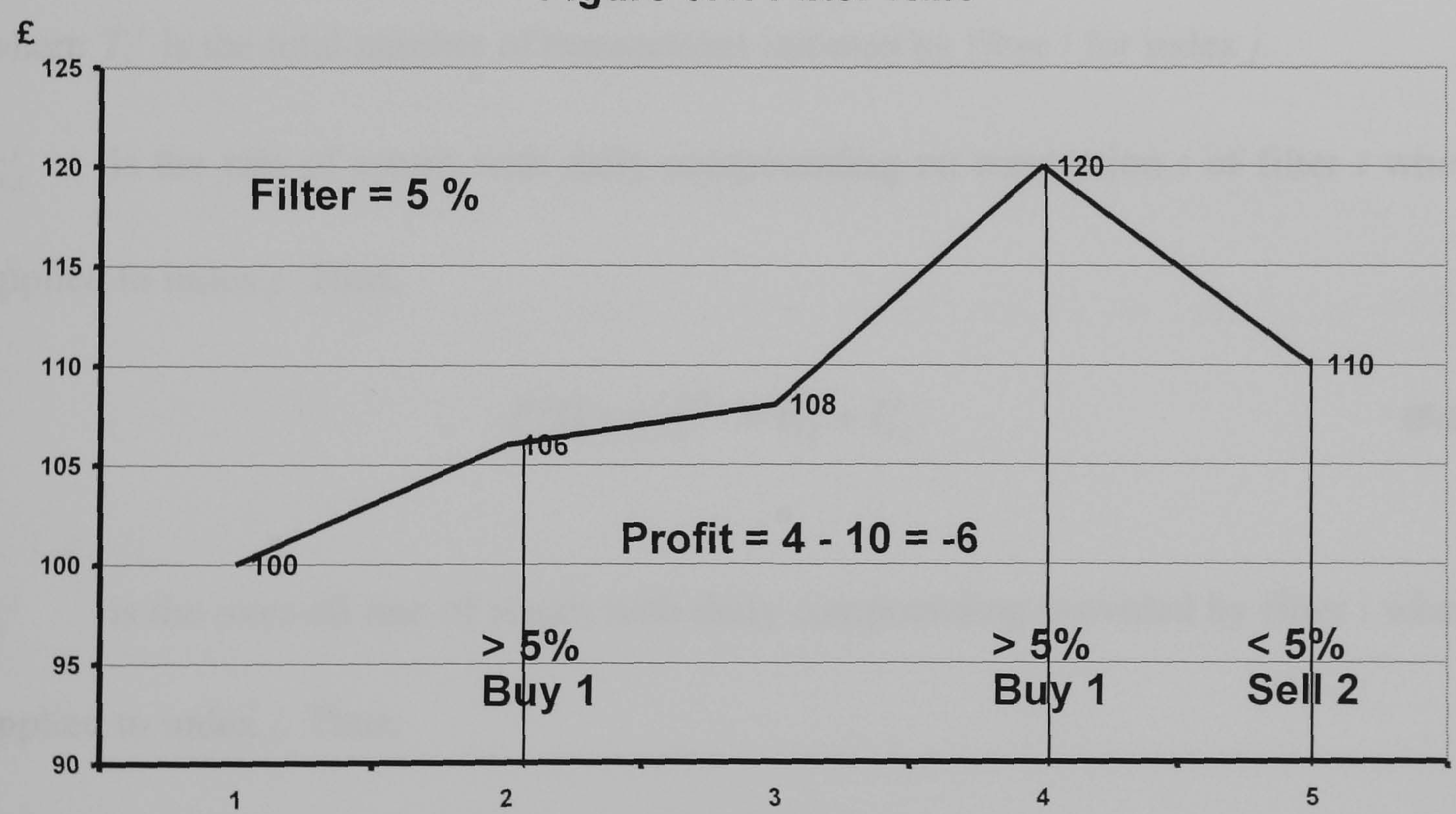
The most notable work in this field is the work of Alexander (1961). This specifies a mechanical trading rule based solely on past price changes. If a trading rule can be used to make the expected profit greater than that of the simple buy-and-hold rule, then a case against the assumption of independence of successive price changes can be made. Thus, this strategy is based upon the assumption that price changes are serially correlated and that there is price momentum, that is, the stock which has gone up strongly in the past is more likely to keep going up than going down.

An X% filter, e.g. 1% is defined as follows: A security is purchased when its price moves up at least X%, and hold until its price moves down at least X% from a subsequent height, at which time the security is sold (short). The short position is maintained until the price is raised at least X% above a subsequent low, at which time security is purchased. Moves less than X% in either direction are ignored. This means that if the stock market has moved up X% it is likely to move up more than X% further before it moves down by X% (Refer to Appendix 3).

In applying the filter technique, an initial position is taken as soon as there is an up-move or a down-move where the total price change is equal to or greater than X%. The position is assumed to be taken on the first day for which the price change equals or exceeds the X% limit. The price on the day a position is opened defines a reference price: a peak in the case of a long transaction and a trough in the case of a short transaction. The position is checked on each subsequent day whether it (the position) should be closed or not, i.e. whether the current price is X% below the reference (peak) price in a long position or X% above the reference (trough) price if the open position is short. If the current position is not to be closed, the reference price should be checked whether it must be changed. In a long position, the reference price must be changed when the current price exceeds the reference price meaning that a new peak has been attained, whereas in a short position a new trough will be attained when the current price is below the reference price (See Figure 5.1). When the reference price changes, all subsequent testing uses the new value as base.

The rate-of-return calculated under the filter technique is compared with the rate-of-return under a buy-and-hold policy.

Figure 5.1: Filter Rule



The calculations of the rate-of-return for index (j) and filter size (i) is conducted as follows (Fama and Blume, 1966) (Refer to Appendix 3):

$P_{t,i}^{j}$ is the closing price of the index j for the day in which transaction t for filter i was initiated.

$I_{t,i}^{j}$ is the profit on transaction t of filter i when applied to index j. The profits are capital gains.

$n_{t,i}^{j}$ is the duration in terms of total trading days of transaction t for filter i when applied to index j.

N_i^j is the total number of trading days during which positions were open under filter i when applied to index j. Thus

$$N_i^j = \sum_{t=1}^{T_i^j} n_{t,i}^{j} \qquad \textbf{(5-1)}$$

where T_i^j is the total number of transactions initiated by filter i for index j.

$r_{t,i}^{j}$ is the rate of return with daily compounding on transaction t of filter i when applied to index j. Thus,

$$P_{t,i}^{j}[1 + r_{t,i}^{j}]^{n_{t,i}^{j}} = P_{t,i}^{j} + I_{t,i}^{j} \qquad \textbf{(5-2)}$$

r_i^j is the over-all rate of return with daily compounding provided by filter i when applied to index j. Thus,

$$r_i^j = \left\{ \prod_{t=1}^{T_i^j} \left[1 + r_{t,i}^{j}\right]^{n_{t,i}^{j}} \right\}^{1/N_i^j} - 1 \qquad \textbf{(5-3)}$$

R_i^j is the nominal annual rate of return for filter i when applied to index j. Thus,

$$R_i^j = 260 r_i^j \quad ^{5} \tag{5-4}$$

R_i^j are the returns shown for filter technique (F) in Table(5.1).

${}_bR_i^j$ is the nominal annual rate of return from buy-and-hold during the time period for which filter i had open positions in index j. Thus,

$${}_bR_i^j = 260\, {}_br_i^j \tag{5-5}$$

where ${}_br_i^j$ is defined as:

$${}_br_i^j = \left\{ \prod_{t=1}^{T_i^j} \left[1 + {}_br_{t,i}^j\right]^{n_{t,i}^j} \right\}^{1/N_i^j} - 1 \tag{5-6}$$

where ${}_br_{t,i}^j = r_{t,i}^j$ if the corresponding filter transaction is long, and ${}_br_{t,i}^j = -r_{t,i}^j$ if the corresponding filter transaction is short. ${}_bR_i^j$ are the returns reported for the buy-and-hold policy (B) in Table(5.1). This procedure for computing buy-and-hold returns is necessary to insure that the buy-and-hold returns cover exactly the same basis as the returns under the filter technique (Refer to Appendix 3).

5.4.1 Data

Data tested were the daily prices of the five indices in ASE from 1st January 1992 to 30th June 2001 (excluding dividend yields)[6]. The period of the study commences at 1/1/1992, as at this date, the Amman Stock Exchange (ASE) changed the form of calculation for the Price Index (from unweighted to market capitalization weighted). A base value of 100 points on December 31st, 1991 was stipulated for the new

[5] Following Fama and Blume (1966), the simple interest rate is used for 260 holding days. The difference between the simple and compound rate is negligible.

[6] Many researchers confirm that their conclusions remain unchanged whether they adjusted their data for dividend or not (for example, Lakonishok and Smidt, 1988; Fishe, Gosnell and Lasser, 1993).

Weighted Price Index (refer to section 3.5.3.2.6). Indices are good proxies for the market, as they reflect a broad base and are composed of relatively actively traded stocks, thereby eliminating thin trading or specific firm effects. Additionally, the presentation of each sector by different index helps in comparison and advance analyses. The five indices calculated in ASE are the General, Banks, Insurance, Industry, and Service indices.

5.4.2 Empirical Results of Filter Rules

Alexander's filter technique has been applied to the series of daily prices for the five indices of Amman Stock market from 1st January 1992 to 30th June 2001. Eleven different filters (0.1%, 0.5%, 0.8%, 1%, 1.2%, 1.4%, 1.6%, 1.8%, 2%, 2.5%, 3%) have been simulated.

As shown in Table (5.1), for each index and filter size, buy-and-hold returns are computed only for the period during which active positions are open under the filter rule, which requires that multiple buy-and-hold figures be reported for each security. The difference between the filter returns and buy-and-hold returns are also calculated.

- The results show that for all ASE indices, filters of 0.1%, 0.5%. 0.8% and 1% produced greater profits than the buy-and –hold strategy, which is considered a violation of the random walk hypothesis (the transactions cost was neglected since it is very small (around 0.006)) and not expected to effect the results). For larger than 1% filters, the buy-and-hold strategy starts outperforming the filter technique for some indices. It is noticeable that when the filter size increases the difference between filter returns and buy-and-hold returns becomes lesser or to the favour of the buy-and-hold returns. On the other hand, the results for the largest filters are probably not reliable since the number of transactions is very small. Omet (1990) reported similar results as he applied the filter test to 16 shares from the ASE using the daily prices for the period of 1980 to 1988. The filter technique produced greater profits than the buy-and-hold strategy even after deducting transaction costs. However, for larger than a 2.0% filter, the buy-and-hold rule starts outperforming the filter technique. On the other hand, over the entire eight year period, the average result of all filters outperformed that of the buy-and-hold rule.[7]

- In Table (5.2) the returns per filter are showed separately for long and short transactions. Although the returns are computed in the same way as those in Table (5.1) column (F), the returns in Table (5.1) column (F) are not a simple average of the returns on long and short positions. In order to use Table (5.2) to compute the returns in Table (5.1) column (F), it is necessary to know the number of days that the long and short positions are open. The breakdown of returns for long and short transactions shows that the long positions returns outperform the short positions and buy-and-hold returns. If the filter technique were restricted to long positions, it would outperform the buy-and-hold strategy. The short positions produced negative returns for some indices higher than 1%, and this is disastrous for the investor.

These results support and complement the results of Chapter 4. In Chapter 4, results reflected a high degree of positive dependency patterns, violating the assumption of

[7] Omet (1990) used filters of 0.1%, 0.2%, 0.3%, 0.4%, 0.5%, 1.0%, 1.5%, 2.0%, 2.5%, 3.0%, 4.0%, and 5.0%. The difference between the return of the filter technique and the buy-and-hold strategy is tested to see whether or not it is statistically significant. For the average of all filters, the differences between the results of the filter technique and the buy-and-hold strategy are statistically significant.

the random walk model. However, whether these findings could be used to increase one's expected profits was not investigated. Filter rules investigate if the stock market trader could utilize market inefficiencies to consistently increase his profits over a naïve buy-and-hold strategy, and develop trading strategies that would allow him to earn abnormal returns. Filter rules suggest that prices are predictable to a certain limit. However, this technique experiences different biases. One of the major sources of bias which overestimates the profitability of the filter technique is that the filter rule is based on the assumption that a trader could always get his transactions executed at the previous closing price.

If we assume that a trader could get his transactions executed at the previous closing price, then the above conclusion would lead us to consider the question of why such a technique is not used by traders. We must realize that ASE participants are largely unprofessional. Broking firms do not have research departments and do not carry out analysis of the quoted companies, and do not use modern investment techniques and security analysis. If this is the case, then it is difficult to envisage ordinary shareholders carrying out statistical (among others) tests even on past prices in order to predict (if possible) future price changes.

Table 5-1: Comparison of Annual Rates of Returns under the Filter Rule (F) and Buy and Hold Strategy (B)

Filter Size 0.1%

Index	N.T[1]	F[2]	B[3]	Difference
General	1816	0.408	0.063	0.345
Bank	1895	0.406	0.144	0.262
Industry	1962	0.462	-0.049	0.511
Insurance	1344	0.197	0.108	0.089
Service	1906	0.398	0.111	0.287

Filter Size 0.5%

Index	N.T	F	B	Difference
General	756	0.343	0.134	0.209
Bank	852	0.310	0.151	0.159
Industry	908	0.365	0.048	0.317
Insurance	414	0.194	0.149	0.045
Service	865	0.374	0.146	0.228

Filter Size 0.8%

Index	N.T	F	B	Difference
General	370	0.309	0.189	0.120
Bank	480	0.261	0.221	0.040
Industry	412	0.438	0.183	0.255
Insurance	218	0.304	0.232	0.072
Service	523	0.312	0.173	0.139

Filter Size 1%

Index	N.T	F	B	Difference
General	261	0.262	0.238	0.024
Bank	338	0.225	0.216	0.009
Industry	371	0.429	0.247	0.182
Insurance	154	0.267	0.233	0.034
Service	375	0.303	0.136	0.167

Filter Size 1.2%

Index	N.T	F	B	Difference
General	178	0.349	0.232	0.117
Bank	239	0.222	0.251	-0.029
Industry	262	0.334	0.236	0.098
Insurance	133	0.245	0.214	0.031
Service	270	0.276	0.142	0.134

Filter Size 1.4%

Index	N.T	F	B	Difference
General	123	0.169	0.221	-0.052
Bank	188	0.269	0.311	-0.042
Industry	197	0.299	0.227	0.072
Insurance	107	0.282	0.265	0.017
Service	202	0.237	0.165	0.072

Table 5.1: Continued

Filter Size 1.6%

Index	N.T	F	B	Difference
General	85	0.055	0.150	-0.095
Bank	144	0.282	0.335	-0.053
Industry	151	0.240	0.167	0.073
Insurance	86	0.243	0.240	0.003
Service	140	0.241	0.163	0.078

Filter Size 1.8%

Index	N.T	F	B	Difference
General	61	0.042	0.201	-0.159
Bank	110	0.199	0.207	-0.008
Industry	115	0.164	0.079	0.085
Insurance	68	0.233	0.260	-0.027
Service	106	0.165	0.218	-0.053

Filter Size 2%

Index	N.T	F	B	Difference
General	42	-0.050	0.247	-0.297
Bank	87	0.178	0.179	-0.001
Industry	87	0.014	0.090	-0.076
Insurance	53	0.303	0.324	-0.021
Service	87	0.210	0.223	-0.013

Filter Size 2.5%

Index	N.T	F	B	Difference
General	21	-0.236	0.130	-0.366
Bank	51	0.146	0.103	0.043
Industry	45	-0.030	-0.105	0.075
Insurance	34	0.069	0.086	-0.017
Service	41	-0.237	-0.033	-0.204

Filter Size 3%

Index	N.T	F	B	Difference
General	13	-0.563	-0.196	-0.367
Bank	29	0.130	0.067	0.063
Industry	27	-0.191	-0.075	-0.116
Insurance	11	-0.167	0.109	-0.276
Service	20	-0.220	0.102	-0.322

(1) Number of Transactions.
(2) Returns According to Filter Rule
(3) Returns According to Buy and Hold Strategy

Table 5-2: Breakdown of Annual Rate of Return by Filter

Filter Size 0.1%						
	LONG			SHORT		
Index	R[1]	N.T[2]	T.D[3]	R	N.T	T.D
General	0.54	902	2589	0.305	914	3335
Bank	0.625	904	2442	0.232	991	3081
Industry	0.522	889	2341	0.422	1073	3538
Insurance	0.363	641	2176	0.076	703	2962
Service	0.565	903	2489	0.26	1003	2996

Filter Size 0.5%						
	LONG			SHORT		
Index	R	N.T	T.D	R	N.T	T.D
General	0.472	400	1955	0.21	356	1893
Bank	0.465	448	1954	0.157	404	1970
Industry	0.491	433	1987	0.272	475	2709
Insurance	0.374	215	1503	0.041	199	1778
Service	0.616	419	1700	0.196	446	2303

Filter Size 0.8%						
	LONG			SHORT		
Index	R	N.T	T.D	R	N.T	T.D
General	0.459	212	1283	0.131	158	1072
Bank	0.484	261	1358	0.039	219	1353
Industry	0.67	165	1495	0.228	247	1855
Insurance	0.621	121	955	0.063	97	1253
Service	0.588	286	1344	0.117	225	1899

Filter Size 1%						
	LONG			SHORT		
Index	R	N.T	T.D	R	N.T	T.D
General	0.411	159	1115	0.029	102	711
Bank	0.429	193	1059	0.006	145	990
Industry	0.705	200	1170	0.172	171	1260
Insurance	0.521	90	852	0.031	64	920
Service	0.499	194	1266	0.148	181	1599

Filter Size 1.2%						
	LONG			SHORT		
Index	R	N.T	T.D	R	N.T	T.D
General	0.369	119	940	0.274	59	253
Bank	0.384	153	939	-0.041	86	580
Industry	0.565	146	873	0.097	116	851
Insurance	0.528	78	746	0.027	55	964
Service	0.464	147	1042	0.121	123	1254

Filter Size 1.4%						
	LONG			SHORT		
Index	R	N.T	T.D	R	N.T	T.D
General	0.3	83	651	-0.078	40	346
Bank	0.44	123	824	-0.066	65	421
Industry	0.534	117	702	0.069	80	731
Insurance	0.599	68	709	0.015	39	839
Service	0.419	116	855	0.068	86	919

Table 5.2: Continued

Filter Size 1.6%

	LONG			SHORT		
Index	**R**	**N.T**	**T.D**	**R**	**N.T**	**T.D**
General	0.162	56	457	-0.135	29	259
Bank	0.469	98	721	-0.081	46	370
Industry	0.461	82	638	0.064	67	797
Insurance	0.44	57	731	0.002	29	587
Service	0.393	86	600	0.078	54	557

Filter Size 1.8%

	LONG			SHORT		
Index	**R**	**N.T**	**T.D**	**R**	**N.T**	**T.D**
General	0.172	40	424	-0.279	21	172
Bank	0.342	71	612	-0.012	39	414
Industry	0.325	62	426	0.066	53	703
Insurance	0.455	45	532	-0.03	23	448
Service	0.302	70	499	-0.077	36	282

Filter Size 2%

	LONG			SHORT		
Index	**R**	**N.T**	**T.D**	**R**	**N.T**	**T.D**
General	0.152	26	265	-0.443	16	134
Bank	0.282	60	601	-0.003	27	344
Industry	0.11	52	380	-0.076	35	407
Insurance	0.646	35	366	-0.022	18	386
Service	0.326	58	478	-0.024	29	237

Filter Size 2.5%

	LONG			SHORT		
Index	**R**	**N.T**	**T.D**	**R**	**N.T**	**T.D**
General	-0.093	12	93	-0.407	9	78
Bank	0.187	36	450	0.063	15	220
Industry	-0.159	26	206	0.061	19	291
Insurance	0.238	20	224	-0.014	14	459
Service	-0.174	28	227	-0.45	13	68

Filter Size 3%

	LONG			SHORT		
Index	**R**	**N.T**	**T.D**	**R**	**N.T**	**T.D**
General	-0.881	6	49	-0.327	7	66
Bank	0.174	21	261	0.071	8	197
Industry	-0.225	15	187	-0.143	12	136
Insurance	-0.07	6	82	-0.232	5	122
Service	-0.074	11	169	-0.692	9	52

(1)Annual Rate of Return by Filter
(2)Number of transactions.
(3)Total Number of Trading Days during which positions were open.

5.5 Moving Average Trading Rules

5.5.1 Data and Technical Trading Rules

The Amman Stock Market Index:

The data series used is the daily General index of Amman stock market from 1/1/1992 to 30/7/2001. The period of the study commences at 1/1/1992 because at this date, the Amman Stock Exchange (ASE) changed the form of calculation for the Price Index (from unweighted to market capitalization weighted) A base value of 100 points on December 31st, 1991 was stipulated for the new Weighted Price Index.

The ASE index is calculated using the latest closing prices and published on a daily basis. It is composed of 60 companies listed on the Regular Market, the selection of these companies being based on the following five criteria which represent the companies' size and liquidity: market capitalization, days traded, turnover ratio, value traded and the number of shares traded. Sector representation is also considered when selecting these companies. The number of companies included in the index sample was increased to 70 companies at the beginning of August, 2001, hence the choice of end date for the analysis. Within the period, the ASE indices have been adjusted to maintain their continuity and to safeguard them from exceptional events.

The Moving Average Trading Rule

The moving average rule is one of the most widely used rules in technical analysis (see for example de Jong and Penzer(1998), Gencay and Sangos(1997), Lui and Mole(1998), Gencay(1998), Neely and Weller(1999), Ojah and Karemera(1999), Ratner and Leal(1999), Szakmary, Davodson and Schwarz(1999), Couts and Cheung(2000), and Goodacre and Kohn-Speyer(2001)) . A moving average is an average of observations of the level of the index over several consecutive time periods. The objective is to smooth out seasonal variation in the data. The standard moving average rule, which utilizes the price line and the moving average of price, generates buy/sell signals as explained by Gartley (1935):

"In an uptrend, long commitments are retained as long as the price trend remains above the moving averages. Thus, when the price trend reaches a top, and turns downward, the downside penetration of the moving average is regarded as a sell signal.... Similarly, in a downtrend, short positions are held as long as the price trend remains below the moving average. Thus, when the price trend reaches a bottom, and turns upward, the upside penetration of the moving average is regarded as a buy signal"

There are numerous variations and modifications that can be applied to this rule. In this study, two moving averages are used to generate trading signals. Buy and sell signals are generated by crossovers of a long moving average (calculated over L days) by a short moving average (S days, $S < L$). That is, the buying signal is generated when the short-period moving average moves higher than the long-period moving average:

$$\frac{\sum_{s=1}^{S} P_{t-(s-1)}}{S} > \frac{\sum_{\lambda}^{L} P_{t-(\lambda-l)}}{L} \quad \Rightarrow \quad Buy\,at\,time\ t \tag{5-7}$$

where P_t is the price at time t. Sell signals are generated when the inequality is reversed: that is,

$$\frac{\sum_{s=1}^{S} P_{t-(s-1)}}{S} < \frac{\sum_{\lambda}^{L} P_{t-(\lambda-l)}}{L} \quad \Rightarrow \quad Sell\ at\ time\ t \tag{5-8}$$

The empirical work examines a range of moving averages for the short and long periods ($S = 1,5$ whilst $L = 2,5,10,25,50,100,150,200$ days). Note that the special case where $S = 1$ is the moving average rule as described above by Garley (1935). The ranges for S,L above cover all the moving average rules typically used in practice. Perhaps the most popular of these rules is the 1-200 rule ($S = 1, L = 200$), where the short period is one day and the long period is 200 days (Brock, Lakonishok and Lebaron (1992)). The shorter the size of the moving average, the closer it follows the market, and the longer the size of the moving average, the more it smooths market fluctuations. Thus a rule with $S = 1$ is very responsive – in that whenever the actual return rises above (below) the moving average, the signal is to buy (sell).

5.5.2 Empirical Results

Summary Statistics for Traditional Tests

Summary statistics for the ASE general index are presented in Table (5.3), and for comparison purposes, so are parallel results for the S&P500. The return is calculated as log differences in the index level (excluding dividend yields). Whilst the average return on the ASE over the time period 1992-2001 is about one third that of the S&P, its variance is somewhat less. This is an interesting observation in its own right: most emerging markets manifest higher volatility than established markets. Kurtosis is comparable, but skewness lies in the opposite direction to that commonly manifested by stock markets. Perhaps the most significant feature is that, in contrast to the S&P500 case, in the ASE there is significant first order autocorrelation (the partial autocorrelation coefficient value of 0.26648 is massively significant). This indicates that stock returns in the ASE are, to an extent, predictable on the basis of past price history. The fall away in the partial autocorrelation coefficients after lag 1 is also suggestive that the underlying generating process for the ASE might be characterised as AR1 (this is studied below).

Table 5-3: Summary Statistic for Daily Returns

Returns are measured as log differences of the level of the index. AC is the estimated autocorrelation and PAC is the estimated partial autocorrelation at lags 1,2,3,4and 5.Q-Stat is the Ljung-Box Q-statistic

	Jordan	S&P				Jordan		
					AC	PAC	Q-Stat	Prob
Mean	0.000154	0.000427		1	0.266418	0.266418	166.6577	3.97E-38
Standard Deviation	0.006831	0.009639		2	0.012861	-0.06256	167.0463	5.33E-37
Sample Variance	0.000047	0.000093		3	-0.02	-0.00754	167.9863	3.46E-36
Kurtosis	5.796881	5.294313		4	-0.02805	-0.02119	169.8358	1.13E-35
Skewness	0.422431	-0.27279		5	-0.01864	-0.0068	170.653	5.29E-35
Range	0.090551	0.121014				**S&P**		
Minimum	-0.04310	-0.07112			AC	PAC	Q-Stat	Prob
Maximum	0.047449	0.049887		1	-0.005	-0.005	0.0717	0.789
Observations	2345	2345		2	-0.03	-0.03	2.35	0.309
				3	-0.053	-0.053	9.2809	0.026
				4	-0.007	-0.008	9.3969	0.052
				5	-0.019	-0.023	10.334	0.066

The moving average rules:

Table (5.4) displays the results for fourteen alternative rules. The rules differ in the length set for the short and long period averages. For example, (2,150) denotes that the short average is 2 days and the long average is 150 days. The entire sample is divided into buy and sell periods, depending on the relative position of the moving averages. This rule imitates a trading strategy where the trader buys when the short moving average penetrates the long from below and stays in the market until the short moving average penetrates the long moving average from above, after which the trader moves out of the market or sells short.

The number of buy and sell signals reported during the sample are shown in Table 5.4 as N (Buy) and N (Sell). The daily mean of buy and sell periods are reported in columns 4 and 5 along with the corresponding *t-statistic*. The latter examines the difference between the unconditional mean (0.000154 as shown in Table 5.3) and the conditional mean for buy and sell periods in order to investigate any predictability for the rule. The *t-statistic* for buys is calculated as $\dfrac{\mu_b - \mu}{(\sigma^2 / N + \sigma^2 / N_b)^{1/2}}$, where μ_b and N_b are the mean return and number of signals for the buys, and μ and N are the unconditional mean and number of observations.[8] The estimated variance for the entire sample is denoted as σ^2. The *t-statistic* for sells is calculated similarly by using μ_S and N_S as the mean return and number of signals for the sells instead of μ_b and N_b. In columns 6 and 7, the fraction of buy and sell returns greater than zero is reported. The last column lists the differences

[8] σ^2 is the estimated variance for the entire sample.

between the mean daily buy and sell returns with corresponding *t-statistic*. calculated

as $\frac{\mu_b - \mu_s}{(\sigma^2 / N_b + \sigma^2 / N_s)^{1/2}}$.

In other words, if technical analysis does not have any power to forecast price movements, then the returns on days when the rules emit buy signals should not differ appreciably from returns on days when the rules emit sell signals.

Table 5-4: Test Results for the Trading Rules

Results for daily prices from 1992 -2000. Rules are identified as (short, long) where short is the short moving average and long is the long moving average. N(Buy) and N(Sell) are the number of buy and sell signals reported during the sample. Bold numbers are standard *t*-ratios testing the difference of the mean buy and mean sell from the unconditional mean, and buy-sell from zero. Buy >0 and Sell >0 are the fraction of buy and sell returns greater than zero. The last row reports the averages across all 14 rules.

Rule	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1, 2)	1102	1239	0.0018	-0.0013	0.6758	0.3388	0.0032
t-statistic			(6.74)**	(-6.19)**			(11.20)**
(1, 5)	1093	1248	0.0014	-0.0009	0.6349	0.3874	0.0023
t-statistic			(4.93)**	(-4.59)**			(8.25)**
(1, 10)	1079	1257	0.0010	-0.0006	0.5994	0.4276	0.0016
t-statistic			(3.45)**	(-3.20)**			(5.76)**
(1, 25)	1165	1156	0.0007	-0.0005	0.5739	0.4475	0.0012
t-statistic			(2.39)**	(-2.47)**			(4.21)**
(1, 50)	1152	1144	0.0006	-0.0003	0.5597	0.4672	0.0009
t-statistic			(1.76)	(-1.80)			(3.08)**
(1, 100)	1141	1105	0.0004	-0.0001	0.5407	0.4848	0.0005
t-statistic			(0.99)	(-1.14)			(1.84)
(1, 150)	1185	1011	0.0004	-0.0002	0.5389	0.4826	0.0005
t-statistic			(0.95)	(-1.18)			(1.83)
(1, 200)	1150	996	0.0004	-0.0002	0.5356	0.4773	0.0006
t-statistic			(0.82)	(-1.35)			(1.86)
(5, 10)	1078	1257	0.0006	-0.0002	0.5585	0.4715	0.0008
t-statistic			(1.74)	(-1.66)			(2.95)**
(5, 25)	1153	1168	0.0005	-0.0002	0.5514	0.4772	0.0007
t-statistic			(1.40)	(-1.46)			(2.48)**
(5, 50)	1153	1143	0.0004	-0.0001	0.5387	0.4918	0.0004
t-statistic			(0.88)	(-0.92)			(1.56)
(5, 100)	1131	1115	0.0003	0.0000	0.5291	0.4991	0.0003
t-statistic			(0.52)	(-0.65)			(1.01)
(5, 150)	1185	1011	0.0003	0.0000	0.5274	0.4987	0.0003
t-statistic			(0.46)	(-0.64)			(0.95)
(5, 200)	1151	995	0.0003	-0.0001	0.5258	0.4911	0.0003
t-statistic			(0.40)	(-0.89)			(1.12)
Average			0.0006	-0.0003			0.0010

Notes:

[1]: The *t-statistic* ratio which tests the hypothesis that the differences of the mean buy returns generated by technical trading rules from mean unconditional return are zero.

[2]: The *t-statistic* ratio which tests the hypothesis that the differences of the mean sell returns generated by technical trading rules from mean unconditional return are zero.

[3]: The *t-statistic* ratio which tests the hypothesis that the differences of the mean buy returns from the mean sell returns are zero.

** denotes $p < 0.01$

As shown in Table 5.4 the number of buy and sell signals generated are fairly similar for all trading rules. The rest of this section discusses the results. However, before turning to these, it is important to note that, since returns are manifestly non-normal (refer to Table 5.3), the *t-tests* of significance have unknown properties, so 'significance' results below are only suggestive. In the following section, a bootstrap methodology is used to derive empirical distributions for the test statistics. This in itself is not a complete solution of course, since applying the bootstrap requires an assumption regarding the underlying generating process. This issue is discussed further in Section 5.6 below.

In columns 4 and 5, the buy returns are all positive with an average one-day return of 0.0006 compared with an unconditional mean of 0.000154. Four of the fourteen tests reject the null hypothesis that the average buy return equals the unconditional average return at the 1 percent significance level using a two-tailed test. The results are systematic, the shorter the moving average, the more significant the result. In the case of the sell return, all are negative with an average one-day return of -0.0003 compared with unconditional mean of 0.000154.

Four of the fourteen tests also reject the null hypothesis that the sell returns are equal to the unconditional return. The fraction of buys and sells greater than zero shown in the Table 5.4 presents material differences between buys and sells. Under the null hypothesis, the fraction of positive returns should be the same for both buys and sells. The last column in Table 5.4 shows that the buy-sell differences are positive and the t-test for seven of the fourteen tests are highly significant, which rejects the null hypothesis of equality of zero. Regarding "Buy>0" and "Sell>0" statistics, the buy fraction is consistently greater than 50 percent, while that for all sells is considerably less.

5.6 Parametric Bootstrap Methodology

The objective of this section is to explore, using the bootstrap methodology, the extent to which the above trading results are consistent with alternative specifications of the underlying price generating process (random walk, AR1 and GARCH-M are considered). For stock returns, there are several well-known deviations from normality, stationarity and time-independence, such as leptokurtosis, autocorrelation, and conditional heteroskedasticity (see Table 5.3). Whilst the 't-statistics' calculated and reported in Table 5.3 give some indication of statistical significance, the theoretical distribution of such statistic is unknown. The bootstrap is a method for estimating the distribution of an estimator or test statistic by resampling one's data or a model estimated from the data. It can provide approximations to distributions of statistics, coverage probabilities of confidence intervals, and rejection probabilities of hypothesis tests that are more accurate than the approximations of first-order asymptotic distribution theory.

However, whilst the parametric bootstrap provides a useful approach to hypothesis testing in situations where the distribution of standard test statistics is unknown, it is worth mentioning that it is an embedded approach, conditional on the specific functional forms used for modeling the volatility process in this study (that is, RW, AR1 or GARCH-M).(These models are studied further in Chapter 6)

The bootstrap methodology also allows the development of a joint test of significance for the set of trading rules in this study. Thus, the basic idea is to compare the time series properties of simulated data from a given model with those from actual data. First, the postulated models are estimated and then bootstrap samples are generated. Next, the trading rule profits are computed for each of the bootstrap samples, and compared with the trading rule profits derived in Section 5.2.2 from actual data. Using this methodology, it is also possible to examine the standard deviations of returns during the buy and sell periods, thus giving an indication of the riskiness of the various strategies.

The bootstrap methodology, which was introduced by Efron (Efron (1979)), requires that information in the sample is "recycled" according to a specific data-generation process to get the sampling distributions of the statistics of interest. It works as follow: Let $(y_1, y_2, \ldots, y_n)$ be the given sample. Draw a sample of size n from this sample with replacement and denote the j^{th} bootstrap sample as $B_j = (y_1^*, y_2^*, \ldots, y_n^*)$, where each y_i^* is a random pick from $(y_1, y_2, \ldots, y_n)$. This step is repeated for $j=1,2,\ldots,m$ and $\hat{\theta}_j$ is computed for each of the bootstrap samples B_j. The distribution of $\hat{\theta}_j$ is the estimated bootstrap distribution for the estimator θ. Clearly, the number of bootstraps m is likely to affect the 'tightness' with which the distribution is estimated. Although asymptotic properties are unknown for this, it is possible to get a crude assessment of the extent of convergence by repeating the bootstrap process for different values for m. In what follows, we report results for m=500 and m=2000. The results generally indicate that the choice of m=2000 is 'large enough'.

Specifying the bootstrap data generating process (DGP) is required in order to generate bootstrap samples with the same characteristics that the real sample would have had if the null hypothesis were true. The null hypothesis of whether the performances of the technical trading rules are consistent with these DGPs are tested under the probability distributions of the performance measures. The DGPs used are outlined below.

5.6.1 Random Walk Model

The random walk model is

$$r_t = b + \varepsilon_t \tag{5-9}$$

(so prices 'walk with drift'). The return series is simulated by scrambling the actual returns (log price difference) of the index. This scrambling procedure involves randomly drawing from the actual series with replacement. The scrambled series will have the same unconditional distribution, same average drift in prices, and the same volatility. The returns of the scrambled series are independent and identically distributed. With the simulated return series exponentiated back to a simulated price series (the first observation of the actual price is used as a first observation of simulated price), the trading rules can then be applied to the simulated price series.

5.6.2 AR(1) Model

The autoregressive model is the second model for the simulation:

$$r_t = b + \rho r_{t-1} + \varepsilon_t \tag{5-10}$$

where r_t is the return on day t and ε_t is independent, identically distributed. The parameters and the residuals are estimated using actual returns of the index. The residuals are then resampled with replacement and used with estimated parameters to generate simulated $AR(1)$'s series. In this model, an autoregressive process that generates stock returns could be responsible for the 'abnormal' returns from the trading strategy, and this model is applied to detect whether the results from the trading rules could be caused by daily serial correlation in the series.

As the ASE index contains the majority of ASE stocks, a non-negligible fraction of them is relatively illiquid and therefore stable prices (due to stocks which are not traded every day) could explain the larger first-order autocorrelation.

5.6.3 GARCH-M Model

It is interesting to investigate the GARCH model as most financial data usually exhibit volatility clustering, perhaps due to increased uncertainty from new information arrival and the time delay for traders to adjust to it.

As mentioned in Chapter 3, the charts for the indices show different volatility over time, and Chapter 4 suggests a high autocorrelation in return series. Hence, GARCH model investigate whether the return variances are autocorrelated or predictable. Also, there is a yearly pattern in dividend payments, which tend to be concentrated in April and May. The clustering of dividends could produce the GARCH effect in the indices series.

The GARCH-M model with MA term is:

$$r_t = \alpha + \gamma h_t + b\varepsilon_{t-1} + \varepsilon_t \tag{5-11}$$

$$h_t = \alpha_0 + \alpha_1 e^2{}_{t-1} + \beta h_{t-1} \tag{5-12}$$

$$\varepsilon_t = h_t^{1/2} z_t \qquad z_t \sim N(0,1) \tag{5-13}$$

where the residual (ε_t) is conditionally normally distributed with zero mean and conditional variance (h_t) and its standardized residuals (z_t) is i.i.d. N(0,1). In this model the conditional returns are a linear function of the conditional variance, h_t, and past disturbance. The conditional variance is a linear function of the square of the last period`s errors and of the last period's conditional variance. Hence, the expected returns are a function of volatility and past returns, and volatility can change over time. The parameters and the standardized residuals are estimated using actual returns of the index. The standardized residuals are then resampled with replacement and used with the estimated parameters to generate the simulated GARCH-M series. Since only the standardized residuals are resampled with replacement, the heteroskedastic structure captured in the GARCH-M model is maintained in simulations. Table (5.5) presents the results of estimated models, which will be used for comparison with the actual index series.

Table 5-5: Parameter estimates for AR(1), and GARCH Models

PanelA:AR(1) Parameter Estimates

$$r_t = b + \rho r_{t-1} + \varepsilon_t$$

	b	*P*
	0.00011	0.26642
t-statistic	(0.8220)	(13.3769)**
Prob.	0.411	0

Panel B:GARCH-M Parameter Estimates

$$r_t = \alpha + \gamma h_t + b\varepsilon_{t-1} + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 e^2{}_{t-1} + \beta h_{t-1}$$
$$\varepsilon_t = h_t^{1/2} z_t$$

$z_t \sim N(0,1)$

	α_0	A_1	B	α	γ	b
	3.44E-06	0.21851	0.711161	-4E-04	8.933	0.25744
t-statistic	(10.4004)**	(12.5907)**	(41.6014)**	(-1.915)	(1.556)	(11.1528)**
Prob.	8.50E-25	3.20E-35	1.27E-283	0.0557	0.12	3.50E-28

As shown in Panel A in Table (5.5), there is a significant first order autocorrelation for the index returns series (ρ = 0.266). Panel B presents the results for the GARCH-M model. They show that the conditional variance of stock returns is time varying and is auto correlated. An insignificant positive relation is present between the conditional variance and conditional mean. The *b* parameter indicates a positive significant first order autocorrelation in the series.

5.6.4 Empirical Results

The results of the three model simulations (Random Walk, AR(1) process, GARCH-M process) are displayed in Tables (5.6, 5.7, and 5.8). Panel A in these tables presents the results for each trading rule. All the numbers presented are the fraction of the simulated result which is larger than the results for the index series. 'Buy', 'Sell' and 'Buy-Sell' columns present results for returns, 'SD Buy' and 'SD Sell' columns present the result for the associated standard deviations. In panel B of Tables (5.6, 5.7, and 5.8), the results are summarized across all the rules. The simple average over the fourteen rules is used to calculate rule averages. For each of 500 and 2000 simulations, an average over all the rules for both returns and standard deviations are computed. The first row of Panel B (Fraction>Actual) follows the same format as the results presented in Panel A. The second row (Mean) presents the returns and standard deviations for the Buys, Sells and Buy-Sells, averaged over the 500 and 2000 simulations. The third row (Actual) presents the same statistic for the original index series.

Random Walk Process

The number in Table (5.6) under Buy column in the first row (1.000) shows that all of the simulated random walks generated a mean buy return larger than the mean buy return from the original index series. This number can be considered as a simulated "*p*-value". The number (0.000) under the Sell column shows that none of the simulated random walks generated mean sell returns larger than the mean sell return from the original index series. The number in the Buy-Sell column (1.000) reports that all of the simulated random walks generated mean buy-sell differences larger than the mean differences for the original series. In the column SD Buy the reported number is (1.000), showing that all of the standard deviations for the simulated random walks are greater than the standard deviations for the original index series, and the number (1.000) under the SD Sell column shows that also all of the standard deviations for the simulated random walks are greater than the standard deviation for the original index series. It is noticeable that the results for (1,2) rule are very different (opposite sign) from the results for the following rules. None of the simulated random walk series for the following three rules generated mean buy returns higher than the mean buy returns from the original index series, and all of the simulated random walk series for the following three rules generated mean sell returns higher than the mean sell returns from the original index series. It implies that the random walk process could explain the predictability of the (1,2) rule since the first autocorrelation is very high. Regarding the results for the Buy returns, seven rules out of fourteen are significant at 5% level for both 500 and 2000 bootstrap. It is noticeable that as the moving average becomes longer, the significance of the rule decreases - except for (1,2) rule. For Sell returns, seven rules show significant differences between the sell and unconditional returns, while ten rules produced significant differences between Buy and Sell returns.

In Panel B, the first row shows insignificant differences between conditional and unconditional means for the rule average. The Mean row - which presents the returns and standard deviations for the buys, sells, and buy-sells, averaged over the 500 and 2000 simulated random walks- shows that the Buy returns are less than the number reported in the Actual row which presents the statistic for the original index. The Sell returns are higher than the Actual, and as a result the number under the Buy-Sell (0.00063) is less than the Actual differences between Buy-Sell (0.00098). The standard deviations for Buys and Sells are close to the numbers reported in the Actual row.

The *p-values* in general cannot reject the null hypothesis that the random walk process is consistent with the data generating process of stock index return. The high fractions given (or simulated *p-values* which are above 5% level) indicate that many of the simulated random walks generated values close to those from the original series. The less the *p-value* the more significant, and less due to chance, are the results of the strategies on the actual series. In other words, the random walk process is capable of generating these results. On the other hand, some rules (with simulated *p-values* less than 5%) suggest that the results generated by the strategies on the actual series is not referred to random walk process, which supports weak form market inefficiency. As shown in Panel B Buy-Sell column, only around 10% of all simulated series produced higher return than actual series, and the mean of Buy-Sell return for the simulated series (0.00063) is less than the actual Buy-Sell return (0.00098). Hence, random walk process reduced the differences between buy and sell returns.

Table 5-6: Simulation Tests From Random Walk Bootstrap for 500 and 2000 Replications

			Panel A				
Rule	**Result**		**Buy**	**SD Buy**	**Sell**	**SD Sell**	**Buy-Sell**
(1, 2)	Fraction>Actual	500bootstrap	1	1	0	1	1
		2000bootstrap	**1**	**1**	**0**	**1**	**1**
(1, 5)	Fraction>Actual	500bootstrap	0	0.212	1	0.924	0
		2000bootstrap	**0**	**0.179**	**1**	**0.91**	**0**
(1, 10)	Fraction>Actual	500bootstrap	0	0.384	1	0.662	0
		2000bootstrap	**0**	**0.3775**	**1**	**0.6755**	**0**
(1, 25)	Fraction>Actual	500bootstrap	0	0.35	1	0.618	0
		2000bootstrap	**0.0015**	**0.349**	**0.9995**	**0.6305**	**0**
(1, 50)	Fraction>Actual	500bootstrap	0.006	0.49	0.986	0.426	0
		2000bootstrap	**0.006**	**0.4945**	**0.991**	**0.4275**	**0.0005**
(1, 100)	Fraction>Actual	500bootstrap	0.058	0.384	0.924	0.62	0.022
		2000bootstrap	**0.068**	**0.395**	**0.935**	**0.6265**	**0.0195**
(1, 150)	Fraction>Actual	500bootstrap	0.068	0.268	0.944	0.692	0.02
		2000bootstrap	**0.0815**	**0.265**	**0.947**	**0.708**	**0.0225**
(1, 200)	Fraction>Actual	500bootstrap	0.106	0.3	0.962	0.63	0.016
		2000bootstrap	**0.119**	**0.3075**	**0.9585**	**0.632**	**0.0225**
(5, 10)	Fraction>Actual	500bootstrap	0.014	0.474	0.978	0.504	0.002
		2000bootstrap	**0.01**	**0.463**	**0.9825**	**0.54**	**0.0005**
(5, 25)	Fraction>Actual	500bootstrap	0.034	0.588	0.974	0.378	0.004
		2000bootstrap	**0.0345**	**0.553**	**0.968**	**0.399**	**0.006**
(5, 50)	Fraction>Actual	500bootstrap	0.1	0.592	0.882	0.322	0.05
		2000bootstrap	**0.1205**	**0.5605**	**0.879**	**0.3465**	**0.044**
(5, 100)	Fraction>Actual	500bootstrap	0.212	0.402	0.828	0.608	0.116
		2000bootstrap	**0.237**	**0.394**	**0.7835**	**0.605**	**0.1325**
(5, 150)	Fraction>Actual	500bootstrap	0.238	0.32	0.802	0.612	0.116
		2000bootstrap	**0.254**	**0.336**	**0.792**	**0.6065**	**0.134**
(5, 200)	Fraction>Actual	500bootstrap	0.258	0.348	0.894	0.584	0.082
		2000bootstrap	**0.2835**	**0.355**	**0.874**	**0.576**	**0.0955**
			Panel B				
	Fraction>Actual	500bootstrap	0.149571	0.436571	0.869571	0.612857	0.102
		2000bootstrap	**0.15825**	**0.430643**	**0.865**	**0.620214**	**0.10554**
	Mean	500bootstrap	0.000504	0.005182	-0.00013	0.00465	0.000629
		2000bootstrap	**0.000503**	**0.005174**	**-0.00013**	**0.004658**	**0.00063**
	Actual		0.001436	0.005228	-0.0011	0.004282	0.002538

AR(1) Process:

Table (5.7) repeats the previous results for a simulated AR(1) process utilizing the estimated residuals from the original series. The aim of this test is to detect if the daily serial correlations are responsible for the results from the trading rules. That is, if the returns are positively autocorrelated, higher returns are expected on the following days. Table (5.6) shows some support for this. The *p-values* for all rules – except (1,2) rule- for mean buy returns, mean sell returns, and buy-sell returns are higher than 10%, which means the null hypothesis that the AR(1) process is consistent with the data generating process of stock index return cannot be rejected. The *p-values* for simulated AR(1) process in general are higher than those for simulated RW process, indicating AR(1) would appear to be a better representation for the original series. Panel B of the table confirms that some differences between Buys and Sells occur with an AR (1) process. More than 22% of the simulated series generated higher returns than actual series. The average Buy return from the simulated AR (1) is 0.05%, and the average Sell return is -0.02%. This compares with an unconditional return of 0.0154 %(Table 5.3) for the entire sample. Also, as shown in Panel B the mean of Buy-Sell return for the simulated series (0.00070) is less than the actual Buy-Sell return (0.00098).

Table 5-7: Simulation Tests From AR(1) Bootstrap for 500 and 2000 Replications

			Panel A				
Rule	Result		Buy	SD Buy	Sell	SD Sell	Buy-Sell
(1, 2)	Fraction>Actual	500bootstrap	0.0300	0.0760	0.9100	0.9380	0.0100
		2000bootstrap	**0.0405**	**0.1205**	**0.8795**	**0.9575**	**0.0165**
(1, 5)	Fraction>Actual	500bootstrap	0.1560	0.2240	0.6740	0.8520	0.1460
		2000bootstrap	**0.1430**	**0.2255**	**0.6795**	**0.8255**	**0.1380**
(1, 10)	Fraction>Actual	500bootstrap	0.2580	0.3660	0.4520	0.6020	0.3500
		2000bootstrap	**0.2890**	**0.3925**	**0.4915**	**0.6125**	**0.3425**
(1, 25)	Fraction>Actual	500bootstrap	0.2780	0.2980	0.6640	0.7000	0.2100
		2000bootstrap	**0.2980**	**0.3405**	**0.6600**	**0.6500**	**0.2450**
(1, 50)	Fraction>Actual	500bootstrap	0.2680	0.4180	0.5980	0.5100	0.2660
		2000bootstrap	**0.3030**	**0.4405**	**0.6175**	**0.4955**	**0.2760**
(1, 100)	Fraction>Actual	500bootstrap	0.4160	0.3040	0.4980	0.7140	0.4460
		2000bootstrap	**0.4465**	**0.3360**	**0.5265**	**0.6870**	**0.4130**
(1, 150)	Fraction>Actual	500bootstrap	0.3360	0.1940	0.6100	0.7920	0.2660
		2000bootstrap	**0.3930**	**0.2025**	**0.6560**	**0.7645**	**0.2775**
(1, 200)	Fraction>Actual	500bootstrap	0.3440	0.2180	0.7440	0.7260	0.1900
		2000bootstrap	**0.3945**	**0.2375**	**0.7680**	**0.7105**	**0.2105**
(5, 10)	Fraction>Actual	500bootstrap	0.2100	0.4660	0.7480	0.5000	0.1500
		2000bootstrap	**0.2010**	**0.4525**	**0.7410**	**0.5300**	**0.1365**
(5, 25)	Fraction>Actual	500bootstrap	0.2200	0.4960	0.7880	0.4460	0.1200
		2000bootstrap	**0.1865**	**0.5135**	**0.8005**	**0.4455**	**0.1100**
(5, 50)	Fraction>Actual	500bootstrap	0.3180	0.4940	0.7000	0.4240	0.2240
		2000bootstrap	**0.2995**	**0.4935**	**0.6720**	**0.4285**	**0.2250**
(5, 100)	Fraction>Actual	500bootstrap	0.4040	0.3380	0.6220	0.6680	0.3140
		2000bootstrap	**0.3765**	**0.3365**	**0.6455**	**0.6865**	**0.2925**
(5, 150)	Fraction>Actual	500bootstrap	0.3980	0.2680	0.6500	0.6660	0.2840
		2000bootstrap	**0.3765**	**0.2730**	**0.6630**	**0.6935**	**0.2690**
(5, 200)	Fraction>Actual	500bootstrap	0.4080	0.2900	0.7680	0.6320	0.2260
		2000bootstrap	**0.3850**	**0.2885**	**0.7560**	**0.6525**	**0.1965**
			Panel B				
	Fraction>Actual	500bootstrap	0.2889	0.3179	0.6733	0.6550	0.2287
		2000bootstrap	**0.2952**	**0.3324**	**0.6826**	**0.6528**	**0.2249**
	Mean	500bootstrap	0.0005	0.0050	-0.0002	0.0046	0.0007
		2000bootstrap	**0.0005**	**0.0050**	**-0.0002**	**0.0046**	**0.0007**
	Actual		0.0014	0.0052	-0.0011	0.0043	0.0025

GARCH-M Process:

Table (5.8) repeats the previous results for a simulated GARCH-M process utilizing the estimated standardized residuals from the original series. Both conditional means and variances are allowed to change over time in this model. A changing conditional mean can potentially explain some of the differences between Buy and Sell returns. As shown in Panel B, GARCH-M generates an average spread (buy-sell returns) of 0.066%, compared with 0.098% for the original data, and around 20% of the simulations generated Buy-Sell returns larger than Buys-Sells generated by original data. For volatility results, given that the focal point of the GARCH-M models is to predict volatility, panel B shows the GARCH-M average standard deviation for Buys to be 0.55% which should be compared with 0.52% for the original data. The "*p*-value" of 56% reduces the significance of this difference. On the other hand, the average standard deviation for Sells for the replications is 0.46% and for the original data is 0.44% which are fairly similar. As a result, the GARCH-M model replicates the Sell returns for the original data, and also predicts the volatility for the Sell returns. These results are consistent with Omet et al (2002) study, which examined the efficiency of the Jordanian stock market and the relationship between returns and conditional volatility. An AR(1)-GARCH(1,1)-M model is estimated for the five daily indices covering the period between January 1992 and December 2000. The empirical results indicate that the return tends to exhibit high persistent volatility clustering. A significant relationship between risk and return was present in only two cases (insurance and service).

Table 5-8: Simulation Tests from GARCH-M Bootstrap for 500 and 2000 Replications

			Panel A				
Rule	**Result**		**Buy**	**SD Buy**	**Sell**	**SD Sell**	**Buy-Sell**
(1, 2)	Fraction>Actual	500bootstrap	0.096	0.536	0.974	0.81	0.022
		2000bootstrap	**0.0895**	**0.506**	**0.97**	**0.787**	**0.0265**
(1, 5)	Fraction>Actual	500bootstrap	0.098	0.63	0.96	0.628	0.026
		2000bootstrap	**0.0955**	**0.608**	**0.9505**	**0.594**	**0.035**
(1, 10)	Fraction>Actual	500bootstrap	0.202	0.69	0.86	0.442	0.102
		2000bootstrap	**0.1915**	**0.6665**	**0.8325**	**0.433**	**0.11**
(1, 25)	Fraction>Actual	500bootstrap	0.27	0.634	0.864	0.488	0.148
		2000bootstrap	**0.2805**	**0.6185**	**0.8475**	**0.464**	**0.1535**
(1, 50)	Fraction>Actual	500bootstrap	0.318	0.646	0.742	0.442	0.222
		2000bootstrap	**0.315**	**0.618**	**0.723**	**0.408**	**0.2315**
(1, 100)	Fraction>Actual	500bootstrap	0.442	0.55	0.568	0.642	0.406
		2000bootstrap	**0.4235**	**0.5305**	**0.5665**	**0.6435**	**0.396**
(1, 150)	Fraction>Actual	500bootstrap	0.39	0.448	0.68	0.78	0.276
		2000bootstrap	**0.3885**	**0.4365**	**0.6775**	**0.7535**	**0.317**
(1, 200)	Fraction>Actual	500bootstrap	0.368	0.44	0.794	0.75	0.2
		2000bootstrap	**0.3855**	**0.433**	**0.782**	**0.7185**	**0.2365**
(5, 10)	Fraction>Actual	500bootstrap	0.184	0.662	0.846	0.428	0.084
		2000bootstrap	**0.1995**	**0.6695**	**0.8535**	**0.4315**	**0.104**
(5, 25)	Fraction>Actual	500bootstrap	0.258	0.642	0.848	0.396	0.138
		2000bootstrap	**0.2625**	**0.673**	**0.8435**	**0.379**	**0.1485**
(5, 50)	Fraction>Actual	500bootstrap	0.324	0.606	0.704	0.424	0.222
		2000bootstrap	**0.3595**	**0.63**	**0.6865**	**0.4015**	**0.2835**
(5, 100)	Fraction>Actual	500bootstrap	0.372	0.486	0.622	0.676	0.32
		2000bootstrap	**0.423**	**0.505**	**0.6205**	**0.667**	**0.349**
(5, 150)	Fraction>Actual	500bootstrap	0.356	0.436	0.636	0.736	0.294
		2000bootstrap	**0.4255**	**0.4515**	**0.64**	**0.7145**	**0.339**
(5, 200)	Fraction>Actual	500bootstrap	0.39	0.42	0.768	0.708	0.238
		2000bootstrap	**0.426**	**0.4465**	**0.7475**	**0.6985**	**0.2715**
			Panel B				
	Fraction>Actual	500bootstrap	0.290571	0.559	0.776143	0.596429	0.192714
		2000bootstrap	**0.304679**	**0.556607**	**0.767214**	**0.578107**	**0.214393**
	Mean	500bootstrap	0.000494	0.005582	-0.00016	0.004653	0.00065
		2000bootstrap	**0.000503**	**0.005544**	**-0.00016**	**0.004634**	**0.000664**
	Actual		0.001436	0.005228	-0.0011	0.004282	0.002538

5.7 Conclusion:

This chapter investigates whether the findings in Chapter 4, which reflect significant positive dependency patterns, could be used to outperform the simple buy-and-hold strategy. Filter rules produced, to some extent, higher profits than buy-and-hold strategy. The breakdown of return by filter rules for long and short transactions shows that the long positions returns outperform the short positions, which is consistent with the results of moving average techniques. The moving average techniques are used to study the extent to which alternative moving average trading rule forecast future prices and hence can be profitable. The results of this part of the study generally suggest that technical analysis helps predict stock price changes in the Jordanian stock market. In common with previous studies, it was found that the returns during buy periods are larger than returns during sell periods.

Of the various trading rules investigated, the moving average rules (1,2), (1,5), (1,10), (1,25), (1,50), (5,10), and (5,25) all had significant predictive power, although several rules were significantly more effective than others.

This chapter also studied the performance of the moving average trading rule under alternative specifications for the underlying generating process (namely, random walk, AR1, GARCH-M). In each case, the model was fitted to the original data – and the residuals from that model used as the basis for a bootstrap study. The bootstrap technique was used to generate trading rule returns for each given model for the underlying generating process. The comparison between returns generated by the bootstrap and those for the actual series reveals that actual trading profits are consistent to a certain limit with those that would be generated using any of the three fitted models (random walk, an AR(1), or a GARCH-M model).

The results are largely consistent with earlier studies conducted in developed markets. For example, when Brock et al.(1992) applied the moving average rule to the daily Industrial Average of Dow Jones, the buy (sell) signals generated returns which are higher (or lower) than normal returns. Hudson et al. (1996) also adopted the same technical trading rules as Brock et al.(1992) and applied this to (UK) stock prices; the study again indicated the predictive ability of technical trading rules. The results in this paper support the results found in Bessembinder and Chan (1995) where the focus was on Asian stock markets, and generally add further weight to the idea that technical analysis can prove most productive when applied in emerging markets.

However, the interpretation of the results in this chapter must be conducted with caution as the results are subject to certain limitations. For example, the computation of the index ignores the payment of dividends on the component stocks. Ignoring dividends' yield leads to underestimation of the buy-and-hold return. The trading rule returns are also underestimated, but to a lesser extent. However, as the dividend yield is relatively low in ASE (in average it is never higher than 4% over the period except for the extraordinary 1993 year) and as the value-weighted index is used, it is expected that the effects of individual dividend payments on the index are diluted and therefore the results should be reliable.

The transaction cost is considered another limitation for interpreting the results. Although the transaction cost in ASE is considered low compared to other markets in the region, it may still affect the results once it is taken into consideration. It is worth mentioning that the transaction cost is a variable (fixed percentage) cost in ASE, and the investor can not use the broker by paying a fixed fee.

Another limitation concerns of the ability of investors to practically implement the filter rule strategy. As there is no market maker who provides offer prices for buying and selling stocks, and as the ASE suffers from thin trading and a non-negligible fraction of the index stocks is relatively illiquid, it is unrealistic to hold and trade the same equities in the same amount as the index. Hence, tracker funds are not available in the ASE and it's not easy to imitate the performance of the stock market index (or sector indices). Moreover, the variable (fixed percentage) transaction costs in ASE would make trading cost for the index portfolio significant.

CHAPTER 6

Efficiency and Price Indices Properties in ASE

Contents:

Summary

Recent econometric procedures are employed in this chapter to investigate the behavioural properties of ASE indices. Box-Jenkins estimation, irrespective of the index examined, produced different models with a high prediction performance, violating the EMH conditions. The unit-root test also confirmed these results since the return series for all indices did not exhibit unit root, and all processes were stationary. The GARCH-M(1,1) model is estimated and present mix results cross the indices. To a certain limit, the results support the existence of a significant link between conditional volatility and stock returns, and the conditional variance is found to change over time as a result of volatility clustering effects.

6.1 Introduction

Previous results in Chapter 4 suggested that the daily returns for the five indices of ASE do not follow the random walk model, as the first order autocorrelation coefficients are high and significant for all indices. Hence, there are several forecasting techniques available to identify patterns in time series data. Regression, exponential smoothing, and decomposition approaches, however, assume that the values of the time series being forecasted are statistically independent from one period to the next. As such, they are not appropriate when identifying a pattern in series which are inherently autocorrelated. Instead, the Box-Jenkins (ARMA) methodology, which does consider the statistical dependence of observations from one time period to the next, will be used. The Box-Jenkins method of forecasting is different from other methods in that it does not assume any particular pattern in the historical data of the series to be forecast. Instead, it uses an iterative approach to identify the underlying pattern. Hence, the aim of Section 6.2 is to follow this technique to identify and estimate a number of competing models which can be interpreted as having generated the data, regardless of the economic forces behind the data.

Furthermore, Section 6.3 deals with the stationary and the random walk tests. If a series displays a unit root (non-stationary), it implies that the series has no tendency to return to a mean value. That is, its behaviour is not mean-reverting and unpredictable. Nevertheless, the presence of a unit root (non-stationarity) in stock prices is only a necessary (but not sufficient) condition for a random-walk process.

On the other hand, considerable amount of research has been recently directed towards detecting nonlinear patterns and chaos of the security returns. Many of these studies (Hsieh, 1991; Willey, 1992; Sewell *et al.*, 1993; Opong *et al.*, 1999; among others) have cast doubt on the conclusion that market efficiency is based only on the lack of serial correlation in returns.

Apart from complicated nonlinear dependence, one of the well known reasons, as to why stock prices may deviate from the random walk model, is that the conditional variance of stock returns is not constant over time. This fact has led to the development of autoregressive conditional heteroscedasticity (ARCH) and generalised ARCH (GARCH) models (Engle, 1982; Bollerslev, 1986). Returns based on equity prices or indices are most often found to have time dependent conditional variance, and hence ARCH and GARCH models are used to take care of the volatility observed in the time series of returns. Some of the tests for (linear) autocorrelation mentioned earlier perform poorly in the presence of conditional heteroscedasticity in the returns. In fact, Diebold (1986), Lo and MacKinlay (1988), Silvapulle and Evans (1993) and others have noted that in the presence of ARCH, the serial correlation tests, if not corrected, can result in misleading inferences. A number of studies examined the return-volatility behaviour of a number of emerging market economies (Haque and Hassan, 2000; Harvey, 1995a,b: Harvey and Bekaert, 1995; Bekaert,1995; Bekaert and Harvey, 1997; Kim and Singal, 1999; Choudhury, 1996; Lee and Ohk, 1991; Claessens, Dasgupta and Glen, 1995). The questions of stock market volatility, persistence of volatility, and risk premia in the stock market are vital for ASE as Jordan tries to attract foreign investment and to achieve economic growth.[1]

However, volatility and market efficiency are two important features which will ultimately determine the effectiveness of the stock market in economic development. For example, in a stock market which is informationally inefficient, investors face difficulty in choosing the optimal investment as information on corporate performance is slow to materialise or simply not available. The resulting uncertainty may induce investors either to withdraw from the market until this uncertainty is resolved or discourage them from investing funds over the long term.

Moreover, on the long run, if investors are not rewarded for taking on higher risk by investing in the stock market, or if excess volatility weakens investors' confidence, they will not invest their savings in the stock market, and this will adversely affect economic growth. The emerging stock markets offer an opportunity to examine the evolution of stock return distributions and stochastic processes in response to economic and political changes in these emerging economies. Such changes are occurring in a magnitude and direction in these countries which are not typically observed in the developed stock markets.

Section 6.4 estimates the GARCH(1,1)-M model for the daily return indices, in order to investigate the link of the stock returns to risk factors expressed by volatility. As reported by Bollerslev et al. (1992), the GARCH(1,1) model appears to be sufficient to describe

[1] Refer to chapter 3 for incentives of foreign investments legislated by new regulations.

the volatility evolution of stock-return series. The summary and conclusion are then presented in Section (6.5).

6.2 Box – Jenkins Estimation

The Box-Jenkins method of forecasting uses an iterative approach. A number of competing models are identified and estimated through following the next five steps, then the simplest (the one with the smallest number of parameters) and most well performed of these models is selected (Refer also to Appendix 4).

- The first step is to difference the prices series of the indices in order to get stationarity (autocorrelation for price levels indicates non-stationarity). The price changes (first differences of price levels) are more likely to be stationary and hence are investigated (more details for stationarity is presented in Section 6.3).
- The second step is to examine the autocorrelation function (AC) and partial autocorrelation function (PAC) of the data in order to identify the appropriate orders of the AR and MA components. If the autocorrelation function dies off smoothly at a geometric rate, and the partial autocorrelations were zero after one lag, then a first-order autoregressive model would be suggested. Alternatively, if the autocorrelations were zero after one lag and the partial autocorrelations declined geometrically, a first-order moving average process would come to mind[2] (Madala, 2000).

[2] In Chapter 4, the examined data showed a significant autocorrelation, implying that the ARMA (p,q) model could describe the data.

- The third step is the estimation of the ARMA model. Different forms of ARMA model are investigated; and in order to test the significance of the estimated parameters, *t* ratios are applied. If higher orders of the estimated parameter prove to be insignificant, then the significant lower order is considered adequate to describe the process. Insignificant parameters are dropped from the model. The randomness of the residuals of the estimated models is then examined. Hence, the disturbance term must be random if the model is correctly specified. The Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) are used to decide the order of the model by choosing the model which has the minimum AIC and SBC (Refer to Appendix 4). The Ljung Box Q-statistics test for autocorrelated disturbances was also applied; these show that the residuals for the chosen models are uncorrelated[3]. On the other hand, the ARCH LM[4] test indicates heteroskedasticity in the disturbance and a strong ARCH effect in all models. Changes in variance also, referred to as conditional heteroscedasticity or stochastic volatility, can be attributed to variations in the amount and importance of relevant price information. This issue will be investigated in more detail in

[3] The residuals of the estimated models are uncorrelated but fail to pass the Jarque-Bera test for normality and have thicker than a normal tails. Thus, t-tests and other regression diagnostics should be interpreted with caution; however, their usefulness is asymptotically justified by the relatively large sample (2345 observations).
[4] Heteroskedasticity in the disturbances, just like autocorrelation, invalidates the conventional standard error formulas and the associated inference procedures. The ARCH LM procedure tests for autoregressive conditional heteroskedasticity (ARCH). Thus the test is based on the regression of squared residuals on lagged squared residuals. If the number of lagged residuals to include is three, the equation is:

$$u_t^2 = \beta_1 + \beta_2 u_{t-1}^2 + \beta_3 u_{t-2}^2 + \beta_4 u_{t-3}^2$$

The output from the test is an F-statistic and a TR2 statistic, distributed as χ^2, each with the relevant probability value. Each statistic provides a test of the hypothesis that the coefficients of the lagged squared residuals are all zero that is no ARCH. The χ^2 statistic is the outcome of a Lagrange multiplier (LM) test and has an asymptotic distribution with degrees of freedom equal to the number of lagged squared residuals.

Section 6.4. The final step is to evaluate the forecast performance of the model (The Theil Inequality Coefficient is used for this purpose).

6.2.1 Empirical Results

The AC and the PAC of the price changes are listed in Table 6-1

Table 6-1 AC and PAC for price changes of the five indices

Lags	General		Banks		Insurance		Industry		Service	
	AC	PAC	AC	PAC	AC	PAC	AC	PAC	AC	PAC
1	0.266**	0.266**	0.227**	0.227**	0.196**	0.196**	0.259**	0.259**	0.22**	0.22**
2	0.013	-.063**	0.018	-0.035	0.029	-0.01	0.022	-0.048*	0.054**	0.007
3	-0.02	-0.008	-0.01	-0.006	0.058**	0.056*	-0.04	-0.035	0.024	0.011
4	-0.028	-0.021	-0.023	-0.019	0.044*	0.023	-0.04	-0.017	0.004	-0.004
5	-0.019	-0.007	-0.025	-0.016	-0.015	-0.03	0.001	0.016	-0.031	-0.033
6	0.01	0.017	0.013	0.023	-0.023	-0.018	0.023	0.018	-0.01	0.003
7	-0.012	-0.023	-0.022	-0.033	0.004	0.009	0.025	0.013	-0.029	-0.027
8	-0.015	-0.006	-0.024	-0.013	0.016	0.016	0.002	-0.009	-0.002	0.011
9	-0.006	-0.001	-0.019	-0.011	-0.005	-0.008	0.014	0.019	-0.022	-0.023
10	0.024	0.027	0.002	0.009	0.005	0.008	0.038	0.035	0.003	0.013
11	0.049*	0.037	0.036	0.035	-0.009	-0.015	0.051*	0.036	-0.003	-0.005
12	-0.017	-0.044*	-0.023	-0.044*	-0.03	-0.028	-0.01	-0.035	0.018	0.019
13	-0.01	0.01	-0.018	-0.002	-0.018	-0.006	0.021	0.038	-0.011	-0.019
14	0.055**	0.061*	0.049*	0.058*	0.014	0.021	0.044*	0.037	0.045*	0.051*
15	0.032	0.002	0.032	0.008	0.033	0.031	0.015	-0.006	0.032	0.014
16	0.016	0.008	0.022	0.013	0.035	0.027	0.008	0.004	0.005	-0.009
17	0.045*	0.043	0.059**	0.051	0.035	0.022	0.03	0.032	0.014	0.016
18	0.033	0.016	0.028	0.008	-0.008	-0.027	0.052*	0.042	0.007	-0.003
19	0.015	0.007	0.017	0.014	0.022	0.025	0.008	-0.018	-0.05*	-0.05
20	-0.017	-0.024	-0.003	-0.011	-0.003	-0.014	-0.03	-0.029	-0.029	-0.008

** Significant at 1% level,
* Significant at 5% level

As shown in Table 6-1, and Figures 6-1 to 6-5, the autocorrelation function, for the all indices, seems to be dead after 1 (or 2) lags, and the partial autocorrelations were close to zero after one or two lag. These results suggest a first or second order autoregressive model. Figures 1 to 5 present the correlogram of the indices and the performance of the autocorrelaction and partial autocorrelation functions through the 20 lags.

Figure 6-1: Correlogram of General Index

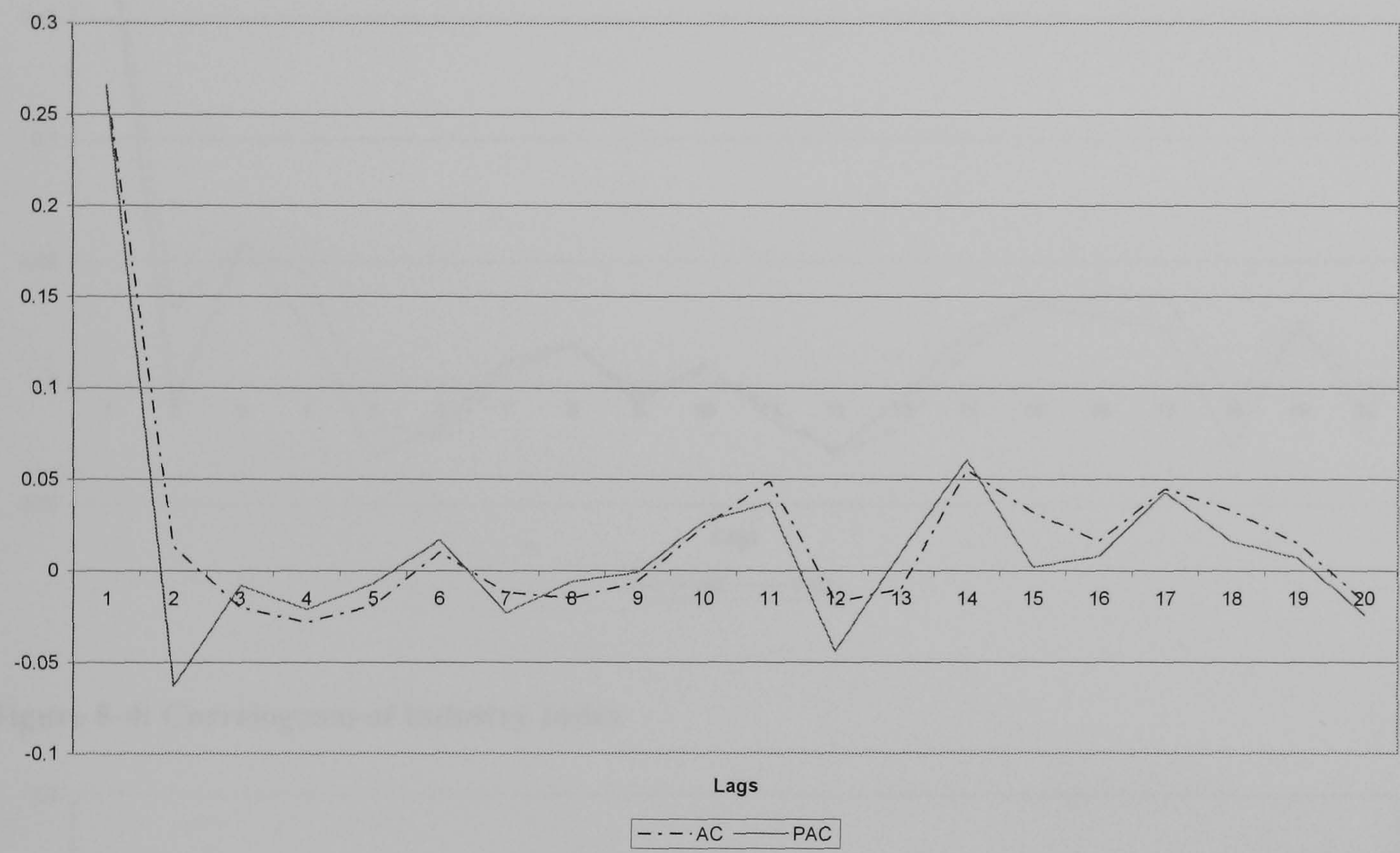


Figure 6-2: Correlogram of Bank Index

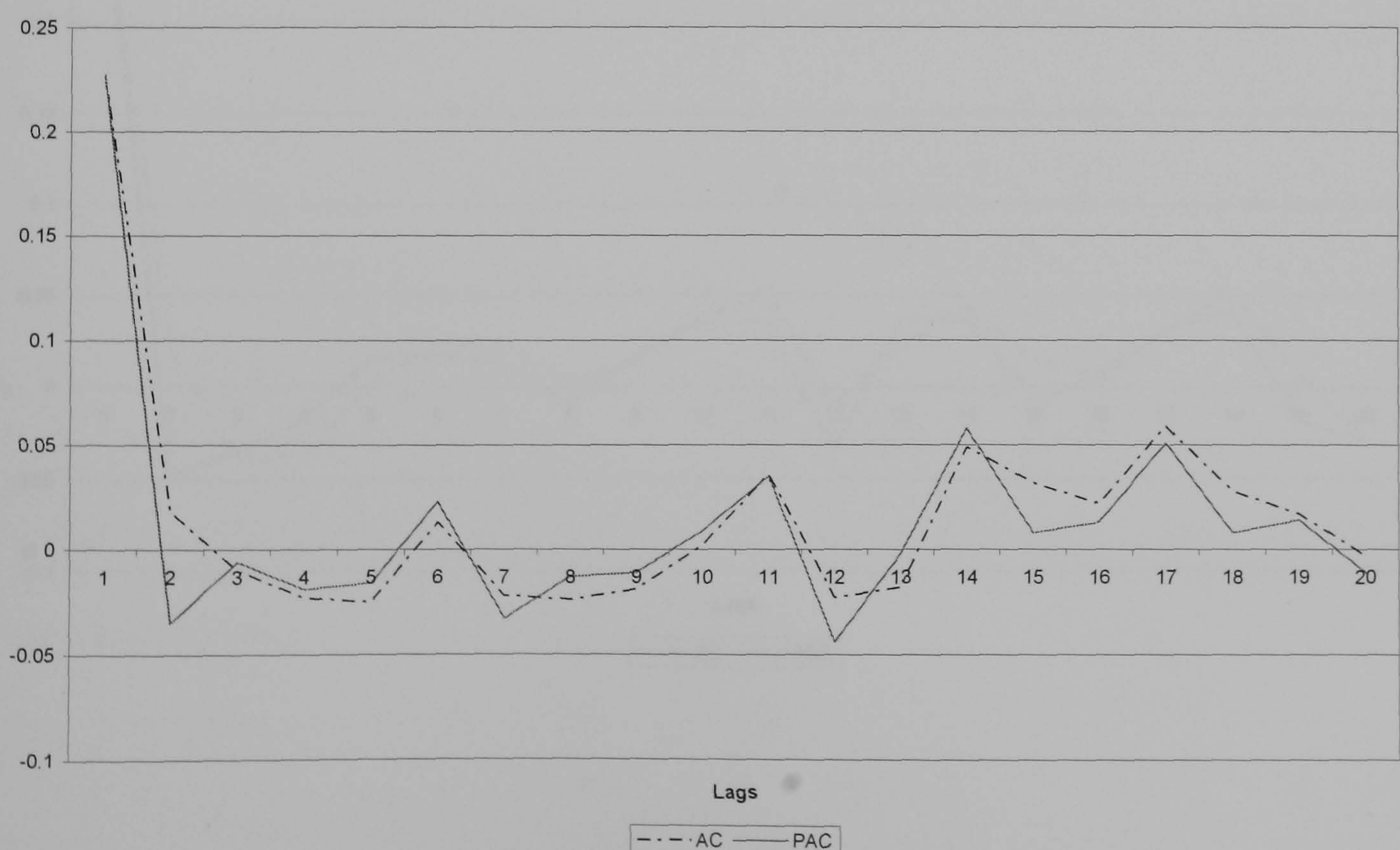


Figure 6-3: Correlogram of Insurance Index

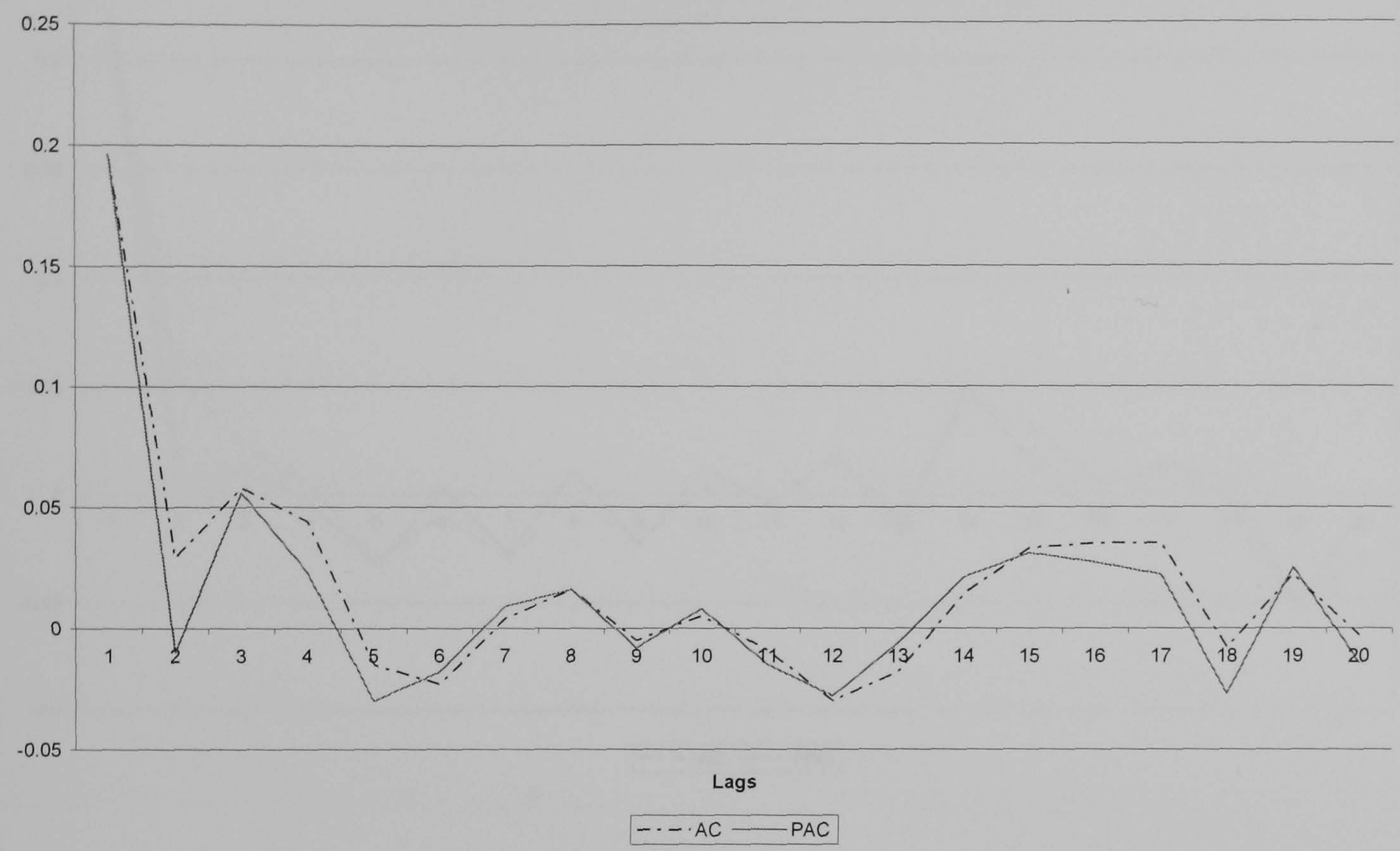


Figure 6-4: Correlogram of Industry Index

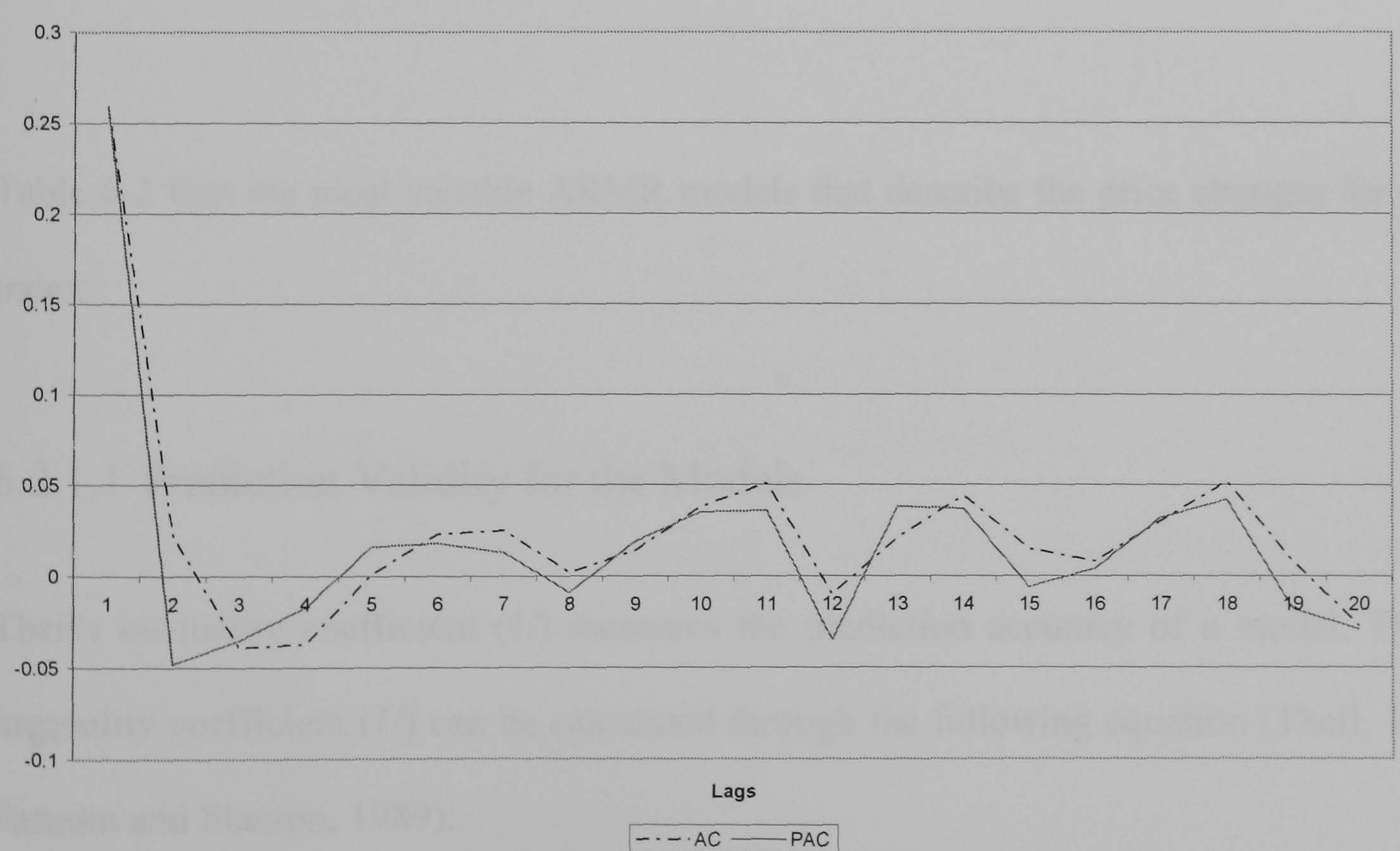


Figure 6-5: Correlogram of Service Index

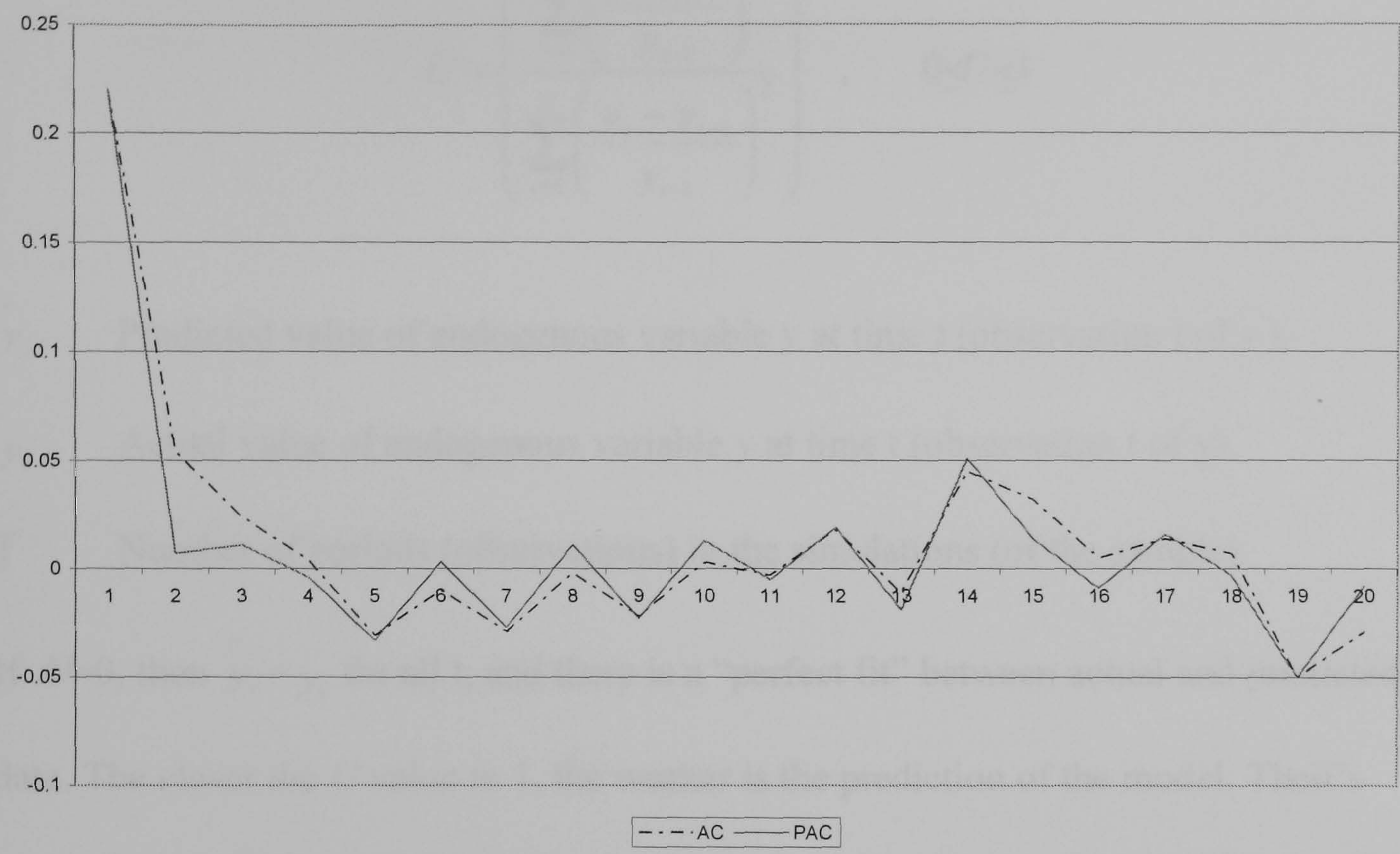


Table 6-2 lists the most suitable ARMR models that describe the price changes for each index.

6.2.1.1 Prediction Validity for the Models

Theil's inequality coefficient (U) measures the prediction accuracy of a model. Theil's inequality coefficient (U) can be calculated through the following equation (Theil, 1970; Farnum and Stanton, 1989):

$$U = \left(\frac{\sum_{t=1}^{T} \left(\frac{\widehat{y}_t - y_t}{y_{t-1}} \right)^2}{\sum_{t=1}^{T} \left(\frac{y_t - y_{t-1}}{y_{t-1}} \right)^2} \right)^{0.5}, \quad 0 \leq U \leq 1 \tag{6-1}$$

$\hat{y}_t$ Predicted value of endogenous variable y at time t (observation t of $\hat{y}$).

y_t Actual value of endogenous variable y at time t (observation t of y).

T Number of periods (observations) in the simulations (of the sample).

If U=0, then $\hat{y}_t = y_t$ for all t, and there is a "perfect fit" between actual and predicted data. The closer the U value to 1, the weaker is the prediction of the model. Theil's inequality coefficient can be decomposed into the following proportions of inequality.

1. Bias proportion: indicates the systematic differences in actual and forecasted values.

$$U^M = \frac{\left(\bar{\hat{y}} - \bar{y} \right)}{\frac{1}{T} \sum_{t=1}^{T} \left(\hat{y}_t - y_t \right)^2} \tag{6-2}$$

$\bar{\hat{y}}, \bar{y}$ are the means of the series $\hat{y}_t$ and y_t respectively.

2. Variance proportion: indicates unequal variances of actual and forecasted values.

$$U^S = \frac{\left(\hat{\sigma} - \sigma \right)^2}{\frac{1}{T} \sum_{t=1}^{T} \left(\hat{y}_t - y_t \right)^2} \tag{6-3}$$

$\hat{\sigma}, \sigma$ are the standard deviations of the series $\hat{y}_t$ and y_t respectively.

3. Covariance proportion: indicates the correlation between the actual and forecasted values. (zero=perfect correlation between actual and forecasted values)

$$U^{C} = \frac{2(1-\rho)\hat{\sigma}.\sigma}{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{y}_t - y_t\right)^2} \tag{6-4}$$

ρ is the correlation coefficient between $\hat{y}_t$ and y_t , and

$$U^{M} + U^{S} + U^{C} = 1 \tag{6-5}$$

the proportions U^M, U^S, and U^C are called the bias, variance, and covariance proportions respectively, and they are useful as a means of breaking the error (difference) down into three characteristic sources.

To test the prediction validity of the models, the models are estimated using the first 2000 observations, then a period of 300 observations ahead is forecasted, and the result in the forecast period is evaluated by using the Theil Inequality Coefficient. Theil Inequality Coefficient is 0 for a perfect forecast and 1 for a naïve static forecast, so under the EMH the coefficient is 1. Since the coefficient is less than 1 and close to 0 for all models, as shown in Table 6-2, the estimated ARMA models explain price changes better than the random walk model. The bias proportion indicates how far the mean of the forecast is from the mean of the actual series, and the variance proportion indicates how far the variation of the forecast is from the variation of the actual series. If the forecast is good, the bias and variance proportions should be small so that most of the bias should be concentrated on the covariance proportions. Empirically, for all models, the bias and variance proportion is small, indicating that bias is indeed concentrated in the covariance proportion. These results are consistent with Chapter 4, again indicating that ASE is not weak form efficient, and that prices do not adjust fully and instantaneously to new information.

As mentioned in Chapter 4, the frequency distribution of the stock price series in ASE does not follow a normal distribution. The results of the runs test and auto-correlation coefficient tests indicate the non-random nature of the series and the violation of the assumption of the null hypothesis that the market is efficient in weak form. Therefore, the predictability of past values in the series using dynamic time series statistical techniques such as the Auto regression model and ARIMA model confirms the previous findings. Similar results are found for all indices.

These results are also consistent with the findings of Nourredine and Khaba (1998), Roux and Gilberson (1978) and Poshakwale (1996) who found evidence of non-randomness in stock price behaviour and market inefficiency (not weak-form efficient) in the Saudi Arabian Financial Market, Johannesburg Stock Exchange and the Indian Market. In conclusion, the results add to the weight of evidence that emerging markets are not weak-form efficient.

Table 6-2: Estimated ARMA models for price changes for the five indices

General Index
Model: ARMA(2,0)

$$\Delta P_t = 0.294\Delta P_{t-1} - 0.078\Delta P_{t-2} + \varepsilon_t$$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.29443	0.020616	14.28181	$< 10^{-5}$
AR(2)	-0.077757	0.020616	-3.771788	0.0002

Forecast Evaluation

Theil Inequality Coefficient	(U)	0.002901
Bias Proportion	(U^M)	0.00375
Variance Proportion	(U^S)	0.013755
Covariance Proportion	(U^C)	0.982494

Bank Index
Model: ARMA(2,0)

$$\Delta P_t = 0.250\Delta P_{t-1} - 0.045\Delta P_{t-2} + \varepsilon_t$$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.249815	0.020656	12.0938	$< 10^{-5}$
AR(2)	-0.04501	0.020656	-2.178984	0.0294

Forecast Evaluation

Theil Inequality Coefficient	(U)	0.004064
Bias Proportion	(U^M)	0.001075
Variance Proportion	(U^S)	0.007360
Covariance Proportion	(U^C)	0.991565

Insurance Index:
Model: ARMA(1,0)

$$\Delta P_t = 0.190\Delta P_{t-1} + \varepsilon_t$$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.189507	0.02032	9.32617	$< 10^{-5}$

Forecast Evaluation

Theil Inequality Coefficient	(U)	0.003388
Bias Proportion	(U^M)	0.003159
Variance Proportion	(U^S)	0.001901
Covariance Proportion	(U^C)	0.994940

Table 6-2: Continued

Industry Index:
Model: ARMA(2,0)

$$\Delta P_t = 0.270\Delta P_{t-1} - 0.068\Delta P_{t-2} + \varepsilon_t$$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.267926	0.020631	12.9865	$< 10^{-5}$
AR(2)	-0.06784	0.02063	-3.288375	0.001

Forecast Evaluation

Theil Inequality Coefficient	(U)	0.003306
Bias Proportion	(U^M)	0.008005
Variance Proportion	(U^S)	0.009067
Covariance Proportion	(U^C)	0.982928

Service index:
Model: ARMA(2,0)

$$\Delta P_t = 0.216\Delta P_{t-1} + \varepsilon_t$$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.21557	0.020181	10.68187	$< 10^{-5}$

Forecast Evaluation

Theil Inequality Coefficient	(U)	0.002403
Bias Proportion	(U^M)	0.003009
Variance Proportion	(U^S)	0.009473
Covariance Proportion	(U^C)	0.987517

6.3 Stationarity and Random Walk Tests

Generally speaking, many econometric problems can arise from non-stationarity (Greene, 1997) (see Appendix 4). Granger and Newbold (1974) concluded that if macroeconomic data were integrated[5], then a regression involving the levels of such data has usually misleading standard significance tests. For example, the conventional t and F tests might

[5] Further discussion of the concept of integration and co-integration can be found in Chapter 7.

incorrectly reject the null hypothesis of the regression, leading to spurious regression. Therefore, economic variables such as stock prices or returns should be modified before using in regression analysis[6].

The random walk model is:

$$X_t = X_{t-1} + \varepsilon_t \tag{6-6}$$

And the random walk with drift is:

$$X_t = \alpha + X_{t-1} + \varepsilon_t \tag{6-7}$$

And the trend stationary process is:

$$X_t = \alpha + \beta t + \varepsilon_t \tag{6-8}$$

Each of these three series is characterized by a unit root. Granger, Newbold and Phillip conclude that the use of data characterized by unit roots has the potential to lead to serious errors in inferences (Phillips and Perron, 1988; Davidson and MacKinnon, 1993). However, an alternative test of the weak EMH (beside the serial correlation and runs tests) is based on the random-walk hypothesis (for prices) which is commonly associated with stationarity and a unit root, since the series must exhibit a unit root (non-stationarity) if it is a random walk.

[6] Usually differencing is used to convert a nonstationary series to a stationary series. A series is called integrated of order one (I(1)) if the series is stationary after first differencing.
Consider $\Delta X_t = X_t - X_{t-1}$, $\Delta^2 X_t = (X_t - X_{t-1}) - (X_{t-1} - X_{t-2})$, and so on, then the time series is integrated of order d (denoted as I(d)) if it must be differenced d times $(\Delta^d X_t)$ in order to induce stationarity. Stationary series are I (0) (Refer to Appendix 4 for more details).

Using,

$$R_t = \ln(P_t) - \ln(P_{t-1}) \qquad \textbf{(6-9)}$$

where P is the price index, the weak EMH implies, that the log of the price is generated by the following process:

$$\ln(P_t) = \beta_0 + \ln(P_{t-1}) + \varepsilon_t \qquad \textbf{(6-10)}$$

which is a random walk with drift in the process generating $\ln(P_t)$. This implies that the $\ln(P_t)$ process has a unit root, an implication which may be tested using standard tests for a unit root in $\ln(P_t)$.[7]

6.3.1 Tests for Unit Roots

In order to check the existence of a unit root, the Augmented Dickey-Fuller (ADF) statistic is employed. The test was developed by Dickey and Fuller (1979).

Considering an AR(1) process with an intercept α:

$$X_t = \alpha + \phi X_{t-1} + \varepsilon_t \qquad \textbf{(6-11)}$$

where α and ϕ are parameters and the ε_t are assumed to be independently and identically distributed with a zero mean and an equal variance. When $-1 < \phi < 1$, the process AR(1)

[7] See Dickey and Fuller (1981) and Phillips and Perron (1988).

is stationary, and if $\phi = 1$, then the process is non-stationary and the series is a random walk with drift. The OLS is applied to (6-11) to obtain $\hat{\phi}$, the estimate of ϕ, and then a *t*-test is performed for the null hypothesis $H_0 : \phi = 1$ against the alternative hypothesis $H_A : \phi < 1$. Rejection of the null hypothesis implies stationary series. Some problems arise in such a procedure. First, the OLS estimator $\hat{\phi}$ is biased downwards in small samples, since there is a lagged dependent variable in (6-11), which poses a risk of concluding that $-1 < \phi < 1$ and that X_t is stationary when it is not. Second, if the process is non-stationary, then standard large-sample distribution results are invalid. In order to apply the unit-root test, (6-11) is rewritten by taking X_{t-1} from each side:

$$\Delta X_t = \alpha + \phi^* X_{t-1} + \varepsilon_t, \tag{6-12}$$

$$\phi^* = \phi - 1 \tag{6-13}$$

According to (6-12) non-stationarity is rejected ($\phi^* = 0$) if the OLS estimate of ϕ^* is sufficiently negative. Dickey and Fuller have performed extensive simulation studies to tabulate the large-sample distribution of the *t* ratio under the null hypothesis that $\phi^* = 0$. The *t* ratio is distributed not about zero because of a downward bias, as it would be if the OLS estimator were unbiased, but about a value that is less than zero (Hegazy, 1998).

As assumed in (6-11), the disturbance is a white noise and the equation is first order AR. If this is not a sensible assumption, the above Dickey – Fuller test is invalid in such circumstances. The Augmented Dickey-Fuller test, that modifies the actual testing procedure by generalizing equation (6-11) is used to test stationarity in such cases. By generalizing (6-11) into the r^{th} – order, then:

$$X_t = \alpha + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots.. + \phi_r X_{t-r} + \varepsilon_t \qquad \textbf{(6-14)}$$

Reparameterize (6-14) to obtain:

$$\Delta X_t = \alpha + \phi^* X_{t-1} + \phi_1^* \Delta X_{t-1} + \phi_2^* \Delta X_{t-2} + \ldots.. + \phi_{r-1}^* \Delta X_{t-r+1} + \varepsilon_t \qquad \textbf{(6-15)}$$

where $\phi^* = \phi_1 + \phi_2 + \ldots.. + \phi_{r-1}$ and the other ϕ_j^* are also functions of the original ϕ_s in(6-14). As noticed, the regressor in the original equation (6-11) has been augmented by extra differenced terms in equation (6-14), and is written sometimes as ADF(k), where k is the number of differenced terms included on the right-hand side of (6-14). The question is what order of AR process best fits the time series under study to determine the differenced terms to be included on the right-hand side of (6-14). Usually, the differenced terms should be included up to the limit which produces non-autocorrelated OLS residuals. The LM tests for autocorrelation are usually used for this purpose[8].

[8] The serial correlation LM test is an alternative test for general serial correlation. It uses the Breusch-Godfrey large sample test for autocorrelated disturbances. It is applicable whether the disturbances follow an AR(p) or MA(p) process, where p can be specified as any positive order. It is also applicable whether or not lagged values of the dependent variable appear among the regressors.
Thus it is advisable to compute the Breusch-Godfrey statistic and respond to any indication of autocorrelated disturbances, since it is almost certainly more dangerous to incorrectly suppose that autocorrelation is not present than to incorrectly suppose that it is.
To use this test, the order, p, of the process thought to be determining the disturbances is specified. For example, if the order,p, suspected to be 3 and the regression is:

$$y_t = \beta_1 + \beta_2 x_t$$

then the test is based on the regression:

$$y_t = \beta_1 + \beta_2 x_t + \beta_3 u_{t-1} + \beta_4 u_{t-2} + \beta_5 u_{t-3}$$

Output from the test consists of an F-statistic and a χ^2 statistic, both of which test the hypothesis that the coefficients of all the lagged residuals are zero. The χ^2 -statistic is the Breusch-Godfrey, Lagrange multiplier test statistic; it can be calculated as T times the R2 of the test regression. The exact distribution of the F-statistic is not known but the χ^2 statistic is asymptotically χ^2 (p) under quite general conditions (Johnston 1984).

Testing the r[th] order process (6-14) for stationarity now is testing whether or not $\phi^* = 0$ in (6-15). To test $H_0 : \phi^* = 1$ the OLS is applied to (6-15) and the t ratio is examined using the critical t ratios table developed by Dickey-Fuller. If ϕ^* is sufficiently negative, the H_0 is rejected in favour of stationarity.

6.3.1.1 Deterministic and Stochastic Trends

Two kinds of trends can appear in the process; deterministic or stochastic trends. Considering nesting the three models (6-6), (6-7), (6-8) in a single equation:

$$X_t = \alpha + \phi X_{t-1} + \beta t + \varepsilon_t, \qquad \alpha \neq 0 \tag{6-16}$$

where ε_t is a white noise and t a time trend. A stochastic trend appears if $\phi = 1$ and $\beta = 0$. Then

$$\Delta X_t = \alpha + \varepsilon_t \tag{6-17}$$

X_t trends upwards or downwards depending on the sign of α. This kind of trend can be removed by first-differencing. X_t is then referred to as a difference stationary.

The deterministic trend appears if $\phi = 0$ and $\beta \neq 0$. Then:

$$X_t = \alpha + \beta t + \varepsilon_t \tag{6-18}$$

X_t trends upwards or downwards depending on the sign of β. This kind of trend cannot be removed by first-differencing, since t doesn't remove from the process. X_t is then referred to as a trend stationary process. Stochastic and deterministic trends are present if $\phi = 1$ and $\beta \neq 0$. The previous ADF test tests only for the non-stationarity of a stochastic trend. Since both types of trends cause spurious regression problems, Dickey and Fuller suggest an F test to detect a deterministic trend, by rewriting (6-16) as:

$$X_t = \alpha + \phi^* X_{t-1} + \beta t + \varepsilon_t \tag{6-19}$$

where $\phi^* = \phi - 1$. *F*-test is used to test the joint hypothesis $\beta = \phi^* = 0$ (critical values of *F* obtained by Dickey – Fuller simulation experience since *F* statistic has a non-standard distribution under the null hypothesis of stochastic trend). Failure to reject this hypothesis would imply that X_t is subject to a stochastic trend only, with the absence of a deterministic trend. To test for a deterministic trend alone, the t ratio on the time trend in (6-19) can be examined using critical values of the *t* ratio provided by Dickey – Fuller simulation.

The unit root test with the exploration of time trend and drift for the series was applied as follows:

1. Estimation of the equation

$$\Delta X_t = \alpha + \beta t + \phi^* X_{t-1} + \phi_1{}^* \Delta X_{t-1} + \phi_2{}^* \Delta X_{t-2} + \ldots.. + \phi_{r-1}{}^* \Delta X_{t-r+1} + \varepsilon \tag{6-20}$$

To determine the order of differenced terms included in the equations in order to achieve ADF test, the serial correlation LM test is applied. If LM suggests autocorrelated residuals for the equation (6-19), then a higher AR process is tried and so on till the LM statistics are satisfactory. The serial correlation LM test is an alternative test for general serial correlation. It uses the Breusch-Godfrey large sample test for autocorrelated disturbances. After determining the sufficient number of lagged differences, the ADF test is applied to the series.

2. Testing the null hypothesis $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$ against the alternative hypothesis $H_A : (\alpha, \beta t, \phi^*) \neq (\alpha, 0, 0)$, through the application of the Wald (coefficient restrictions) test by imposing zero coefficients on βt, ϕ^* . The computed value (Φ_1) of the Wald test (F-statistic) was compared with the critical value taken from the Dickey and Fuller (1981) tables, which is 6.25 under 95% significance level. If the result accepts H_0 (computed value of $\Phi_1 < 6.25$), Path A is followed. If H_0 is rejected, Path B is followed.

- Path A: there is a unit root ($\phi^* = 0$) with no trend (βt = 0), with possible drift. To reinforce the inference that the series contains a unit root, the reported value of the *t*-statistic of the coefficient ϕ^* must be smaller than the critical value obtained from the Dickey and Fuller (1981) tables. To investigate the presence of the drift component, Φ_2 is used to test $H_0 : (\alpha, \beta t, \phi^*) = (0,0,0)$ against the alternative hypothesis $H_A : (\alpha, \beta t, \phi^*) \neq (0,0,0)$, the tabulated value for the F statistic of 4.68 from Dickey and Fuller (1981) tables was used. If H_0 is rejected, then the series is a random walk with drift, otherwise, it is a random walk without drift. Then the equation (6-21) is estimated

$$\Delta X_t = \alpha + \phi^* X_{t-1} + \phi_1^* \Delta X_{t-1} + \phi_2^* \Delta X_{t-2} + ... + \phi_{r-1}^* \Delta X_{t-r+1} + \varepsilon \qquad \textbf{(6-21)}$$

The F-test Φ_3 is used to test $H_0 : (\alpha, \phi^*) = (0,0)$ against $H_A : (\alpha, \phi^*) \neq (0,0)$ using the tabulated critical value for the F statistic of 4.59 from Dickey and Fuller (1981) tables. If H_0 is rejected then the series is random walk with drift, otherwise, it is random walk without drift.

- Path B: Either [$\beta t \neq 0 \, and \, \phi^* = 0$], [$\beta t = 0 \, and \, \phi^* \neq 0$] or [$\beta t \neq 0 \, and \, \phi^* \neq 0$]. To test if $\phi^* = 0$, the reported t statistic of ϕ^* coefficient is compared with the critical value taken from the standard normal tables. If $\phi^* = 0$ is rejected, then the series does not have a unit root and is considered stationary, otherwise it has a unit root. To test if $\beta t = 0$, the reported t statistic of the βt coefficient is compared with the critical value taken from the standard normal tables. If $\beta t = 0$ is rejected, then the series has linear trend, otherwise it has no linear trend. To test if the intercept is zero, the t statistic test for α is applied. If $\alpha = 0$ then the series is without intercept. Otherwise, it has a non-zero drift.

6.3.2 Empirical Results

The unit root test was conducted first for the five price indices series, then to the five return series. The results in Table 6-3 show that the computed values of Φ_1 for the general, bank, and insurance price indices are less than 6.25, implying a unit root. Analysing the calculated t-statistic of the coefficient ϕ^* and comparing it with the critical values obtained from the Dickey and Fuller (1981) tables supports this conclusion. Additionally, the computed values of Φ_2 for the mentioned series are less than 4.68, implying the absence of a drift in these processes. Then (4.36) is estimated since $\beta t = 0$ as inferred from the Φ_1 test. The Φ_3 values are also under the critical values, leading to the conclusion that the series are random walk without drift. From the sequence of these tests, the conclusion is that the three series contain a unit root but not a deterministic trend or a drift term.

For the industry and the service price indices, the values of Φ_1 is higher than 6.25 (even though the value is very close to 6.25 in the industry index). Comparing the reported t statistic of ϕ^* coefficients (-3.334, -4.09 respectively) with the critical value of 1.96 taken from the standard normal tables, the H_0: of $\phi^* = 0$ is rejected, implying no unit root. The two series have also reported a t statistic of coefficients βt of -3.6 and -3.84 respectively, comparing with the critical value of 1.96. This implies a linear trend, possibly with an intercept. Using a conventional t–test in order to test whether the intercept is zero, the t- statistic for the two indices was found to be 3.48 and 4.18 respectively, thereby rejecting the null hypothesis and implying a drift. As a conclusion, the industry and service price indices are stationary with a linear trend and a non-zero drift.

On the other hand, all indices of stock prices exhibited a unit root when different specifications for a unit root were used, such as different number of lags, with or without intercept, with or without trend, and the combinations of these alternatives.

Whilst the price indices series showed deterministic or stochastic trends, nevertheless, the presence of a unit root (non-stationarity) in stock prices is only a necessary (but not sufficient) condition for a random-walk process. As Campbell *et al.* (1997) demonstrated, unit root tests only explore the permanent/temporary nature of shocks to the series and, as such, have no bearing on the random-walk hypothesis (or predictability).[9]

Moreover, the random walk model needs to fit the model ARIMA(0,1,0) where the future value of share prices can not be determined on the basis of past information. Specifically, future share prices will not depend on past (lag) values of share prices or on the disturbance terms as mentioned in Section 6.2. The significant coefficients different from zero suggest dependency of the series in variables other than simply P_{t-1}, and this violates the assumption of a random walk model and weak-form efficiency.

On the other hand, when the unit root test was performed using the return indices, none of them (as shown in Table 6-4) exhibited a unit root; that is, as expected, all the indices of stock returns are stationary. As the return is the log for first difference of the prices, the

[9] In this light, the use of unit root tests to examine the random-walk hypothesis appears doubtful. See Liu *et al.* (1997) and Long *et al.* (1999).

price series can be considered as I (1) series, whilst returns are I(0) (Refer to Appendix 4 and note 6).

However the hypothesis of random walk is rejected, for the return indices, by the Dickey-Fuller test at a very high level of confidence (> 99 %). Those results lead us to the conclusion, at this stage, that the random walk model is not satisfactory for ASE returns. Note that rejection of random walk in itself does not imply stationarity. However, these results are in line with the results reported by Neaime (2002) which suggested that, according to the (ADF) tests results, the MENA(Middle East and North Africa) stock market price series are non-stationary. However, unit roots in the first differences of the stock prices are rejected at the 1 percent significance level, suggesting that price indices in the MENA regions are I (1).

Table 6-3: Unit Root Tests (Price level of the General Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.

LS // Dependent Variable is D(GENERAL)

Variable	Coefficient	Std. Error	t-Statistic
C	0.452081	0.172718	2.617454
GENERAL(-1)	-0.00278	0.001223	-2.27518
Trend	-1.61E-05	3.39E-05	-0.47576
D(GENERAL(-1))	0.293729	0.020595	14.26228
D(GENERAL(-2))	-0.07735	0.020604	-3.75423

2)Serial Correlation LM Test (suggests no autocorrelated residuals)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.582463	Probability	0.558602
Obs*R-squared	1.167835	Probability	0.557709

3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$

Equation: D(general)=c1+c2(general(-1))+c3(trend)+ c4(D(general(-1))+c5(D(general(-2))

Null Hypothesis:	C(2)=0	
	C(3)=0	
F-statistic (Φ_1)	**3.788438**	
Chi-square	7.576876	

There is a unit root ($\phi^* = 0$) with no trend ($\beta t = 0$), with possible drift.

Path A

Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$

Equation: D(general)=c1+c2(general(-1))+c3(trend)+ c4(D(general(-1))+c5(D(general(-2))

Null Hypothesis:	C(1)=0	
	C(2)=0	
	C(3)=0	
F-statistic (Φ_2)	**2.689135**	
Chi-square	8.067405	**random walk without drift**

LS // Dependent Variable is D(GENERAL)

Variable	Coefficient	Std. Error	t-Statistic
C	0.469156	0.168919	2.777399
GENERAL(-1)	-0.00302	0.001115	-2.71164
D(GENERAL(-1))	0.294033	0.020582	14.28627
D(GENERAL(-2))	-0.07696	0.020584	-3.73873

Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$

Equation: D(general)=c1+c2(general(-1))+ c3(D(general(-1))+c4(D(general(-2))

Null Hypothesis:	C(1)=0	
	C(2)=0	
F-statistic (Φ_3)	**3.921828**	
Chi-square	7.843656	**Unit root and zero drift**

Continued-Table 6-3: Unit Root Tests (Price level of the Bank Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(BANKS)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.302578	0.150209	2.014377
BANKS(-1)	-0.00167	0.001125	-1.47922
Trend	5.30E-05	8.45E-05	0.627171
D(BANKS(-1))	0.249235	0.020655	12.06675
D(BANKS(-2))	-0.04496	0.020666	-2.17543
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.480197	Probability	0.618723
Obs*R-squared	0.962876	Probability	0.617894
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(banks)=c1+c2(banks(-1))+c3(trend)+ c4(D(banks(-1))+c5(D(banks(-2))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**1.636362**		
Chi-square	3.272725		
There is a unit root (ϕ^* = 0) with no trend (βt = 0), with possible drift.			
Path A			
Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0,0,0)$			
Equation: D(banks)=c1+c2(banks(-1))+c3(trend)+ c4(D(banks(-1))+c5(D(banks(-2))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
	C(3)=0		
F-statistic (**Φ_2**)	**1.692606**		
Chi-square	5.077818	**random walk without drift**	
LS // Dependent Variable is D(BANKS)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.469156	0.168919	2.777399
BANKS(-1)	-0.00302	0.001115	-2.71164
D(BANKS(-1))	0.294033	0.020582	14.28627
D(BANKS(-2))	-0.07696	0.020584	-3.73873
Wald Test: $H_0 : (\alpha, \phi^*) = (0,0)$			
Equation: D(banks)=c1+c2(banks(-1))+ c3(D(banks(-1))+c4(D(banks(-2))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
F-statistic (**Φ_3**)	**2.342845**		
Chi-square	4.68569	**Unit root and zero drift**	

Continued-Table 6-3: Unit Root Tests (Price level of the Insurance Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(INSURANCE)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.448257	0.172104	2.604575
INSURANCE(-1)	-0.00297	0.001195	-2.48546
Trend	-4.19E-05	2.76E-05	-1.51614
D(INSURANCE(-1))	0.193639	0.02066	9.372631
D(INSURANCE(-2))	-0.03199	0.021025	-1.5213
D(INSURANCE(-3))	0.035181	0.021055	1.670919
D(INSURANCE(-4))	0.032545	0.020683	1.57352
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.486782	Probability	0.226313
Obs*R-squared	2.981238	Probability	0.225233
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(insurance)=c1+c2(insurance(-1))+c3(trend)+ c4(D(insurance(-1))+c5(D(insurance(-2))+ c6(D(insurance(-3))+c7(D(insurance(-4))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	3.230248		
Chi-square	6.460497		
There is a unit root ($\phi^* = 0$) with no trend ($\beta t = 0$), with possible drift.			
Path A			
Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0,0,0)$			
Equation: D(insurance)=c1+c2(insurance(-1))+c3(trend)+ c4(D(insurance(-1))+c5(D(insurance(-2))+ c6(D(insurance(-3))+c7(D(insurance(-4))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
	C(3)=0		
F-statistic (Φ_2)	2.356554		
Chi-square	7.069662	**random walk without drift**	
LS // Dependent Variable is D(INSURANCE)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.301301	0.142253	2.118064
INSURANCE(-1)	-0.00222	0.001087	-2.03949
D(INSURANCE(-1))	0.193852	0.020665	9.380557
D(INSURANCE(-2))	-0.03192	0.021031	-1.51788
D(INSURANCE(-3))	0.035343	0.02106	1.67817
D(INSURANCE(-4))	0.032725	0.020688	1.581806
Wald Test: $H_0 : (\alpha, \phi^*) = (0,0)$			
Equation: D(insurance)=c1+c2(insurance(-1))+ c3(D(insurance(-1))+c4(D(insurance(-2))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
F-statistic (Φ_3)	2.384168		
Chi-square	4.768335	**Unit root and zero drift**	

Continued-Table 6-3: Unit Root Tests (Price level of the Industry Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(INDUSTRY)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.730324	0.209701	**3.482685****
INDUSTRY(-1)	-0.00455	0.001364	**-3.33469****
Trend	-0.00019	5.28E-05	**-3.59985****
D(INDUSTRY(-1))	0.266808	0.020582	12.96337
D(INDUSTRY(-2))	-0.06763	0.020585	-3.28516
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.805247	Probability	0.447101
Obs*R-squared	1.614208	Probability	0.446148
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(industry)=c1+c2(industry(-1))+c3(trend)+ c4(D(industry(-1))+c5(D(industry(-2))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	6.713993		
Chi-square	13.42799		
Path B			
The series is stationary with time trend and intercept.			

Continued-Table 6-3: Unit Root Tests (Price level of the Service Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(INDUSTRY)			
Variable	Coefficient	Std. Error	t-Statistic
C	1.144109	0.273537	**4.182647****
SERVICES(-1)	-0.0075	0.001834	**-4.08991****
Trend	-0.0002	5.15E-05	**-3.84709****
D(SERVICES(-1))	0.215842	0.020117	10.72925
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.17191	Probability	0.842066
Obs*R-squared	0.344651	Probability	0.841705
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(industry)=c1+c2(services(-1))+c3(trend)+ c4(D(services(-1))+c5(D(services(-2))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	8.905464		
Chi-square	17.81093		
Path B			
The series is stationary with time trend and intercept.			

Table 6-4: Unit Root Tests (Returns of General Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(RGENERAL)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.000547	0.000273	**2.006365****
RGENERAL(-1)	-0.78204	0.025019	**-31.2576****
Trend	-3.63E-07	2.01E-07	-1.80688
D(RGENERAL(-1))	0.063881	0.020634	3.095963
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.268087	Probability	0.764865
Obs*R-squared	0.537428	Probability	0.764362
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rgeneral)=c1+c2(rgeneral(-1))+c3(trend)+ c4(D(rgeneral(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic **(Φ_1)**	488.5179		
Chi-square	977.0358		
Path B			
The series is stationary with intercept and without time trend.			

Continued: Table 6-4: Unit Root Tests (Returns of Bank Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(RBANKS)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.000703	0.000332	**2.115362****
RBANKS(-1)	-0.80164	0.025702	**-31.1895****
Trend	-3.59E-07	2.45E-07	-1.46465
D(RBANKS(-1))	0.036264	0.020664	1.754988
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.60309	Probability	0.547204
Obs*R-squared	1.208652	Probability	0.546442
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rbanks)=c1+c2(rbanks(-1))+c3(trend)+ c4(D(rbanks(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic **(Φ_1)**	486.3935		
Chi-square	972.787		
Path B			
The series is stationary with intercept and without time trend.			

Continued: Table 6-4: Unit Root Tests (Returns of Insurance Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(RINSURANCE)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.000237	0.000242	0.981456
RINSURANCE(-1)	-0.76734	0.031085	**-24.6849****
Trend	-1.11E-07	1.78E-07	-0.62428
D(RINSURANCE(-1))	-0.03411	0.026463	-1.28897
D(RINSURANCE(-2))	-0.05631	0.020663	-2.72521
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.284342	Probability	0.277028
Obs*R-squared	2.573553	Probability	0.27616
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rinsurance)=c1+c2(rinsurance(-1))+c3(trend)+ c4(D(rinsurance(-1))+c5(D(rinsurance(-2))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	304.6779		
Chi-square	609.3558		
Path B			
The series is stationary without time trend or intercept.			

Continued: Table 6-4: Unit Root Tests (Returns of Industry Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(RINDUSTRY)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.000393	0.000334	1.177036
RINDUSTRY(-1)	-0.77872	0.025157	**-30.9538****
Trend	-4.27E-07	2.46E-07	-1.7324
D(RINDUSTRY(-1))	0.049527	0.02065	2.398346
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.635828	Probability	0.195014
Obs*R-squared	3.275471	Probability	0.19442
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(industry)=c1+c2(industry(-1))+c3(trend)+ c4(D(industry(-1))+c5(D(industry(-2))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	479.0701		
Chi-square	958.1402		
Path B			
The series is stationary without time trend or intercept.			

Continued: Table 6-4: Unit Root Tests (Returns of Service Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(RSERVICE)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.000341	0.000327	1.041102
RSERVICES(-1)	-0.77629	0.025838	**-30.0446****
Trend	-2.85E-07	2.42E-07	-1.17826
D(RSERVICES(-1))	-0.0059	0.020671	-0.28534
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.010051	Probability	0.364359
Obs*R-squared	2.023538	Probability	0.363575
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rservice)=c1+c2(rservice(-1))+c3(trend)+ c4(D(rservice(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	451.3391		
Chi-square	902.6782		
Path B			
The series is stationary without time trend or intercept.			

6.4 GARCH Model and Return-Volatility Behaviour

Interest in testing the return-volatility behaviour in emerging markets has increased after the integration of the world economies in general and financial markets in particular became more crucial. The globalization and integration of these markets has created enormous opportunities for domestic and international investors to diversify their portfolios across the globe (further tests for integration will be conducted in chapter 7). As a result, rigorous empirical studies examining the efficiency and other characteristics of these markets would be of great benefit to investors and policy makers at home and abroad.

The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982) allows the variance of the error term to vary over time, in contrast to the standard time series regression models which assume a constant variance[10]. Bollerslev (1986) generalized the ARCH process by allowing for a lag structure for the variance. The generalized ARCH models, i.e. the GARCH models, have been found to be valuable in modelling the time series behaviour of stock returns (Baillie and DeGennaro, 1990; Akgiray, 1989; French et al. 1987; Koutmos, 1992; Koutmos et al. 1993). Bollerslev (1986) allows the conditional variance to be a function of the prior period's squared errors as well as of its past conditional variances. This approach allows for an empirical assessment of the relationship between risk and returns in a setting that is consistent with the characteristics of leptokurtosis and volatility clustering observed in the time series of ASE indices returns.[11]

The GARCH model has the advantage of incorporating heteroscedasticity into the estimation procedure. The GARCH models are capable of capturing the tendency for volatility clustering in financial data. Clustering in stock returns implies that large (small) price changes follow large (small) price changes of either sign. Engle *et al.* (1987) provides an extension to the GARCH model where the conditional mean is an explicit function of the conditional variance. Such a model is known as the GARCH in the mean or GARCH-M model. Following Choudhry (1996) and Mecagni and Sourial (1999), stock returns can be represented by the GARCH *(p,q)*-M model as follows:

---

[10] ARMA models and all models used in the previous sections assume constant variance.

[11] The GARCH approach incorporates volatility clustering characteristics in the estimation process by allowing for time variation and temporal dependence of conditional second order moments (conditional on the information set at time $_{t-1}$). In turn, this is consistent with excess kurtosis in the unconditional distribution of returns, as shown by Campbell, Lo and MacKinley(1997).

$$y_t = u_t + \delta_1 h_t^{1/2} + \varepsilon_t \tag{6-22}$$

$$\varepsilon_t | \Psi_{t-1} \sim N(0, h_t) \tag{6-23}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + ... + \beta_p h_{t-p} \tag{6-24}$$

where u_t is an exogenous or predetermined vector of variables capturing past information[12]; ε_t is a zero mean, serially uncorrelated random error term with a normal distribution conditional on past information; and h_t is the conditional variance of the error term. The GARCH (p,q)-M model thus allows for stock returns y_t to be determined by the vector u_t and by the own conditional variance h_t with a general parameterisation of heteroschedasticity which encompasses simpler specification as special cases. The conditional variance h_t in fact may vary over time as a result of own temporal persistence (with serial correlation up to p periods indicated by nonzero β coefficients). The squared innovation terms imply that volatility shocks are likely to continue to be large if it were so in the past, and therefore capture the observed tendency for volatility to cluster in time. In order to ensure a positive conditional variance h_t, the GARCH (p,q)-M model imposes the following inequality restrictions[13]:

[12] Past information may include past returns and other financial variables as lagged nominal interest rates (Glosten, Jagannathan, and Runkle (1993)), dividend yield (Attanasio and Wadhwani (1989)) or the money supply (Engle and Rodrigues (1989)). However, the lack of daily time series for these variables, in the case of ASE, prevents their use in modelling stock returns. The conditioning information set therefore includes only past stock returns.

[13] The persistence of shocks to volatility depends on the sum of the ($\alpha+\beta$) parameters (Engle and Bollwelev, 1986; Chou, 1988; Bollweslev, Chou and Kroner, 1992). Values of the sum lower than unity imply a tendency for the volatility response to decay over time, at a slower rate the closer the sum is to unity. In contrast, values of the sum equal (or greater) than unity imply indefinite (or increasing) volatility persistence to shocks over time.

$$\alpha_0 > 0 \tag{6-25}$$

$$\alpha \geq 0 \quad for \quad i = 1, \ldots\ldots, q \tag{6-26}$$

$$\beta_i \geq 0 \quad for \quad i = 1, \ldots\ldots, p \tag{6-27}$$

The u_t term provides a conditioning information set that includes the sequence of past stock returns; it may used to test for the weak form of the efficient market hypothesis (EMH). The EMH involves ascertaining whether there is any systematic pattern of time dependence in stock returns that may allow for past information to be used to improve the predictability of future returns. On an efficient market, current asset prices tend to incorporate all available information at any given time, and therefore future returns should be unpredictable on the basis of current and past observations. On the other hand, the term $h_t^{1/2}$ links market returns to stocks' volatility, measured by the standard deviation of the conditional distribution of returns. A positive and statistically significant parameter δ_1 is expected to indicate that investors trading stocks were rewarded with higher returns for bearing extra risk; that is the reward varies with h_t, in turn reflecting periods of relatively low or high volatility.[14]

[14] Choudhry (1996) interpreted the parameter δ_1 as the risk premium associated with time-varying volatility effects on stock return. A significant and positive coefficient δ_1 implies that investors trading stocks were compensated with higher returns for bearing higher levels of risk. A significant negative coefficient indicates that investors were penalised for bearing risk aversion. However, this interpretation for this study is not fully warranted since the market returns are modelled rather than excess returns, i.e. the difference between market returns and a risk-free asset return. Regarding ASE, like in many other emerging markets, the identification of a risk-free asset is not straightforward. The interpretation of δ_1 as term or liquidity risk premium is more intuitive in applications to return differentials for assets of different maturities or characteristics.

Chou (1988) suggested that the GARCH-M model provides a more flexible framework for capturing various dynamic structures of conditional variance, and allows simultaneous estimation of parameters of interest and hypotheses. The size and significance of α_j indicates the magnitude of the effect imposed by the lagged error term ε_{t-1} on the conditional variance h_t. In other words, the size and significance of α_j implies the existence of the ARCH process in the error term (volatility clustering).

In a GARCH (1,1)-M model, the series ε_t is covariance stationary if the sum of α and β is significantly less than unity. As the sum of α and β approaches unity, the persistence of shocks to volatility is greater. A GARCH (1,1) of the following form is used in this study:

$$Y_t = u_t + \delta_1 h_t^{1/2} + \varepsilon_t \quad \textbf{(6-28)}$$

$$\varepsilon_t | \Psi_{t-1} \sim N(0, h_t) \quad \textbf{(6-29)}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^{\ 2} + \beta_1 h_{t-1} \quad \textbf{(6-30)}$$

The parameters are estimated using nonlinear estimation techniques based on the Berndt-Hall-Hall-Hausman algorithm, which involves recursive calculation of the variance, h_t (Eviews software is used to perform these tests). In a GARCH (p,q) model, the order of p and q can be identified by the Box and Jenkins identification techniques to the time series and by examining the autocorrelations and partial autocorrelations for the squared residuals. The primary specification test for a lack of serial correlation in the residuals is the Ljung-Box statistics which is asymptotically chi-square distributed. The ARMA (p,q) process for modelling the autocorrelation structure of the indices returns is conducted in section (6.2). In this study, the GARCH-M(1,1)[15] model is employed to control the autoregressive conditional heterskedasticity for the five ASE indices.

6.4.1 Empirical Results

6.4.1.1 Volatility and Return in ASE Indices

The estimated parameters of GARCH (1,1)-M model for the five indices are presented in Table 6-6. The hypothesis that volatility is a significant determinant of stock returns is not confirmed for all ASE indices. The estimated parameter δ_1, capturing the influence of volatility on stock returns, is positive for all indices. However it is statistically significant for only three indices: the general index (at the 5 percent level), and the industry and service indices (at the 10 percent level). The range of estimates is of similar order of magnitude for all indices except the general index, which presents a stronger impact of conditional variability of stock returns[16]. The results of positive δ_1 confirm a positive relation between risk and return, which is consistent with the basic postulate of the portfolio theory, and indicate that on average investors trading stocks were compensated with higher returns for bearing risk.

[15] Many studies have shown that a small number of parameters are sufficient to model the dynamics of the sample conditional variance, and empirical applications adopt values for the lag length (of p and q) in the GARCH model typically ranging from 1 to 2 (Mecagni and Sourial, 1999; Bollerslev, Chou and Kroner, 1992).

[16] The sign and magnitude of the risk-return parameter depends on the investors' utility function and risk preference, and the supply of assets under consideration (Engle, Lilien and Bobins, 1987; Bollerslev, Chou and Kroner, 1992). However, empirical applications to date found mixed results regarding the sign and statistical significance of the risk-return parameter. Elyasiani and Mansur (1998) estimates on U.S data were negative and statistically significant. Chou (1989) and Poterba and Summers (1986) estimated on excess returns for daily S&P index, weekly NYSE returns and U.K stock indices were positive and significant. In emerging markets, Thomas (1995) found that the risk-return parameter was positive but not significant using daily returns for the Bombay Stock Exchange.

6.4.1.2 ARCH, GARCH effects and Volatility Persistence:

The estimates reject the hypothesis of time-invariant conditional volatility for all ASE return indices. The conditional variance h_t is found to change over time as a result of volatility clustering effects, indicated by statistically significant α parameters, at the 1 percent level, in the models for all five indices. The clustering could represent the arrival of information in clusters, or delays in the market adjustment process as traders try to measure its content. As Engle et al. (1990) point out, if information arrives in clusters, then the asset returns or prices may exhibit ARCH behaviour even if the market perfectly and instantaneously adjusts to the news. Thus ARCH behaviour can be consistent with market efficiency. Furthermore, even if the market takes time to resolve expectational differences, it may be still informationally efficient in the sense of being unbiased. The results below confirm the tendency for shocks to persist, which means periods of relatively high (or low) volatility are found to be time-dependent, which indicates some degree of forecastability. The estimates of volatility persistence ($\alpha + \beta$ coefficients) are close to unity. This indicates the tendency for a volatility response to shocks to display a long memory[17].

[17] Several papers found evidence that some volatility measures, based on daily returns, have a long memory property.

6.4.1.3 Prediction Validity for the Models

To test the prediction validity of the models, the models are estimated using the first 2000 observations, then the period of 300 observations ahead is forecasted, and the result of the estimation period is evaluated using Theil Inequality Coefficient as presented in Table 6-5. Theil Inequality Coefficients are high for the all the GARCH-M(1,1) models, indicating a poor fit with the actual data. The ARMA models perform better, in forecasting ability, than the GARCH-M(1,1) according to this criterion.

Table 6-5 Estimation for GARCH (1,1)-M Model for Indices Daily Returns

$$(Y_t = u_t + \delta_1 h_t^{1/2} + \varepsilon_t \ , \quad h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^{\ 2} + \beta_1 h_{t-1})$$

Index Daily Returns	General	Bank	Insurance	Industry	Services
u	-0.0006***	-0.0004*	-0.0003***	-0.0008***	-0.0005***
δ_1	11.7373**	6.0000	6.4693	6.9046*	6.5966*
α_0	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***
α_1	0.2547***	0.2454***	0.1157***	0.2451***	0.1410***
β_1	0.6695***	0.6758***	0.8586***	0.6755***	0.8389***
$\alpha_1 + \beta_1$	0.9242	0.9212	0.9743	0.9207	0.9799
Forecast Evaluation					
Theil Inequality Coefficient (U)	0.904906	0.956965	0.950825	0.876695	0.855314
Bias Proportion (U^M)	0.000724	0.000014	0.015259	0.000748	0.010254
Variance Proportion (U^S)	0.999276	0.999986	0.984741	0.999252	0.989746
Covariance Proportion (U^C)	0	0	0	0	0

** *Significant at 1% level,
* *Significant at 5% level
**Significant at 10% level,

6.5 Conclusion

This chapter has investigated empirically some important aspects of price indices and return behaviour properties for the ASE. The Efficient Market Hypothesis has been assessed using recent econometric procedures. The Box-Jenkins estimation, irrespective of the index examined, produced models with high prediction validity; this implies the existence of deviations from market efficiency in the pricing of equities in the ASE. The unit-root test also confirmed these results, as the return series for all indices did not exhibit unit root and all processes were stationary. Although, the prices series for the general, bank, and insurance indices, exhibited unit roots, it is not sufficient for a random walk process since the series did not fit the ARIMA (0,1,0) model. As Campbell *et al.* (1997) demonstrated, unit root tests only explore the permanent/temporary nature of shocks to the series and, as such, have no bearing on the random-walk hypothesis or predictability.

The results also support the existence of a significant link, to a certain limit, between conditional volatility measures and three indices of stock returns as indicated by the GARCH-M(1,1) estimation. The risk-return parameter is positive and statistically significant. On the other hand, the conditional variance is found to change over time as a result of volatility clustering effects. The clustering could represent the arrival of information in clusters, or delays in the market adjustment process as traders try to measure its content, breaching the efficient market conditions. Unlike ARMA estimations, GARCH-M(1,1) prediction validity is low, which lessens the importance of the GARCH effect, especially given that GARCH-M(1,1) parameters are not significant for all indices.

It is expected that the ASE exhibits ARCH and GARCH effects as most financial data usually exhibit volatility clustering due to increased uncertainty from new information arrival and the time delay for traders to adjust to it. Beside that, there is a yearly pattern in dividend payments in ASE, dividends tend to be concentrated in April and May, and the clustering of dividends could produce the GARCH effect in the indices series. In addition, the existence of noise traders may also affect the volatility in asset prices.

The results of the model showed that the ARCH and GARCH effects are significant for all series and the volatility persistence is also close to unity and significant. However, the 'out of sample' predictability power of the model was poor. Intuitive thinking suggests that an asset that reports non-trading responds to new information with a time lag. These lagged responses may induce biases in the moments of daily return series. The serial correlation may influence tests of predictability as well as volatility risk and expected returns.

The results showed low ARCH coefficients and high GARCH coefficients. In the case of non-trading, the observed return is considered zero and may produce artificial shocks for the volatility process. Therefore spurious and low ARCH coefficients may be observed for thinly traded series. On the other hand, non-trading effects may also cause spurious autocorrelation in the conditional volatility process which produces high GARCH coefficients. This may distort any volatility patterns for non-trading series. In conclusion, series strongly influenced by zero return observations may emphasise the autocorrelation in conditional volatility too much, which may result in spurious persistence coefficients.

Although this chapter produced some ARMA models with highly predictive power for return series, it is still remarkably hard to profit from exploiting these models or even from any extreme violations of market efficiency. It has been demonstrated that, superior in-sample performance often fails to translate into superior out-of-sample performance (Roll, 1994). However, the importance of the efficient market hypothesis is demonstrated by the fact that apparently profitable investment opportunities are still referred to as anomalies. Anomalies have potential explanations based on mis-estimation of risks or costs, and they are only too often chance events that do not persist into the future.
Yet as Roll (1994) observed, it is remarkably hard to profit from even the most extreme violations of market efficiency.

CHAPTER 7

Financial Integration and Market Efficiency

Contents:

Summary

This chapter applies the cointegration and Granger causality tests to investigate the concept of market integration and comovements. These techniques are applied using, firstly, the five Jordan daily indices, and secondly, the weekly price indices for ten MENA (Middle East and North Africa) markets. The cointegration test between the Jordan index and every other market index is applied. Moreover, different groups of markets (GCC, Africa, and Europe) are composed and the cointegration test is applied for each group. Results suggest that the Jordan stock market does not exhibit a long run relationship with most other markets, and there is an advantage for investors looking for diversification in the Middle East markets to include the Jordanian market in their portfolios.

7.1 Introduction

The integration of the world major stock markets has been the subject of extensive research, and considerable advances have been made in empirical techniques and their application. The concept of stock market integration is broad. Greater degrees of co-movements displayed by equity markets over time generally reflect greater stock market integration. The economic implication of cointegration in international stock price movements is that national stock prices may be nonstationary, but certain combinations of these stock prices may be stationary. Two price indices with a unit root are said to be cointegrated if a linear combination of them does not have a unit root. Thus, we may say that while they are each non-stationary, their non-stationarity is off-setting and they may be said to be in a long-run relationship. The relevance of the notion of cointegration for semi-strong market efficiency follows since if two variables are related in the long run, then one may be used to predict the other (even if each of them is unpredictable on the basis of its own past). This violates the semi-strong Efficient Market Hypothesis (EMH)[1]. The benefit of international diversification is limited when national equity markets are cointegrated effectively, because the presence of common factors limits the amount of independent variation. By contrast, a lack of cointegration suggests that such variables have no long-run link and that transnational investments in stock markets can improve portfolio's diversification.

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[1] The semi strong EMH is a special case of the general EMH when the information set includes not only past returns but all publicly-available information. In this study, the information set is expanded by including the past returns in other countries in the data set. The first set of tests estimate whether a particular country's return can be predicted using the past returns for another country.

Equity market integration[2] in terms of pricing efficiency, international diversification of portfolios and the existence of lead-lag relationships between stock exchanges have been heavily investigated in the literature (see for example, Kim and Wadhani (1990), Joen and Von Furstenberg (1990), Arshanapalli and Doukas (1993), Eun and Shim (1989), and Kasa (1992)). Recently, there has been a shift in attention to the emerging markets of developing countries (Bekaert and Harvey 1997, DeSantis and Imrohoroglu 1997). However, Bekaert (1993), and Bekaert and Harvey (1997) found that stock market returns in emerging markets were high and predictable, but lacked strong correlation with major markets. As emerging markets mature, they are likely to become increasingly sensitive to the volatility of stock markets elsewhere. Their increasing degree of integration with world markets will diminish their ability to enhance and diversify international portfolios[3]. Hence, the concept of market integration concerns both equity investors and companies in the region that make capital budgeting decisions. Portfolio theory suggests that the greater the degree of integration of stock markets, the smaller the gains from international diversification will be. However, if inefficiency exists in individual national markets, there will be profitable arbitrage opportunities for international portfolio investment.

In terms of efficiency, if asset prices in different markets are cointegrated, then this may indicate the existence of inefficiency in asset markets. Granger (1986) has demonstrated

[2] One of the main advantages of this approach is that it relies on the condition of absence of arbitrage opportunities –which is directly related to the idea that more integration means less barriers to trade across markets- and does not depend on any particular asset pricing model.

[3] Ajayi and Mehdian (1995) and Bowman and Comer (2000) conclude that adding stocks from emerging markets to a portfolio of stocks from developed markets will benefit the efficient diversification of the portfolio.

that the prices of two different assets, each priced in efficient markets, cannot be cointegrated. Thus a necessary condition for semi-strong efficiency is that the logs of the share price indices for any pair (or set) of countries should not be cointegrated. Tests of cointegration have been used recently in the analysis of share market interrelationships - see Forbes (1993), Kasa (1992), Byers and Peel (1993), Chan et al. (1992), Corhay, Tourani Rad and Urbain (1993), Arshanapalli and Doukas (1993), Abbott and Chow (1993), Espitia and Santamaria (1994), Akdogan (1995), Meric and Meric (1997), Chaudhuri (1997), Christofi and Pericli (1999), Darbar and Deb (1997), Francis and Leachman (1998), Kwan *et al.* (1995) Janakiramanan et al. (1998), Masih and Masih (1999) and Cheung and Lai (1999). It appears that previous empirical studies of the interrelationship of the major world stock price indices have not provided consistent results. The sizes and signs of correlation coefficients varied depending on the choice of markets, the sample period chosen, the frequency of observations (daily, weekly, or monthly), and the different methodologies employed to investigate the interdependence of stock markets.

Jaffe and Westerfield (1985) suggest that the return correlation among different markets is positive and significant. Eun and Shim (1989), who used vector autoregressions, found substantial cross-country interactions and also recorded an influential role for the US market. King and Wadhwani (1990), in a significant study of the period surrounding the 1987 crash, document a 'contagion effect' where a 'mistake' in one market is transmitted to other markets. Kasa (1992) has studied the presence of common stochastic trends in the stock markets of the United States, Canada, Japan, the United Kingdom and Germany and found that one common stochastic trend lies behind the co-movement of the five stock markets. Taylor and Tonks (1989) have also examined cointegration between the British stock price index and the stock price indices of the United States, Japan, Germany and the Netherlands. The findings of Kasa (1992) and Taylor and Tonks (1989) are suggestive of a certain link between financial integration and cointegration among stock prices.

Copeland and Copeland (1998) explore the lead and lag relation of market returns using the Dow Jones global industry indices. They found a strong contemporaneous relationship among regional exchanges that open at the same time. Chan et al. (1992), Arshanapalli et al. (1995) and Ghosh et al. (1999) examine the stock price movements between the US and Asian equity markets using cointegration methods. Other studies suggest that significant capital market integration exists among major industrialized countries, thus limiting the potential benefits from international diversification (Meric and Meric (1989), Koutmos (1996), Sinquefield (1996), Ben Zion et *al*. (1996), Freimann (1998), and Bowe and Mylanidis (1999)). In contrast, linkages among emerging markets and between these markets and other developed markets appear to be relatively weak (Korajczyk (1996), Hakim and Andary (1997), and Bekaert and Harvey (1997)). Under market segmentation, there may be significant potential benefits from investing in emerging markets, and a great deal of research has in fact looked into such possibilities (Errunza (1994), and Ben Zion et al . (1996)).

However, the assumed inconsistency between cointegration and efficient markets has been challenged in the last few years. It has been argued that the definition of efficient markets as markets in which changes in asset prices are unpredictable does not have much economic content. However, market efficiency can be defined as the lack of arbitrage opportunities (see Ross (1987)). This concept is adopted by Dwyer and Wallace (1992), who demonstrated that cointegration or lack of cointegration of two or more spot rates has no implications for the inefficiency of international capital markets "with market efficiency defined as the lack of arbitrage opportunities, there is no general equivalence between market inefficiency and cointegration". Their argument is that spot rate changes can be predictable in an efficient market if all information relevant to predicting changes in the spot rate is used to determine the forward rate. Hence, although cointegration of two or more spot rates implies predictability of at least one spot rate, but that is not evidence of inefficiency of international capital markets and they show cointegration can be consistent with market efficiency in various contexts in which the converse has been suggested

Crowder (1994) claims that what accounts for the predictability of exchange rate changes in an efficient market is the fact that the forward risk premium is not stationary. Engel (1996) criticizes this argument, and uses a simple monetary model of the exchange rate, in which capital markets play no role, to show that spot rates can be predictable in an efficient market regardless of the time series properties of the risk premium, and concluded that cointegration and international capital market efficiency are separate issues. In his reply, Crowder (1996) agrees that cointegration does not necessarily imply market efficiency, and reiterates that the non-stationarity of the risk premium is one reason it might not. Other conceivable explanations for the predictability associated with cointegration are the existence of peso problems[4] or regime switches[5], the low power of cointegration tests, and the possibility that error correction models do not provide very useful information to market participants.

Caporale and Pittis (1998) argue that whatever concerns one might have about the identification of a cointegrating relationship with market inefficiency, cointegration tests can still be usefully employed to investigate the predictability of asset prices. They show that in the presence of *r* cointegrating vectors, only *r* prices are predictable and therefore, the standard assumption made in the literature that cointegration implies predictability of all *n* asset prices is not valid

Some studies tried to highlight the reasons why different countries' stock prices may have a significant long-run relationship. A range of factors that could strengthen the linkages among stock markets in different parts of the world can be identified, and the more these factors are presented the more the cointegration relation is expected to occur. These factors include:

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[4] The peso problem may be defined as the presence of potential large events, whose possibility affects behaviour significantly even though they occur rarely. The peso problem takes its name from the futures market in the Mexican peso during the years before the 1977 devaluation, which put the peso at a consistent discount. As a number of people have pointed out, any test of the efficiency of that market before 1977 would have concluded that it was inefficient, since the futures price of a peso consistently mispredicted the actual price, which itself had very little variance. Yet, that discount was the result of a belief by investors that there was some probability of a large devaluation, a belief that turned out to be justified.

[5] In the time-series literature, regime means that time series behavior lies in a state and regime switch is defined as a transition from one state to another.

- The increasing importance of international capital flows and mobility, resulting from the progressive removal of controls on capital movements by the major industrialized countries and some developing countries.
- A general world-wide move to deregulate financial markets. The reduction of the degree of government intervention allows freely floating (market determined) prices and quantities to transmit excess demand pressures to other related markets.
- Technological advances which improved the speed of international financial transactions, improved the international flow of information between markets.
- Increases in the number of multinational companies whose shares are cross-listed on more than one major international stock exchange. Such companies also tend to be involved in economic activities in a number of different countries around the world and hence their performance will increasingly tend to be affected by global rather than country-specific factors.
- Increasing international trade.
- The presence of strong economic ties and policy coordination between relevant countries can indirectly link their stock prices over time.

Jeon and Chiang (1991) cite deregulation and market liberalization measures, rapid developments in communication technology and computerized trading systems, and increasing activities by multinational corporations as factors contributing to such integration. The formation of common trading blocks (e.g. ASEAN, EU, and NAFTA) and the development of integrated economic systems (e.g., EU and EMU) also foster closer linkages of stock markets within the constituent countries. Gelos and Sahay (2000) suggest that the strong economic ties and policy coordination between the relevant countries can indirectly link their stock prices over time. With technological and financial innovation, the advancement of international finance and trade, and deliberate regional and global co-operation, the geographical divide among various national stock markets are less obvious.

The main objective of this chapter is to use recently developed techniques (i.e. unit root tests, cointegration, and Granger causality) to investigate the relation among the five indices of the Jordan market and to analyze the behavior of the Jordan equity market in relation to another ten emerging markets[6] in the Middle East. This study is significant for investors interested in the Middle East markets for different reasons; it examines the weak-form efficient market hypothesis for each of the ten emerging stock markets indices by applying unit root tests. The exchange fluctuations are included in the analysis, hence the indices are measured in US dollars. Furthermore, pair-wise cointegration tests, using the Johansen test, along with the Engle-Granger two-step methodology are employed to detect the interdependence between ASE and the other emerging markets. The Johansen cointegration tests are also conducted for different groups of countries[7].

Section 7.2 presents the cointegration methodology which will be followed in the chapter to investigate the long run relationship among variables, and its role in testing market efficiency. Two techniques are selected: the two step regression based technique and the Johansen multivariate technique. A brief explanation of both techniques and a quick

[6] These are Egypt, Bahrain, Greece, Turkey, Kuwait, Jordan, Saudi Arabia, Oman, Morocco, and Tunisia.
[7] The pair-wise cointegration test is incapable of determining the all interdependence among the investigated markets since more than two markets can be cointegrated.

comparison is given. The methodology of the causal relationship and testing market efficiency is discussed in Section 7.3, and the Granger causality is highlighted as a testing technique for the causal relationship. The cointegration and Granger causality techniques are applied for the five Jordan indices and for ten Middle Eastern markets' indices.

Section 7.4 presents the empirical results of the cointegration and Granger causality test for the Jordan indices. The cointegration test is performed for each pair of Jordan indices by the two techniques: the Engle-Granger two step method and the Johansen approach. The results for the two techniques are very close, suggesting no cointegration equation between each pair. The cointegration test is also applied for a group containing all indices; the result confirms the previous results indicating no long-term relationship among indices. The last test in this section is the Granger causality test which shows a short run relationship between all pairs of indices. The same procedures applied in Section 7.4 are reapplied in Section 7.5 using ten Middle Eastern markets' price indices. The unit root tests are performed firstly for these indices to investigate the stationarity and to detect the order of integration. All indices are found to be I(1), and hence, appropriate to perform cointegration tests. Pair-wise cointegration between the Jordan price index and other markets' price indices are achieved by the Engle-Granger two step method and the Johansen approach. The results proved no long-term relationship between the Jordan price index and any other price index in the sample, except for Bahrain and MENA. On the other hand, the Granger causality tests also show a short relation only between the Jordan price index and Bahrain and MENA indices. In the last part of this section, the ten indices are divided into three groups: GCC, Africa, and Europe. The cointegration tests are then employed twice for each group: once including the Jordan index, and once excluding the Jordan index. The results for the first two groups indicate one cointegration equation when the Jordan index is excluded, and reject any cointigration equation once the Jordan index is included. The third group has one cointegration equation whether or not the Jordan index is included. The summary and conclusion are then presented in Section 7.6.

7.2 Cointegration Methodology

The test of cointegration identifies the long run structural relationship among the variables under consideration. In other words, it tries to establish whether in the long run the variables under study would move in the same direction or not. The cointegration techniques are used to test the concept of 'efficiency'. Fama's definition that a market is efficient if "all prices fully reflect all relevant information", and the joint null hypothesis developed based on such a definition is that:

-The market participants exploit all available information in a rational way, and

-There is constancy in the expected equilibrium returns.

When the null hypothesis is verified, the prices of different shares cannot be cointegrated. According to MacDonald and Power(1993) , if time series prices are cointegrated , this implies Granger-causality running in at least one direction between the different price series, which allows using one share price to forecast the others. As a result, the share price either does not correctly manifest all available information or there are important variations in the expected returns.

The theory of cointegration was developed by Granger (1981) and elaborated by Engle and Granger (1987). Non-stationary two time series are cointegrated if there is a stationary linear combination of them, that is, the combination does not have a stochastic trend. This implies that the series don't drift too far apart from each other over time. Thus there is a long run equilibrium relationship between them[8]. Hence, cointegration is the statistical equivalent of the existence of a long run economic relationship between I(1) variables. This indicates the existence of a long run equilibrium relationship. Thus, if X_t and Y_t series are both integrated of order one I(1) and the linear combination Z_t given by (7-1) is integrated to order zero I(0) , then X_t and Y_t are said to be cointegrated with α being the cointegrating parameter.

$$Z_t = Y_t - \alpha X_t \tag{7-1}$$

Equilibrium means a relationship between a set of variables that has, on average, been maintained for a long period. Thus Z_t given by (7-1) measures the extent to which the system is out of equilibrium, and is therefore considered as an equilibrium error. Since Z_t is stationary in case of cointegration, which means I(0), then Z_t rarely drifts far from zero and often crosses the zero line if it has zero mean, and equilibrium will occasionally occur. If Z_t is I(1), then X_t and Y_t are not cointegrated, and the equilibrium error can wander widely and zero crossing is rare.

[8] The relevance of the notion of cointegration for semi strong market efficiency follows since if two variables are related in the long run, then one may be used to predict the other (even if each of them is unpredictable on the basis of its own past). This violates the semi strong EMH.

For a group of non-stationary series N I(1), it is possible for there to be up to N-1 stationary linear combination or cointegrating vectors. The existence of a cointegrating relationship among a vector of variables implies the existence of error correction representation, which is defined by MacDonald and Power (1993) as:

$$(1-L)\Delta X_t = -\rho Z_{t-1} + \varepsilon_t \tag{7-2}$$

where X is a $N \times 1$ vector of I(1) variables, Z represents the error correction term, L denotes the lag operator and ε denotes a vector of residuals. Since the past prices could not be used to improve the forecasts of the current prices under the efficient market hypothesis, then equation (7-2) represents a violation of market efficiency. Hence, finding that cointegration exists among stock prices is a strong evidence of static inefficiency (MacDonald and Power (1993)). Two techniques are employed to test for cointegration, the two-step regression based technique proposed by Engle and Granger (1987) and the Johansen multivariate technique. These are outlined below.

7.2.1 The Two Step Regression Based Technique

The method suggested by Engle and Granger looks for a linear combination of level series that minimizes the variance of the linear combination using OLS. According to this technique, the first step is to estimate a cointegrating regression given by (7-3) for the potential cointegration set by employing OLS. Then, the second step is to examine the stationarity of the residuals for this cointegrating regression using:

- Durbin Watson for the cointegration regression given by (7-3)

$$y_t = c + \alpha x_t + u_t \tag{7-3}$$

- Dickey Fuller test for the regression given by (7-4)

$$\Delta u_t = -\phi u_{t-1} + \varepsilon_t \tag{7-4}$$

- Augmented Dickey Fuller test for the regression given by (7-5)

$$\Delta u_t = -\phi u_{t-1} + b_1 \Delta u_{t-1} + ... + b_1 \Delta u_{t-p} + \varepsilon_t \tag{7-5}$$

The statistics tabulated by Engle and Granger are used as the distributions of these statistics are nonstandard.

In spite of the potentially powerful results of the Engle Granger two step regression and its inherent simplicity, it has been argued that this procedure suffers from a number of deficiencies. Doing the cointegrating regression in different ways can get different results for each alternative. For example, and taking into consideration that the estimation of the long run equilibrium regression requires that one variable be placed on the LHS and the others used as regressors, in the case of two variables it is possible to run the Engle-Granger test by using the residuals from either side of the following two "equilibrium" regressions:

$$y_t = c_1 + \alpha_1 x_t + u_{1t} \tag{7-6}$$

or

$$x_t = c_2 + \alpha_2 y_t + u_{2t} \tag{7-7}$$

As the sample size grows infinitely large, the test for a unit root in the u_{1t} sequence becomes equivalent to the test for a unit root in the u_{2t} sequence. However, this result is derived on large sample properties and may not be applicable to small sample sizes. In practice, it is possible to find that one regression shows that the variables are cointegrated whereas reversing the order indicates no cointegration. This is a major disadvantage of the procedure since the test for cointegration should be invariant of the choice of the variable selected for normalization. MacDonald and Power (1993) also argued that the use of OLS to estimate a cointegration relationship for an N dimensioned vector does not clarify whether one is dealing with a unique cointegration vector or simply a complex linear combination of all the distinct cointegration vectors which exist within the system. This technique also fails to capture the underlying time series properties of the data and its test procedures do not have well defined limiting distribution. In addition, the step-wise procedure implies the compounding of errors. Any error introduced in step1 is carried into step 2. Another drawback is that it can estimate only up to one cointegration relationship between the variables. If there are three variables in the system, there could potentially be up to two linearly independent cointegrating relationships.

Due to the drawbacks mentioned earlier, the application of Engle-Granger methodology may not give the desired results. Hence the same test for cointegration is performed using Johansson's procedure.

7.2.2 The Johansen Multivariate Technique

The Johansen procedure is nothing but a multivariate generalization of the Dickey-Fuller test. However, the Johansen multivariate technique provides estimates of all the cointegration vectors that exist within a vector of variables, fully captures the underlying time series properties of the data, and offers a test statistic for the number of cointegrating vectors with an exact limiting distribution (Refer to Appendix 5 for more details).

Considering the n variable case in (7-8)

$$x_t = A_1 x_{t-1} + \varepsilon_t \qquad \textbf{(7-8)}$$

so that

$$\Delta x_t = \pi x_{t-1} + \varepsilon_t \qquad \textbf{(7-9)}$$

where x_t and ε_t are (nx1) vectors and

A_1 an (nxn) matrix of parameters

I an (nxn) identity matrix

And π is defined to be (A_t-I)

The rank of (A_1-I) equals the number of cointegrating vectors. If (A_1-I) consists of all zeros, so that rank (π) =0, all the { Δx_{it} } sequences are unit root processes. Since there is no linear combination of the { x_{it} } processes that is stationary, the variables are not cointegrated.

The multivariate model can also be generalized to allow for a higher-order auto regressive process. Considering (7-10)

$$x_t = A_1 x_{t-1} + A_2 x_{t-2} + \ldots.. + \varepsilon_t \qquad \textbf{(7-10)}$$

where , x_t the (nx1) vector (x_{1t}, x_{2t},.......... x_{nt})

ε_t an independently and identically distributed n-dimensional vector with zero mean and variance matrix $\Sigma\varepsilon$..

Subtracting x_{t-1} from each side to get (7-11)

$$\Delta x_t = (A_1 - I)x_{t-1} + A_2 x_{t-2} + A_3 x_{t-3} + ...+ A_p x_{t-p} + \varepsilon_t \tag{7-11}$$

Now add and subtract (A_1-I) x_{t-2} followed by (A_2+A_1-I) x_{t-3} and so on to get (7-12)

$$\Delta x_t = \sum_{i=1}^{p-1} \pi_i \Delta x_{t-1} + \pi x_{t-p} + \varepsilon_t \tag{7-12}$$

where

$$\pi_i = -\sum_{j=i+1}^{p} A_j \tag{7-13}$$

$$\pi = \sum_{i=1}^{p} A_i - I \tag{7-14}$$

The number of distinct cointegrating vectors can be found by checking the significance of the characteristic roots of π. Suppose that the n characteristic roots of matrix π are ordered such that $\lambda_1 > \lambda_2 > .....\lambda_n$. If the variables in x_t are not cointegrated, rank (π)=0 and all these characteristic roots will equal zero. If the variables are not cointegrated, each of the expressions ln(1- λ_i) will be zero.

The following two tests statistics are used to test for the number of characteristic roots that are insignificantly different from unity.

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\lambda_i) \quad \textbf{(7-15)}$$

$$\lambda_{\max}(r, r+1) = -T\ln(1-\lambda_{r+1}) \quad \textbf{(7-16)}$$

where, λ_i, $i = 1,2,......n$ is the eigenvalues obtained from the estimated π matrix, and T is the number of usable observations.

The λ_{trace} statistic tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r (the number of cointegration relationships) against the alternative hypothesis of more than *r* cointegrating relationships. The further the estimated eigenvalues are from zero, the larger the λ_{trace} statistic. The λ_{max} tests the null hypothesis that the number of cointegrating vectors is r against the alternative of r+1 cointegrating vectors. If the estimated eigenvalue is close to zero, λ_{max} will be small.

7.3 Granger Causality for Causal Relationship Methodology

The Granger causality test is a popular way to test if there is any temporal statistical relationship with a predictive value between two time series (Granger, 1969). This test indicates any possible short-run predictive interrelationships among the stock prices.

Granger starts from the premise that the future cannot cause the present or the past. For example, if event A occurs after B, then A cannot cause B and even if A occurs before B, it doesn't necessarily imply that A causes B (Maddala, 2000). It is important to note that the statement "X Granger causes Y" does not imply that Y is the effect or the result of X. Granger causality measures precedence and information content but does not by itself indicate causality in the common-sense use of the term. Thus "causality" is defined in terms of predictability, hence variable X causes variable Y if present Y can be better predicted by using past values of X(lagged) than by not doing so, with respect to a given information set that includes X and Y.

Considering two time series Y_t and X_t , the series X_t fails to Granger cause Y_t if in a regression of Y_t on lagged Y's and lagged X's , the coefficient on the latter are zero. Considering (7-17) and (7-18):

$$Y_t = \alpha + \sum_{i=1}^{k} \beta_i Y_{t-1} + \sum_{i=1}^{k} \gamma_i X_{t-1} + \varepsilon_t \tag{7-17}$$

$$X_t = c + \sum_{i=1}^{k} \delta_i X_{t-1} + \sum_{i=1}^{k} \xi_i Y_{t-1} + v_t \tag{7-18}$$

Four patterns of causality can be distinguished: (a) unidirectional causality from X to Y; if $\gamma_i \neq 0$ $(i = 1,2,....k)$, and $\xi_i = 0$ $(i = 1,2,....k)$, then X_t Granger cause Y_t; (b) unidirectional causality from Y to X; if $\gamma_i = 0$ $(i = 1,2,....k)$, and $\xi_i \neq 0$ $(i = 1,2,....k)$ then Y_t Granger causes X_t; (c) feedback or bi-directional causality; if γ_i and ξ_i are different from zero , then there is a bi-directional causality in the sense that X_t Granger cause Y_t and Y_t Granger cause X_t; and (d) no causality; if X_t fails to Granger cause $Y_t(\gamma_i = 0 \quad (i = 1,2,....k))$and Y_t fails to Granger cause X_t $(\xi_i = 0 \quad (i = 1,2,....k))$ concluding that the two series are temporally unrelated.

As the efficient market hypothesis implies that asset prices are not predictable, therefore, in the case of no significant Granger causality between price series, the efficient market hypothesis will hold since the prices are not predictable. If there is Granger causality between two price series in one direction, then the efficient market hypothesis will possibly be violated since one price series can be used to predict the other. Finally, bi-directional causality would imply market efficiency since there is no clear prediction relationship. This kind of causality implies that Y_t proceeds X_t at some point in time, but at some other point in time X_t proceeds Y_t. There is a feedback between the two series but not a clear relationship in terms of predictability (Morkerjee, 1987).

Some important drawbacks challenge the test. The arbitrary specification of the lag length (which affects the F statistic, for example) is one such criticism. The choice of lag length is suggested to be in accordance with the data time interval in order to avoid any problems of autocorrelation due to misspecified dynamics or seasonal effects.

Another weakness is that the test doesn't utilize all the information contained in the data because the usual practice is to use stationarity data (Maddala, 2001). That is. the Granger casualty test should be performed on differenced data (returns in this study) to achieve stationarity- but differencing filters out valuable low frequency information in the data which effects the long run inferences about any possible predictive relationships between different stocks. The concept of cointegration was developed to resolve this weakness; the cointegration technique doesn't request differencing and cointegration theory states that when two variables are cointegrated then the Granger causality runs in at least one direction. Hence in an efficient market price, different stocks cannot be cointegrated (Hall and Henry, 1986)

7.4 Jordan Indices Properties

The cointegration methodology is applied to test Jordan market efficiency from a domestic point of view, by using the five prices indices, and from a national point of view, by using price indices of different countries. In this section, an investigation of the cointegration equations among the five prices indices for the Jordan market is conducted, and the existence of such cointegration relations is found. This is considered a clear violation of market efficiency since it implies that information in past prices could have been used to improve the forecasts of the current prices.

Two techniques are employed to test for cointegration: the Engle-Granger two-step method and the Johansen test. Pair-wise cointegration between each pair of indices is conducted, and then all the indices are used together to investigate any overall cointegration relationship.

7.4.1 Pair-Wise Cointegration

7.4.1.1 The Engle-Granger Two-Step Method

The Engle-Granger two-step method is conducted, before implementing the Johansen method, as a preliminary test for cointegration, as well as for comparative purposes. Based on the results of chapter 6, all the price indices series can be considered I(1).

The regressions (7.3), (7.4) and (7.5) are estimated for each pair of indices and Table (7-1) presents some simple bivariate cointegration results for the five price indices of the Jordan market. The tests indicate one possible cointegration equation between banks and services[9] indices at the 10% significance level, depending on DF and ADF statistics. Hence, the stock market does appear to be efficient for the most of the sample since no long run relationship seems to exist between most of the indices. The Engle-Granger two-step test implies no long run structural relationship for each pairs of price indices as the linear combination of each pairs has stochastic trend and is not stationary.

[9] Depending on Chapter 6 results, the service index is potentially I(0)

Table 7-1: Engle-Granger Cointegration Test for each Pair of the Jordan Indices:

$$General = 93.7 + 0.29 Banks$$

t-statistic (101.4) (63.2)

DW	0.003
DF	1.745
ADF	1.900

$$General = 126.2 + 0.19 Inusrance$$

t-statistic (39.4) (7.6)

DW	0.003
DF	2.362
ADF	2.344

$$General = 148.2 + 0.018 Industry$$

t-statistic (86.0) (1.24)

DW	0.003
DF	2.626
ADF	2.560

$$General = 159.6 - 0.076 Service$$

t-statistic (159.6) (-3.75)

DW	0.004
DF	2.719
ADF	2.671

$$Banks = 311.6 - 0.91 Insurance$$

t-statistic (37.0) (-14.2)

DW	0.002
DF	2.302
ADF	2.135

$$Banks = 321.7 - 1.13 Industry$$

t-statistic (84.8) (-34.8)

DW	0.003
DF	2.582
ADF	2.556

$$Banks = 386.1 - 1.59 Service$$

t-statistic (70.8) (-35.8)

DW	0.004
DF	**3.087***
ADF	**3.066***

$$Insurance = 83.9 + 0.40 Industry$$

t-statistic (79.2) (44.5)

DW	0.005
DF	1.458
ADF	1.783

$$Insurance = 51.9 + 0.64 Service$$

t-statistic (39.6) (60.3)

DW	0.010
DF	1.929
ADF	2.562

$$Industry = -34.2 + 1.21 Service$$

t-statistic (-20.9) (91.3)

DW	0.008
DF	2.120
ADF	2.341

DW, DF, and ADF denote respectively, Durbin Watson, Dickey Fuller and Augmented Dickey Fuller statistics on the residuals generated from the cointegrating equation. The critical values for these statistics as mentioned in Table II, Engle and Granger (1987), are as follows:

	Significance Levels		
	1%	5%	10%
DW	0.511	0.386	0.322
DF	4.070	3.370	3.030
ADF	3.770	3.170	2.840

If the values of DW, DF, and ADF from the regression are exceeding the critical values, the null hypothesis of no cointegration is rejected.

*Significance at 10% level.

7.4.1.2 Johansen Approach

The Johansen approach is applied to test the cointegration between the Jordan indices, and then the Johansen multivariate approach is implemented to test cointegration using all the price indices.

Table 7-2 shows similar results to those obtained through the Engle-Granger two-step method except for the cointegration between the general and service indices. The test suggests two cointegration equations at the 5% significance level. This result indicates that none of the series is actually integrated since the cointegrating rank equals the number of endogenous variables. This enhances the probability mentioned in Chapter 6 that the service index is I(0). In the next section, the multivariate Johanson approach is applied to investigate any cointegration equation. It is applied twice: by using all indices together and by using all indices except the service index which is potentially I(0).

Table 7-2: Johansen Cointegration Test for each Pair of Jordan Indices (General and Bank Indices)

Johansen Cointegration Test

Series: General Banks

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.007331	21.35479	25.32	30.45	None
0.001762	4.128848	12.25	16.26	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-2 (General and Insurance Indices)

Johansen Cointegration Test

Series: General Insurance

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.005066	15.49667	25.32	30.45	None
0.001539	3.606439	12.25	16.26	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-2 (General and Industry Indices)

Johansen Cointegration Test

Series: General Industry

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.007417	21.78051	25.32	30.45	None
0.001846	4.33138	12.25	16.26	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-2 (General and Service Indices)

Johansen Cointegration Test

Series: General Service

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.00667	20.37905	15.41	20.04	**None** **
0.002011	4.713048	3.76	6.65	**At most 1** *

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 2 cointegrating equation(s) at 5% significance level

Continued: Table 7-2 (Bank and Insurance Indices)

Johansen Cointegration Test

Series: Bank Insurance

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.00424	12.73873	15.41	20.04	None
0.001192	2.7913	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-2 (Bank and Industry Indices)

Johansen Cointegration Test

Series: Bank Industry

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.007834	22.82382	25.32	30.45	None
0.001883	4.411195	12.25	16.26	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-2 (Bank and Service Indices)

Johansen Cointegration Test

Series: Bank Service

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.007336	19.39871	15.41	20.04	**None** *
0.000923	2.162334	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating equation(s) at 5% significance level

Continued: Table 7-2 (Insurance and Industry Indices)

Johansen Cointegration Test

Series: Insurance Industry

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.002106	5.012788	15.41	20.04	None
3.35E-05	0.078457	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-2 (Insurance and Service Indices)

Johansen Cointegration Test

Series: Insurance Service

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.004559	13.84197	15.41	20.04	None
0.001342	3.144472	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-2 (Industry and Service Indices)

Johansen Cointegration Test

Series: Industry Service
Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.004584	11.52714	15.41	20.04	None
0.00033	0.771933	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

The Table presents the trace test, using Eviews software to determine the number of cointegration relations. The eigenvalues are presented in the first column, while the second column (Likelihood Ratio) presents the LR test statistic (trace statistic)[10]:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\lambda_i)$$

for r=0, 1, .. , n-1 (in this Table n=2 as tow series are used to perform the test) where λi is the i-th largest eigenvalue. To determine the number of cointegrating relations r, we can proceed sequentially from r=0 to r=n-1 until we fail to reject the null hypothesis of cointegration. The first row in the Table tests the hypothesis of no cointegration, the second row tests the hypothesis of one cointegration relation, the third row tests the hypothesis of two cointegrating relations, and so on, all against the alternative hypothesis of full rank, i. e. all series in the VAR are stationary.

7.4.2 Group Cointegration Johansen Approach

The results demonstrated in Table 7-3 suggest that there is one cointegration equation at the 5% significance level when all indices are used, but the hypothesis of cointegration is rejected at the 5% significance level when the service index is omitted and the other four indices are used. This result supports the previous results and indicates no long run relationship between indices in the Jordan financial market. In general, these findings contradict the findings in the last chapters which suggested that the Jordan market is not weak form efficient. However, some studies were skeptical about using the cointegration method to test market efficiency[11].

[10] Refer to Appendix 5 for more details

[11] Dwyer and Wallace (1992) argue that there is no general equivalence between market efficiency and cointegration, or a lack of cointegration, and demonstrate that cointegration in financial markets can be consistent with market efficiency. Engle (1996) also discusses predictability in an efficient market, and concludes that co-integration has nothing to do with EMH.

Table 7-3: Johansen Cointegration Test for All Jordan Indices

Johansen Cointegration Test
Series: General Banks Insurance Industry Service

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.017477	77.94434	68.52	76.07	None **
0.008158	36.66938	47.21	54.46	At most 1
0.005249	17.49422	29.68	35.65	At most 2
0.001865	5.175048	15.41	20.04	At most 3
0.000344	0.80504	3.76	6.65	At most 4

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating equation(s) at 5% significance level

Continued: Table 7-3(Johansen Cointegration for All Jordan Indices except Service Index)

Johansen Cointegration Test
Series: General Banks Insurance Industry

Included observations: 2341
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.010173	37.62554	47.21	54.46	None
0.003774	13.68964	29.68	35.65	At most 1
0.001685	4.836993	15.41	20.04	At most 2
0.00038	0.888948	3.76	6.65	At most 3

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

The Table presents the trace test, using Eviews software to determine the number of cointegration relations. The eigenvalues are presented in the first column, while the second column (Likelihood Ratio) presents the LR test statistic (trace statistic)[12]:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\lambda_i)$$

for r=0, 1, .. , n-1 (in this Table n=5 as tow series are used to perform the test) where λi is the i-th largest eigenvalue. To determine the number of cointegrating relations r, we can proceed sequentially from r=0 to r=n-1 until we fail to reject the null hypothesis of cointegration. The first row in the Table tests the hypothesis of no cointegration, the second row tests the hypothesis of one cointegration relation, the third row tests the hypothesis of two cointegrating relations, and so on, all against the alternative hypothesis of full rank, i. e. all series in the VAR are stationary.

[12] Refer to Appendix 5 for more details

7.4.3 Granger Causality Test

Granger causality tests are used to examine the short run dynamics of the series and to investigate causality between each pair and its direction. The indices returns are used rather than levels because the inferences based on the standard regression do not hold when the regressors are non-stationary. Table 7-4 summarizes the results of testing the null hypothesis that the first index series does not Granger cause the second. The results are striking, all indices have a short run relationship with the each other, some pairs have the relationship in both directions, others in one direction.

The results indicate that stock prices are highly predicted since six of the pairs have a relationship in both directions, which violate the EMH. However, it is worth mentioning that some studies questioned the cointegration and Granger causality as tests for EMH. Granger (1992) argues that when the cointegration relations and causality exist among the financial data, then price changes would be consistently predictable, and so a money machine could be created. This argument is based on the logic that cointegration is a causal relationship which contains at least one exogenous variable and, hence, cointegration would necessarily imply predictability. Stock and Watson (2001) examine empirical evidence of the forecasting ability of asset prices and conclude that some asset prices are predictable in some countries in some periods. Which series predicts what, when and where, is however, itself difficult to predict. Most empirical evidence, as summarized in Stock and Watson (2001), shows that a significant Granger causality statistic contains little or no information about whether the indicator has been a reliable predictor. Hence, the predictability inferred from cointegration and causality tests does not necessarily mean creating a money machine or violating market efficiency.

Table 7-4: Pairwise Granger Causality Test for Jordan Return Indices:

Null Hypothesis:	Obs	F-Statistic	Probability
RBANKS does not Granger Cause RGENERAL	2343	2.38443	0.09237*
RGENERAL does not Granger Cause RBANKS		5.73143	0.00329***
RINDUSTRY does not Granger Cause RGENERAL	2343	2.93564	0.05329*
RGENERAL does not Granger Cause RINDUSTRY		5.63516	0.00362***
RINSURANCE does not Granger Cause RGENERAL	2343	0.50279	0.60491
RGENERAL does not Granger Cause RINSURANCE		4.42385	0.01209**
RSERVICES does not Granger Cause RGENERAL	2343	4.50654	0.01113**
RGENERAL does not Granger Cause RSERVICES		4.93017	0.0073***
RINDUSTRY does not Granger Cause RBANKS	2343	6.43275	0.00164***
RBANKS does not Granger Cause RINDUSTRY		5.48508	0.0042***
RINSURANCE does not Granger Cause RBANKS	2343	1.10312	0.33201
RBANKS does not Granger Cause RINSURANCE		3.69665	0.02495**
RSERVICES does not Granger Cause RBANKS	2343	3.86455	0.02111**
RBANKS does not Granger Cause RSERVICES		4.42081	0.01213**
RINSURANCE does not Granger Cause RINDUSTRY	2343	0.98248	0.37454
RINDUSTRY does not Granger Cause RINSURANCE		3.55951	0.02861**
RSERVICES does not Granger Cause RINDUSTRY	2343	7.5261	0.00055***
RINDUSTRY does not Granger Cause RSERVICES		2.71244	0.06658*
RSERVICES does not Granger Cause RINSURANCE	2343	1.42869	0.23983
RINSURANCE does not Granger Cause RSERVICES		4.34268	0.01311**

*** Significant at 1% level
** Significant at 5% level
* Significant at 10% level

7.5 Jordan within the Context of Middle Eastern Emerging Markets

Equity market integration, measured through the identification of common mutual long run stochastic trends using cointegration techniques, and its impact in terms of pricing efficiency and international diversification of portfolios, has been the basis of many studies. Diversification into international stock markets cannot be effective if those markets have comovements, i.e. they are cointegrated. For example, if stock prices in Egypt declined steadily over a long period of time, and stock prices in Jordan followed the decline closely, then the two markets are cointegrated. The diversification in these two markets would not be effective because the systematic (country) risk cannot be diversified away. Thus, it is not in the best interest of investors who want diversified portfolios to invest in cointegrated markets (Chen et al., 1992, and Arshanaplli and Doukas, 1993).

This section explores the interdependence of the Jordan market and other markets in the Middle East region. First, the weak-form efficient market hypothesis is examined for the indices of each of the ten emerging stock markets, by applying the unit root test. Then pair-wise cointegration tests by using the Johansen test, along with the Engle-Granger two-step methodology are employed to detect the interdependence between ASE and the other emerging markets. Moreover, the Johansen cointegration tests are also conducted for different groups of countries[13]. The Johansen test is applied for each group twice: by including and excluding the ASE. These groups are:

[13] The pair-wise cointegration test is incapable of determining the all interdependence among the investigated markets since more than two markets can be cointegrated.

1) The Gulf Cooperation Council (GCC)[14] Countries

The GCC countries have traditionally discriminated against non-GCC investors. As mentioned in Table 3.8, the foreign investment ceiling in Bahrain and Oman is up to 49% of ownership if the company approves; 100% for GCC nationals. However in Saudi Arabia, the market is closed for foreign investment and the ceiling for GCC nationals is up to 25%. The GCC market capitalization during the last decade has remained relatively low and did not grow by as much as in its MENA counterparts (Refer to Tables 3.10-3.17). This can be attributed to the 1991 Gulf war and to the fact that these markets have remained closed and fairly illiquid (Neaime, 2002). The shares of ownership of the respective governments in these markets have rendered the role of private firms rather limited in this scope.

2) The African Countries: Egypt, Tunisia, and Morocco.

Unlike the GCC countries, the Egyptian, Tunisian, and Moroccan markets provide a complete open access for international investors. They also recorded high capitalization growth rates (refer to Table 3.10), probably for the following reasons: 1) the massive privatization plans introduced in these countries, 2) the extensive sale of government assets to private firms, and 3) the considerable efforts devoted recently towards enhancing the efficiency, depth, and liquidity of the three stock markets (Neaime, 2002).

[14] The GCC countries are mainly the MENA oil-producing countries: Bahrain, Oman, Kuwait, Saudi Arabia, Qatar, and United Arab Emirates. In this study, the first four countries are included due to data availability.

3) The European Countries: Turkey and Greece.

This group has the longest available time series compared with other groups. These markets have a high capitalization growth rate and are fully opened towards international investors.

7.5.1 Data and Summary Statistics

The data consists of the weekly Standard & Poor's/International Finance Corporation Global index (S&P/IFCG)[15] price indices for ten markets and the MENA[16] (Middle East and North Africa) price index. These markets are: Bahrain, Egypt, Greece, Oman, Morocco, Saudi Arabia, Jordan, Kuwait, Tunisia, Turkey, and MENA. All indices are measured in US dollars in order to avoid currency risk, which is more relevant for international investors. Weekly data is used to reduce the problem of nonsynchronous trading since the investigated indices may be influenced by some thinly traded stocks. The period covers the ten years from May 9, 1993 to May 9, 2003. The data for Jordan, Turkey, and Greece is available for the full period (523 observations). However, the available data for the other indices doesn't start from May 9, 1993. For Tunisia, the available data starts from December 29, 1995, (385 observations), Egypt and Morocco from January 31, 1997, (328 observations), Saudi Arabia from November 27, 1998, (233 observations), MENA from December 18, 1998, (230 observations), Bahrain and Oman from January 4, 2000, (161 observations) and Kuwait from May 12, 2000, (157

[15] S&P/IFCG provides value-weighted indices of a representative sample of equities in each country covering at least 60 percent of the market's capitalization.
[16] Except for Kuwait price index since Kuwait is classified as developed country and not included by S&P IFCG. The KUWAIT AL - SHALL GENERAL Price index, included in the Data Stream, is used.

observations). The summary statistics for the weekly markets returns, where the return is calculated as log differences in the index level, are presented in Table 7-5.

Table 7-5: Summary Analysis of Weekly Returns

	No.of observations	Mean[1] (1000)	Std. Dev. (1000)	Autocorrelation				
				ρ_1	ρ_2	ρ_3	ρ_4	ρ_5
Jordan	522	0.584	18.7	-0.02	-0.002	0.094**	0.018	-0.0003
Bahrain	160	-0.968	15.4	0.224**	0.11	-0.116	-0.183**	-0.158**
Egypt	327	-4.37	31.9	0.058	-0.017	0.078	-0.031	-0.138
Greece	522	0.429	41.5	0.041	-0.051	0.007	0.002	0.084*
Morocco	327	0.245	21.3	0.136**	0.089	0.025	0.024	0.051
Oman	160	-0.534	21.7	0.201**	0.023	-0.049	0.01	-0.012
Saudi Arabia	232	2.52	19.2	0.148**	0.129**	-0.077	-0.057	-0.097
Tunisia	384	-2.58	25.7	0.022	-0.002	-0.012	0.129**	0.03
Turkey	522	0.112	89.6	-0.066	0.069	0.006	0.01	0.033
Kuwait	156	4.34	26	-0.235***	0.072	0.03	0.032	-0.015
MENA	229	1.54	21.8	0.143**	0.036	-0.044	-0.114*	0.087

[1]Means are the weekly returns mean measured in US dollar and multiplied by 1000
***** Significant at 1% level**
**** Significant at 5% level**
*** Significant at 10% level**

As shown in Table 7-5, the mean weekly return for Jordan is higher than seven markets in the sample and less than two market members in GCC, Saudi Arabia and Kuwait[17]. However, the weekly mean return is still less than the MENA index. On the other hand, Jordan has the lowest standard deviation after Bahrain; Bahrain has a negative mean return, which indicates low risk for investors with high returns, compared to other

[17] MENA, in general, performed poorly in 1997 and after. With the exception of GCC countries, indexes registered low or even negative performance. Much of this was due to specific domestic issues. But the problem was compounded by the financial turmoil that hit emerging markets beginning in the summer of 1997. The turmoil tended to have the greatest effect on those MENA markets with the highest foreign exposure. Egypt, for example, has the lowest negative average return. Egypt over the last five years experienced a series of economic shocks. In November 1997, the tourism industry was temporarily wiped out after the terrorist attack in Luxor. At about the same time, the price of oil, also a major revenue earner, was falling, the Asian finance caused foreign investment and Suez Canal revenue to shrink, while the decline in oil revenue in the Gulf reduced worker remittances. These events affected the investment and the stock market performance (www.erf.org.).

markets in the sample. The autocorrelation results for Jordan are overwhelming when compared to daily autocorrelation results. The autocorrelation coefficient for the first lag of the weekly return is -0.02, whilst, 0.22 for the first lad of the daily general index return[18].

Compared with markets included in the sample, Jordan has the closest first order autocorrelation coefficient to zero. It is worth mentioning that any comparison of national markets must take into account the fact that stocks on different national securities are quoted in different national currencies, so that any relationship between the movements in the two securities is likely to be obscured by fluctuations in the exchange rate. Hence, to abstract from this problem, the US dollar is used as the common currency unit. Moreover, it is believed that the US dollar helps in attaining more integrated emerging stock markets, by facilitating greater arbitrage because of the absence of uncertainty about exchange rate volatility. In addition, using the US dollar returns eliminates the location inflation in sample series.

By looking at the diagram in figure 7-1, we can decide roughly that the GCC countries share the same trend since the series go up and down in a compatible way, especially Saudi Arabia and Oman. However the Jordan market doesn't share this trend. For instance, in the second half of year 2000, the series for the GCC group fell down while it rose for Jordan. Also, Figure 7.2 shows that the Jordan index does not follow the same trend of the other series - especially at the end of the sample period. Figure 7.3 shows that

[18] The daily interval produces a large number of observations but the biases associated with nontrading and asynchronous prices are troublesome. Weekly sampling compromises the large number of observations and minimizes the biases inherent in daily data.

Turkey and Greece exhibit very close trends, and a cointegration relation is expected in this.

Figure7-1: The Price Index Series for the GCC Group

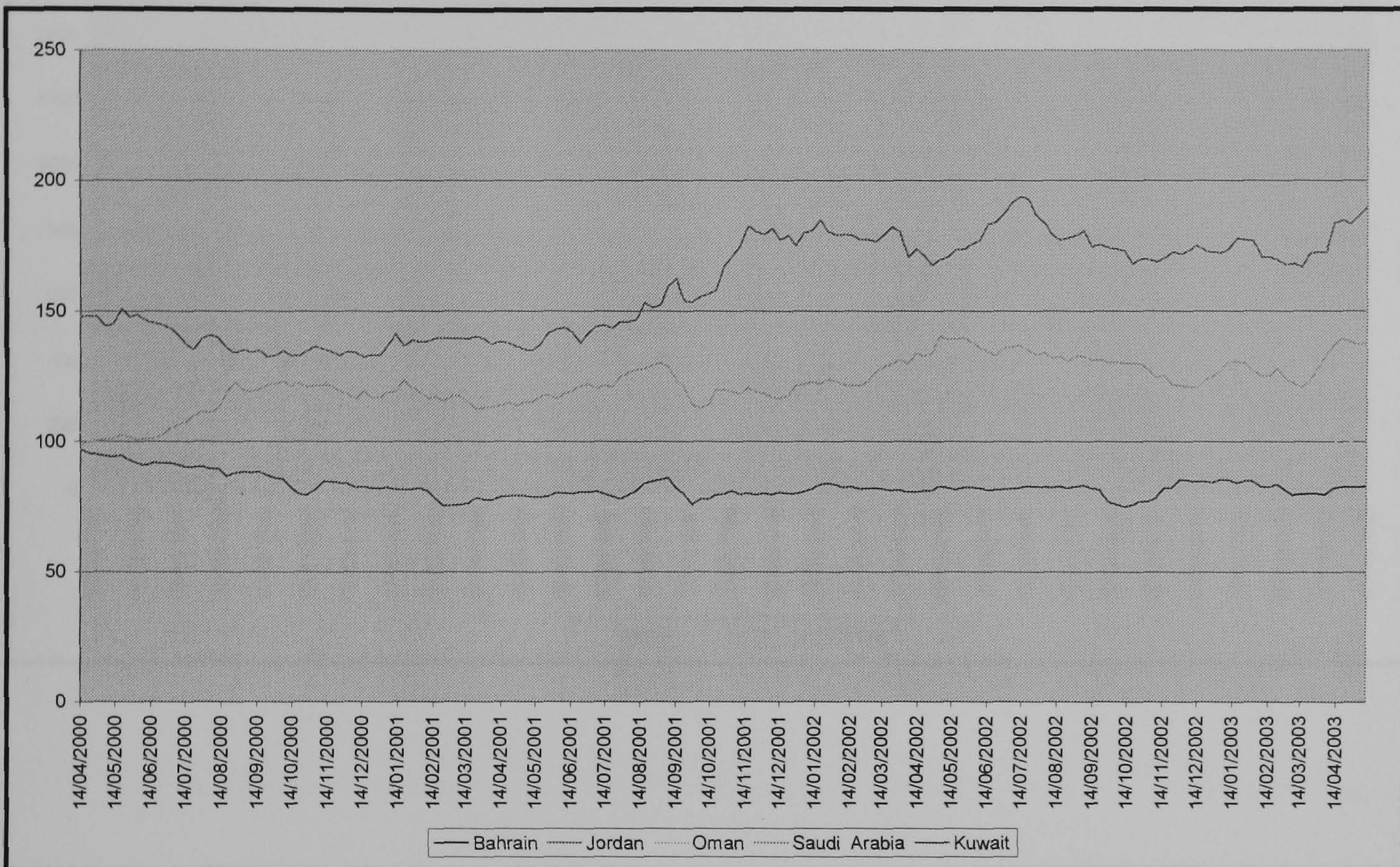


Figure7-2: The Price Index Series for the African Group

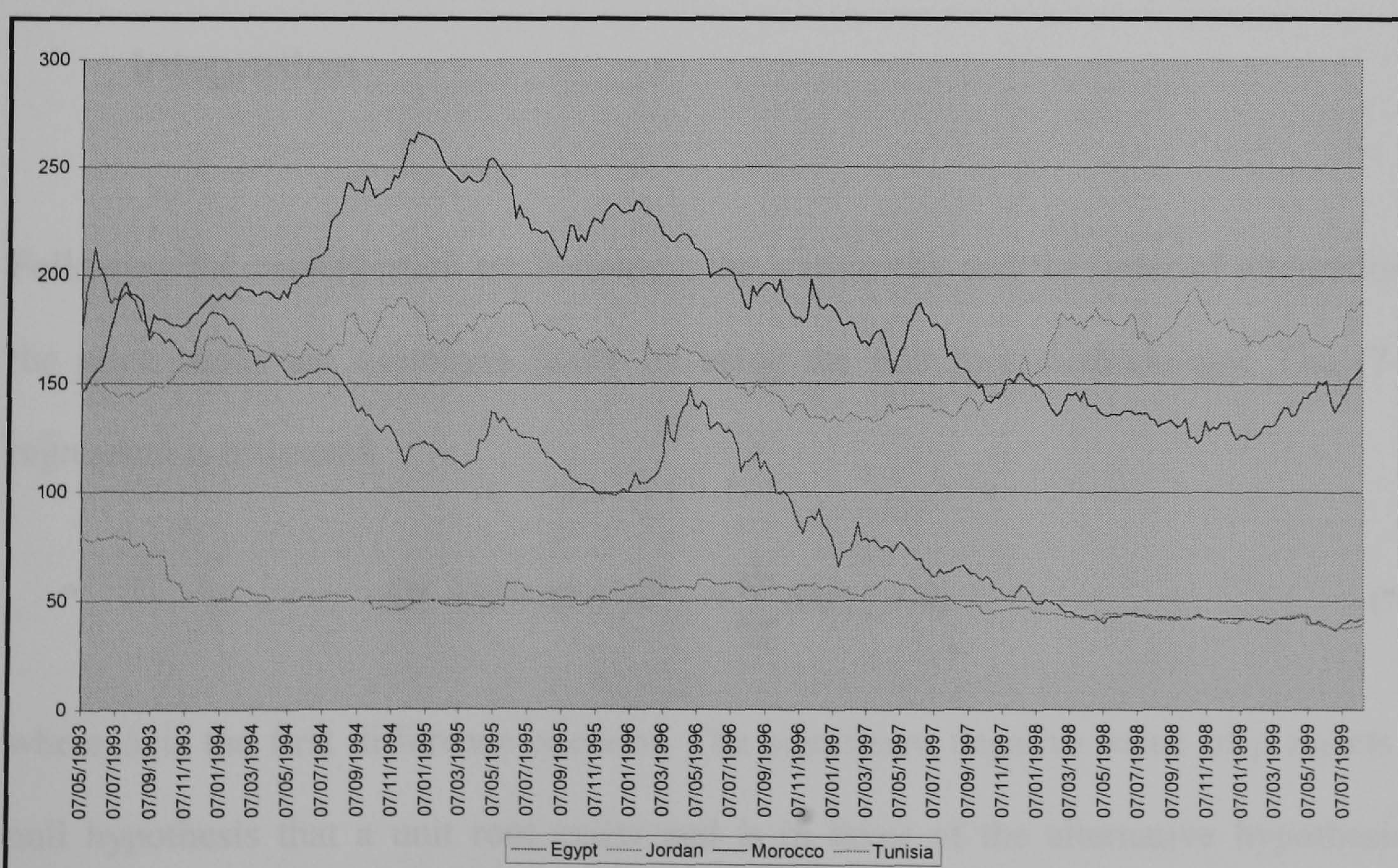
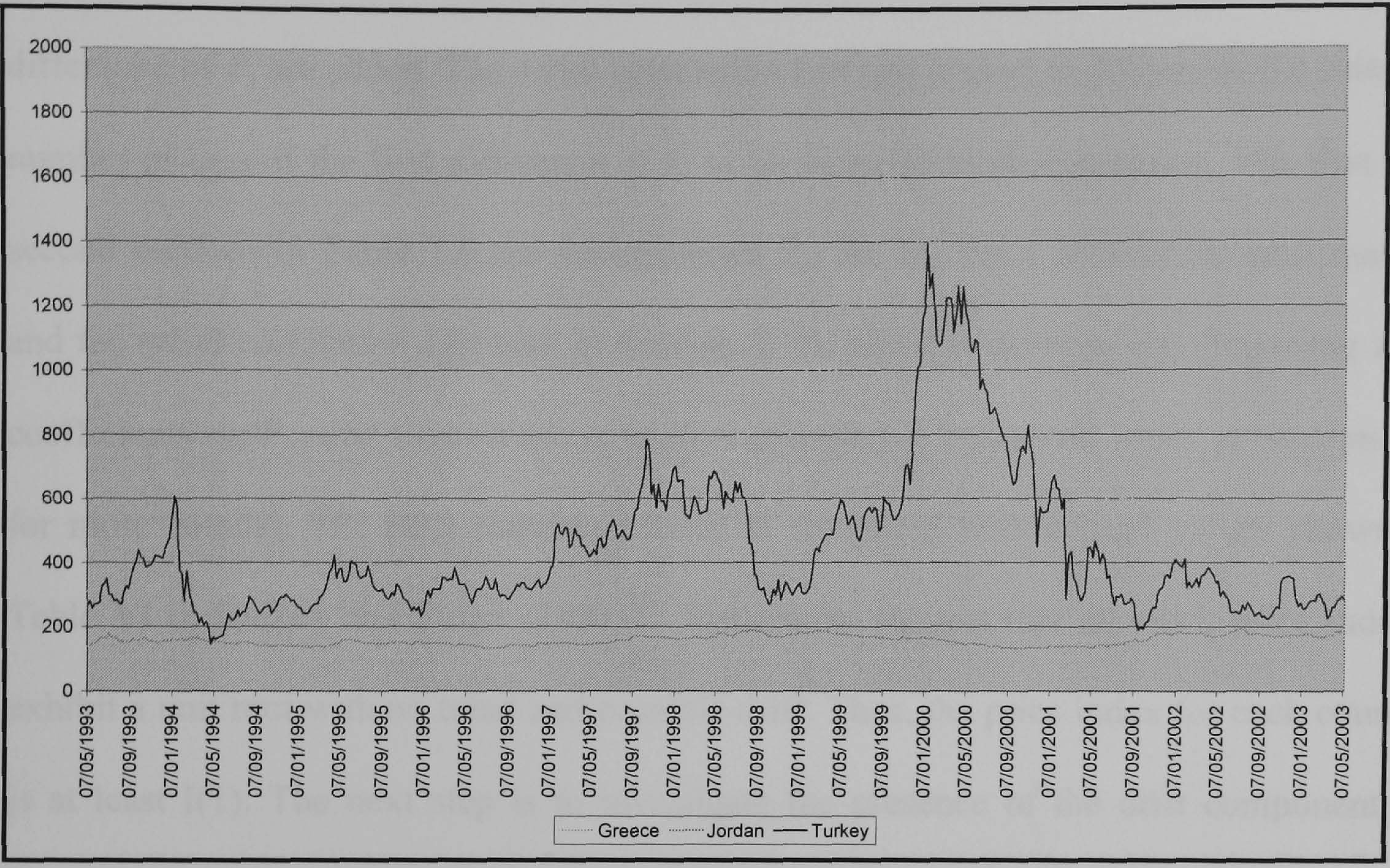


Figure7-3: The Price Index Series for the European Group



7.5.2 Unit Root and Stationarity Test for Detecting the Order of Integration

Following the cointegration methodology, the stationarity and the order of integration of the price series are examined firstly by using the unit root methodology. The (7-19) regression is estimated.

$$\Delta P_t = \alpha + \beta t + \rho P_{t-1} + \sum_{i=1}^{q} \delta \Delta P_{t-i} + \varepsilon_t \tag{7-19}$$

where Δ is the first difference operator. The significant negative value of ρ rejects the null hypothesis that a unit root exists and is in favor of the alternative hypothesis of stationarity, *I(0)*. To eliminate any serial correlation in the residuals, lags of the first difference of P_t are added. The serial correlation LM test is used to determine the suitable number of lags of the first difference of P_t to be included in the regression. The first and second sections in Table 7.6 are the estimated 7.1 for the price indices for each market and the serial correlation LM test. In Section 3, the variable deletion test (imposing zero coefficients on P_{t-1} and time trend) is applied and **(Φ_1)** is computed (refer to Section 6.3 for more details). The **(Φ_1)** computed value is compared with critical values shown in Table VI in Dickey and Fuller (1981)[19]. The results suggest that all stock price indices exhibit a unit root with no trend and possible drift. Thus, the price index for each country is at least I(1). The next step is to investigate the presence of the drift component by imposing zero coefficients on P_{t-1}, time trend, and intercept. The computed **Φ_2**, compared with critical values is shown in Table V in Dickey and Fuller (1981)[20]. The last step is to estimate (7-20)

$$\Delta P_t = \alpha + \rho P_{t-1} + \sum_{i=1}^{q} \delta \Delta P_{t-i} + \varepsilon_t \tag{7-20}$$

[19] The critical values for this study are as follows:

Sample size	Significance 0.90	0.95	0.975	0.99
100	5.47	6.49	7.44	8.73
250	5.39	6.34	7.25	8.43
500	5.36	6.30	7.20	8.34
>500	5.34	6.25	7.16	8.27

[20] The critical values for this study are as follows:

Sample size	Significance 0.90	0.95	0.975	0.99
100	4.16	4.88	5.59	6.50
250	4.07	4.75	5.40	6.22
500	4.05	4.71	5.35	6.15
>500	4.03	4.68	5.31	6.09

and apply the variable deletion test (imposing zero coefficients on P_{t-1} and intercept) using the F statistic from Table IV of Dickey and Fuller (1981)[21] to decide whether the series is random walk with drift or random walk without drift.

As shown in Table 7.6, all price indices series exhibited a unit root, most of them without drift, at the 5% level of significance (Egypt, Greece, Jordan, Morocco, Oman, Saudi Arabia, Turkey, and Kuwait), while some were with drift (Bahrain, Tunisia, and MENA).

[21] The critical values for this study are as follow:

Sample size	Significance 0.90	0.95	0.975	0.99
100	3.86	4.71	5.57	6.70
250	3.81	4.63	5.45	6.52
500	3.79	4.61	5.41	6.47
>500	3.78	4.59	5.38	6.43

Table 7-6: Unit Root Tests for the Weekly Price Series of the ten markets and MENA indices (Bahrain Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.

LS // Dependent Variable is D(**BAHRAIN**)

Variable	Coefficient	Std. Error	t-Statistic
C	6.480016	2.138727	3.029847
BAHRAIN(-1)	-0.07841	0.02476	**-3.16686**
Trend	-0.00071	0.002313	-0.30588
D(BAHRAIN(-1))	0.231842	0.076318	3.037823

2)Serial Correlation LM Test (suggests no autocorrelated residuals)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.731345	Probability	0.180496
Obs*R-squared	3.518844	Probability	0.172144

3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$

Equation: D(Bahrain)=c1+c2(Bahrain(-1))+c3(Trend)+ c4(D(Bahrain(-1))

Null Hypothesis:	C(2)=0	
	C(3)=0	
F-statistic (**Φ_1**)	**5.75115**	
Chi-square	11.5023	

Conclusion: There is a unit root (ϕ^* = 0) with no trend (βt = 0), with possible drift at 5% significance level.

Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0,0,0)$

Equation: D(Bahrain)=c1+c2(Bahrain(-1))+c3(Trend)+ c4(D(Bahrain(-1))

Null Hypothesis:	C(1)=0	
	C(2)=0	
	C(3)=0	
F-statistic (**Φ_2**)	**3.967559**	
Chi-square	11.90268	**random walk without drift**

LS // Dependent Variable is D(BAHRAIN)

Variable	Coefficient	Std. Error	t-Statistic
C	6.146526	1.834602	3.350332
BAHRAIN(-1)	-0.07507	0.022162	-3.38754
D(BAHRAIN(-1))	0.228355	0.075243	3.034911

Wald Test: $H_0 : (\alpha, \phi^*) = (0,0)$

Equation: D(Bahrain)=c1+c2(Bahrain(-1))+c3(D(Bahrain(-1))

Null Hypothesis:	C(1)=0	
	C(2)=0	
F-statistic (**Φ_3**)	**5.939067**	
Chi-square	11.87813	**Unit root with drift**

Continued: Table 7-6(Egypt Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**EGYPT**)			
Variable	Coefficient	Std. Error	t-Statistic
C	6.383581	2.613674	2.442379
EGYPT(-1)	-0.03935	0.014177	**-2.77577**
Trend	-0.01713	0.007229	-2.36959
D(EYGPT(-1))	0.072708	0.054708	1.329025
D(EYGPT(-2))	0.017425	0.053304	0.32689
D(EYGPT(-3))	0.158533	0.052951	2.993948
D(EYGPT(-4))	-0.03038	0.051413	-0.59092
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.351957	Probability	0.703587
Obs*R-squared	0.72247	Probability	0.696815
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(Egypt)=c1+c2(Egypt(-1))+c3(Trend)+c4(D(Egypt(-1))+c5(D(Egypt(-2))+ c6(D(Egypt(-3))+ c7(D(Egypt(-4))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**4.571185**		
Chi-square	9.142371		
Conclusion: There is a unit root (ϕ^* = 0) with no trend (βt = 0), with possible drift at 5% significance level.			
Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0,0,0)$			
Equation: D(Egypt)=c1+c2(Egypt(-1))+c3(Trend)+c4(D(Egypt(-1))+c5(D(Egypt(-2))+ c6(D(Egypt(-3))+ c7(D(Eygpt(-4))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
	C(3)=0		
F-statistic (**Φ_2**)	**4.869971**		
Chi-square	14.60991	**random walk with drift**	
LS // Dependent Variable is D(Egypt)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.266026	0.410579	0.647929
EYGPT(-1)	-0.00691	0.003705	-1.86462
D(EYGPT(-1))	0.059044	0.054798	1.077481
D(EYGPT(-2))	0.00095	0.053232	0.017846
D(EYGPT(-3))	0.140941	0.052808	2.668924
D(EYGPT(-4))	-0.05203	0.050962	-1.02092
Wald Test: $H_0 : (\alpha, \phi^*) = (0,0)$			
Equation: D(Egypt)=c1+c2(Egypt(-1))+c3 (D(Egypt(-1))+c4(D(Egypt(-2))+ c5(D(Egypt(-3))+ c6(D(Egypt(-4))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
F-statistic (**Φ_3**)	**4.43294**		
Chi-square	8.86587	**Unit root and zero drift**	

Continued: Table 7-6(Greece Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.

LS // Dependent Variable is D(**GREECE**)

Variable	Coefficient	Std. Error	t-Statistic
C	4.670554	3.500953	1.334081
GREECE(-1)	-0.00317	0.005088	**-0.62217**
Trend	-0.00987	0.01107	-0.89111
D(GREECE(-1))	-0.02751	0.04382	-0.6278
D(GREECE(-2))	-0.12657	0.04381	-2.88911

2)Serial Correlation LM Test (suggests no autocorrelated residuals)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.505945	Probability	0.603236
Obs*R-squared	1.023679	Probability	0.599392

3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$

Equation: D(Greece)=c1+c2(Greece(-1))+c3(Trend)+ c4(D(Greece(-1))+c5(D(Greece(-2))

Null Hypothesis:	C(2)=0	
	C(3)=0	
F-statistic (**Φ_1**)	**1.026287**	
Chi-square	2.052574	

Conclusion: There is a unit root (ϕ^* = 0) with no trend (βt = 0), with possible drift at 5% significance level.

Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$

Equation: D(Greece)=c1+c2(Greece(-1))+c3(Trend)+ c4(D(Greece(-1))+c5(D(Greece(-2))

Null Hypothesis:	C(1)=0	
	C(2)=0	
	C(3)=0	
F-statistic (**Φ_2**)	**0.689242**	
Chi-square	2.067726	**random walk without drift**

LS // Dependent Variable is D(GREECE)

Variable	Coefficient	Std. Error	t-Statistic
C	3.262796	3.123627	1.044554
GREECE(-1)	-0.00514	0.00458	-1.12206
D(GREECE(-1))	-0.02442	0.043674	-0.55906
D(GREECE(-2))	-0.12354	0.043669	-2.82892

Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$

Equation: D(Greece)=c1+c2(Greece(-1))+c3(D(Greece(-1))+c4(D(Greece(-2))

Null Hypothesis:	C(1)=0	
	C(2)=0	
F-statistic (**Φ_3**)	**0.637083**	
Chi-square	1.274165	**Unit root and zero drift**

Continued: Table 7-6(Jordan Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.

LS // Dependent Variable is D(**Jordan**)

Variable	Coefficient	Std. Error	t-Statistic
C	2.895621	1.390538	2.082375
JORDAN(-1)	-0.01969	0.009247	**-2.12921**
Trend	0.001133	0.000939	1.205844
D(JORDAN(-1))	-0.00912	0.044029	-0.20715

2)Serial Correlation LM Test (suggests no autocorrelated residuals)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.852196	Probability	0.427078
Obs*R-squared	1.718562	Probability	0.423466

3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$

Equation: D(Jordan)=c1+c2(Jordan(-1))+c3(Trend)+c4(D(Jordan(-1))

Null Hypothesis:	C(2)=0	
	C(3)=0	
F-statistic (Φ_1)	**2.365488**	
Chi-square	4.730975	

Conclusion: There is a unit root (ϕ^* = 0) with no trend (βt = 0), with possible drift at 5% significance level.

Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$

Equation: D(Jordan)=c1+c2(Jordan(-1))+c3(Trend) +c4(D(Jordan(-1))

Null Hypothesis:	C(1)=0	
	C(2)=0	
	C(3)=0	
F-statistic (Φ_2)	**1.733646**	
Chi-square	5.200939	**random walk without drift**

LS // Dependent Variable is D(Jordan)

Variable	Coefficient	Std. Error	t-Statistic
C	2.537536	1.359055	1.867133
JORDAN(-1)	-0.01553	0.008585	-1.80943
D(JORDAN(-1))	-0.01075	0.044027	-0.24422

Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$

Equation: D(Jordan)=c1+c2(Jordan(-1))+c3D(Jordan(-1))

Null Hypothesis:	C(1)=0	
	C(2)=0	
F-statistic (Φ_3)	**1.8718**	
Chi-square	3.7435	**Unit root and zero drift**

Continued: Table 7-6(Morocco Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.

LS // Dependent Variable is D(**MOROCCO**)

Variable	Coefficient	Std. Error	t-Statistic
C	5.436109	1.758801	3.090804
MOROCCO(-1)	-0.02114	0.007357	**-2.8732**
Trend	-0.00912	0.003068	-2.97246
D(MOROCCO(-1))	0.131194	0.054594	2.403083

2)Serial Correlation LM Test (suggests no autocorrelated residuals)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.789516	Probability	0.454947
Obs*R-squared	1.600739	Probability	0.449163

3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$

Equation: D(Morocco)=c1+c2(Morocco(-1))+c3(Trend)

Null Hypothesis:	C(2)=0	
	C(3)=0	
F-statistic (**Φ_1**)	**5.067993**	
Chi-square	10.13599	

Conclusion: There is a unit root ($\phi^* = 0$) with no trend ($\beta t = 0$), with possible drift at 5% significance level.

Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$

Equation: D(Morocco)=c1+c2(Morocco(-1))+c3(Trend)

Null Hypothesis:	C(1)=0	
	C(2)=0	
	C(3)=0	
F-statistic (**Φ_2**)	**3.384529**	
Chi-square	10.15359	**random walk without drift**

LS // Dependent Variable is D(MOROCCO)

Variable	Coefficient	Std. Error	t-Statistic
C	1.152784	1.020565	1.129554
MOROCCO(-1)	-0.00609	0.005402	-1.1268
D(MOROCCO(-1))	0.145619	0.055034	2.646002

Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$

Equation: D(Morocco)=c1+c2(Morocco(-1))+ c3(D(Morocco(-1))+c4(D(Morocco(-2))

Null Hypothesis:	C(1)=0	
	C(2)=0	
F-statistic (**Φ_3**)	**0.643435**	
Chi-square	1.286869	**Unit root and zero drift**

Continued: Table 7-6(Oman Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**OMAN**)			
Variable	Coefficient	Std. Error	t-Statistic
C	2.129537	1.35997	1.56587
OMAN(-1)	-0.03168	0.016019	**-1.97753**
Trend	0.005437	0.003039	1.788909
D(OMAN(-1))	0.214995	0.078421	2.74156
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.419555	Probability	0.658094
Obs*R-squared	0.867259	Probability	0.648152
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(Oman)=c1+c2(Oman(-1))+c3(Trend)+c4(D(Oman(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic **(Φ_1)**	**3.79329**		
Chi-square	7.58658		
Conclusion: There is a unit root ($\phi^* = 0$) with no trend ($\beta t = 0$), with possible drift at 5% significance level.			
Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0,0,0)$			
Equation: D(Oman)=c1+c2(Oman(-1))+c3(Trend)+c4(D(Oman(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
	C(3)=0		
F-statistic **(Φ_2)**	**2.544492**		
Chi-square	7.633477	**random walk without drift**	
LS // Dependent Variable is D(OMAN)			
Variable	Coefficient	Std. Error	t-Statistic
C	2.719295	1.328678	2.046617
OMAN(-1)	-0.03348	0.0161	-2.07976
D(OMAN(-1))	0.24706	0.076881	3.213531
Wald Test: $H_0 : (\alpha, \phi^*) = (0,0)$			
Equation: D(Oman)=c1+c2(Oman(-1))+c3 (D(Oman(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
F-statistic **(Φ_3)**	**2.185813**		
Chi-square	4.371625	**Unit root and zero drift**	

Continued: Table 7-6(Saudi Arabia Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**SAUDIARABIA**)			
Variable	Coefficient	Std. Error	t-Statistic
C	3.48897	1.332881	2.617616
SAUDIARABIA(-1)	-0.03918	0.016356	**-2.39572**
Trend	0.00932	0.004769	1.954383
D(SAUDIARABIA(-1))	0.197834	0.064595	3.062686
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.337123	Probability	0.264679
Obs*R-squared	2.71331	Probability	0.257521
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(Suadi)=c1+c2(Suadi(-1))+c3(Trend)+ c4(D(Suadi(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic **(Φ_1)**	**3.025435**		
Chi-square	6.050871		
Conclusion: There is a unit root ($\phi^* = 0$) with no trend ($\beta t = 0$), with possible drift at 5% significance level.			
Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$			
Equation: D(Suadi)=c1+c2(Suadi(-1))+c3(Trend)+ c4(D(Suadi(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
	C(3)=0		
F-statistic **(Φ_2)**	**3.043163**		
Chi-square	9.129488	**random walk without drift**	
LS // Dependent Variable is D(SAUDIARAB)			
Variable	Coefficient	Std. Error	t-Statistic
C	1.346584	0.762914	1.765054
SAUDIARABIA(-1)	-0.01005	0.006767	-1.48459
D(SAUDIARABIA(-1))	0.181624	0.064455	2.817843
Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$			
Equation: D(Suadi)=c1+c2(Suadi(-1))+c3(D(Suadi(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
F-statistic **(Φ_3)**	**2.622505**		
Chi-square	5.24501	**Unit root and zero drift**	

Continued: Table 7-6(Turkey Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.

LS // Dependent Variable is D(**TURKEY**)

Variable	Coefficient	Std. Error	t-Statistic
C	8.432891	4.739542	1.779263
TURKEY(-1)	-0.01861	0.008406	**-2.21369**
Trend	-0.00065	0.012613	-0.05163
D(TURKEY(-1))	-0.03677	0.04384	-0.83869
D(TURKEY(-2))	0.116624	0.0438	2.662671

2)Serial Correlation LM Test (suggests no autocorrelated residuals)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.065023	Probability	0.937054
Obs*R-squared	0.131786	Probability	0.936231

3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$

Equation: D(Turkey)=c1+c2(Turkey(-1))+c3(Trend)+ c4(D(Turkey(-1))+c5(D(Turkey(-2))

Null Hypothesis:	C(2)=0	
	C(3)=0	
F-statistic (Φ_1)	**2.616508**	
Chi-square	5.233017	

Conclusion: There is a unit root (ϕ^* = 0) with no trend (βt = 0), with possible drift at 5% significance level.

Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$

Equation: D(Turkey)=c1+c2(Turkey(-1))+c3(Trend)+ c4(D(Turkey(-1))+c5(D(Turkey(-2))

Null Hypothesis:	C(1)=0	
	C(2)=0	
	C(3)=0	
F-statistic (Φ_2)	**1.744568**	
Chi-square	5.233705	**random walk without drift**

LS // Dependent Variable is D(TURKEY)

Variable	Coefficient	Std. Error	t-Statistic
C	8.306059	4.049184	2.051292
TURKEY(-1)	-0.01871	0.008172	-2.28921
D(TURKEY(-1))	-0.03666	0.043745	-0.83797
D(TURKEY(-2))	0.116734	0.043705	2.670932

Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$

Equation: D(Turkey)=c1+c2(Turkey(-1))+c3(D(Turkey(-1))+c4(D(Turkey(-2))

Null Hypothesis:	C(1)=0	
	C(2)=0	
F-statistic (Φ_3)	**2.620585**	
Chi-square	5.24117	**Unit root and zero drift**

Continued: Table 7-6(Tunisia Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**Tunisia**)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.658479	0.582374	1.130679
TUNISIA(-1)	-0.01203	0.006576	**-1.82889**
Trend	-0.0006	0.001149	-0.51904
D(TUNISIA(-1))	0.057931	0.051109	1.133468
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.037471	Probability	0.963226
Obs*R-squared	0.076119	Probability	0.962655
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(Tunisia)=c1+c2(Tunisia(-1))+c3(Trend)+c4D(Tunisia(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**2.753738**		
Chi-square	5.507476		
Conclusion: There is a unit root (ϕ^* = 0) with no trend (βt = 0), with possible drift at 5% significance level.			
Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$			
Equation: D(Tunisia)=c1+c2(Tunisia(-1))+c3(Trend)+c4(D(Tunisia(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
	C(3)=0		
F-statistic (**Φ_2**)	**3.233822**		
Chi-square	9.701467	**random walk without drift**	
LS // Dependent Variable is D(Tunisia)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.386042	0.252063	1.53153
TUNISIA(-1)	-0.00935	0.004082	-2.29089
D(TUNISIA(-1))	0.055883	0.050908	1.097728
Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$			
Equation: D(Tunisia)=c1+c2(Tunisia(-1)) +c3(D(Tunisia(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
F-statistic (**Φ_3**)	**4.725115**		
Chi-square	9.45023	**Unit root with drift**	

Continued: Table 7-6(Kuwait Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.

LS // Dependent Variable is D(**Kuwait**)

Variable	Coefficient	Std. Error	t-Statistic
C	27.21661	18.5084	1.4705
KUWAIT(-1)	-0.06356	0.042301	**-1.50246**
Trend	0.206254	0.108793	1.89584
D(KUWAIT(-1))	-0.09922	0.086966	-1.14086

2)Serial Correlation LM Test (suggests no autocorrelated residuals)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.366406	Probability	0.258199
Obs*R-squared	2.791656	Probability	0.247628

3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$

Equation: D(Kuwait)=c1+c2(Kuwait(-1))+c3(Trend)+c4(D(Kuwait(-1)))

Null Hypothesis:	C(2)=0	
	C(3)=0	
F-statistic **(Φ_1)**	**2.617782**	
Chi-square	5.235564	

Conclusion: There is a unit root ($\phi^* = 0$) with no trend ($\beta t = 0$), with possible drift at 5% significance level.

Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0,0,0)$

Equation: D(Kuwait)=c1+c2(Kuwait(-1))+c3(Trend)+ c4(D(Kuwait(-1)))

Null Hypothesis:	C(1)=0	
	C(2)=0	
	C(3)=0	
F-statistic **(Φ_2)**	**4.182293**	
Chi-square	12.54688	**random walk without drift**

LS // Dependent Variable is D(Kuwait)

Variable	Coefficient	Std. Error	t-Statistic
C	-5.31535	6.994883	-0.75989
KUWAIT(-1)	0.013941	0.010974	1.270358
D(KUWAIT(-1))	-0.15303	0.082902	-1.84585

Wald Test: $H_0 : (\alpha, \phi^*) = (0,0)$

Equation: D(Kuwait)=c1+c2(Kuwait(-1))+ c3(D(Kuwait(-1)))

Null Hypothesis:	C(1)=0	
	C(2)=0	
F-statistic **(Φ_3)**	**4.401218**	
Chi-square	8.802436	**Unit root and zero drift**

Continued: Table 7-6(MENA Price Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**MENA**)			
Variable	Coefficient	Std. Error	t-Statistic
C	4.201487	1.314781	3.195578
MENA(-1)	-0.05804	0.018775	**-3.09134**
Trend	1.43E-05	0.001571	0.009109
D(MENA(-1))	0.148792	0.065194	2.28228
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.42566	Probability	0.65387
Obs*R-squared	0.87099	Probability	0.646944
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(MENA)=c1+c2(MENA(-1))+c3(Trend)+c4(D(MENA(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	**4.957168**		
Chi-square	9.914336		
Conclusion: There is a unit root ($\phi^* = 0$) with no trend ($\beta t = 0$), with possible drift at 5% significance level.			
Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (0, 0, 0)$			
Equation: D(MENA)=c1+c2(MENA(-1))+c3(Trend)+ c4(D(MENA(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
	C(3)=0		
F-statistic (Φ_2)	**3.511555**		
Chi-square	10.53466	**random walk without drift**	
LS // Dependent Variable is D(MENA)			
Variable	Coefficient	Std. Error	t-Statistic
C	4.200814	1.309785	3.207254
MENA(-1)	-0.05801	0.018381	-3.15571
D(MENA(-1))	0.148744	0.064841	2.293993
Wald Test: $H_0 : (\alpha, \phi^*) = (0, 0)$			
Equation: D(MENA)=c1+c2(MENA(-1))+ c4(D(MENA(-1))			
Null Hypothesis:	C(1)=0		
	C(2)=0		
F-statistic (Φ_3)	**5.290803**		
Chi-square	10.58161	**Unit root with drift**	

In Table 7.7 the unit root technique is reapplied for return series (the first differences for log price) to investigate whether the price indices are I(1) or higher. Tests for stationarity of the return series result in rejection of I(1) for all return series, at the 5% level of significance. Rejection of I(1) in favour of I(0) for returns indicates that the price series are I(1) and that all the weekly stock prices follow a random walk. These results confirm earlier results reported by different studies conducted in the emerging markets. Chen, et. al, (2002) reported that, depending on the unit root test results, the null hypothesis that the stock indices[22] in the levels are non stationary is not rejected for all the markets. However, the null hypothesis that first log differences in these stock indices are non stationary is strongly rejected. The study of Groenewold and Ariff (1998) suggested that the null hypothesis of a unit root can be rejected for all their markets[23] indices prices included in the sample except for Singapore. The Singapore results are not very robust since results changed with a shorter lag length.

[22] The market indices included in Chen et.al, study are: Brazil, Mexico, Chile, Argentina, Colombia, and Venezuela.
[23] The markets included are: Australia, Hong Kong, Indonesia, Japan, Korea, Malaysia, New Zealand, Singapore, Taiwan, and United States.

Table 7-7: Unit Root Tests for the Weekly Return Series of the ten markets and MENA indices (Bahrain Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RBAHRAIN**)			
Variable	Coefficient	Std. Error	t-Statistic
C	-0.00331	0.002519	-1.31466
RBAHRAIN(-1)	-0.86849	0.11627	-7.46954
Trend	3.16E-05	2.68E-05	1.17955
D(RBAHRAIN(-1))	0.080028	0.102122	0.783647
D(RBAHRAIN(-2))	0.169896	0.079898	2.126425
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	2.334752	Probability	0.100344
Obs*R-squared	4.739861	Probability	0.093487
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rBahrain)=c1+c2(rBahrain(-1))+c3(Trend)+ c4(D(rBahrain(-1))+c5(D(rBahrain(-2))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	**27.89722**		
Chi-square	55.79444		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Egypt Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**REGYPT**)			
Variable	Coefficient	Std. Error	t-Statistic
C	-0.00536	0.003556	-1.50855
REGYPT(-1)	-0.97324	0.075942	-12.8155
Trend	4.14E-06	1.87E-05	0.221989
D(REGYPT(-1))	0.019753	0.054933	0.359575
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.781871	Probability	0.169994
Obs*R-squared	3.590657	Probability	0.166073
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rEgypt)=c1+c2(rEgypt(-1))+c3(Trend)+ c4(D(rEgypt(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	**82.19115**		
Chi-square	164.3823		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Greece Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RGREECE**)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.005569	0.003685	1.511156
RGREECE(-1)	-1.01926	0.061	-16.7091
Trend	-1.94E-05	1.22E-05	-1.59314
D(RGREECE(-1))	0.057721	0.043941	1.313591
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.035772	Probability	0.964863
Obs*R-squared	0.072368	Probability	0.964463
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rGreece)=c1+c2(rGreece(-1))+c3(Trend)+ c4(D(rGreece(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**139.5967**		
Chi-square	279.1933		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Jordan Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RJORDAN**)			
Variable	Coefficient	Std. Error	t-Statistic
C	-0.00022	0.001652	-0.1347
RJORDAN(-1)	-1.02765	0.062825	-16.3574
Trend	2.75E-06	5.47E-06	0.503811
D(RJORDAN(-1))	0.003077	0.043912	0.070069
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.285015	Probability	0.752122
Obs*R-squared	0.576046	Probability	0.749744
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rJordan)=c1+c2(rJordan(-1))+c3(Trend)+ c4(D(rJordan(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**133.814**		
Chi-square	267.628		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Morocco Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RMOROCCO**)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.002334	0.002387	0.977658
RMOROCCO(-1)	-0.81247	0.073549	-11.0466
Trend	-1.35E-05	1.26E-05	-1.07557
D(RMOROCCO(-1))	-0.0672	0.055716	-1.20612
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.058004	Probability	0.943656
Obs*R-squared	0.118148	Probability	0.942637
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rMorroco)=c1+c2(rMorocco(-1))+c3(Trend)+ c4(D(rMorocco(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**61.04697**		
Chi-square	122.0939		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Oman Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**ROMAN**)			
Variable	Coefficient	Std. Error	t-Statistic
C	-0.00618	0.003574	-1.72933
ROMAN(-1)	-0.86937	0.105725	-8.2229
Trend	7.28E-05	3.86E-05	1.886087
D(ROMAN(-1))	0.04676	0.081764	0.571895
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.517441	Probability	0.59709
Obs*R-squared	1.068459	Probability	0.586121
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rOman)=c1+c2(rOman(-1))+c3(Trend)+ c4(D(rOman(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**33.89715**		
Chi-square	67.79429		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Saudi Arabia Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RSAUDIARABIA**)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.003904	0.00255	1.5312
RSAUDIARAB(-1)	-0.76237	0.08582	-8.88329
Trend	-1.53E-05	1.87E-05	-0.81937
D(RSAUDIARAB(-1))	-0.10758	0.065311	-1.64721
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	3.693778	Probability	0.026406
Obs*R-squared	7.343255	Probability	0.025435
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(RSAUDIARAB)=c1+c2 D(RSAUDIARAB(-1))+c3(Trend)+ c4D(RSAUDIARAB(-2))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	**39.47089**		
Chi-square	78.94178		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Turkey Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RTURKEY**)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.004623	0.007914	0.584111
RTURKEY(-1)	-0.99766	0.064106	-15.5625
Trend	-1.69E-05	2.62E-05	-0.64592
D(RTURKEY(-1))	-0.06382	0.043898	-1.45385
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.001009	Probability	0.998991
Obs*R-squared	0.002042	Probability	0.998979
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rTurkey)=c1+c2(rTurkey(-1))+c3(Trend)+ c4(D(rTurkey(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	**121.0975**		
Chi-square	242.195		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Tunisia Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RTUNISIA**)			
Variable	Coefficient	Std. Error	t-Statistic
C	-0.00465	0.002687	-1.73037
RTUNISIA(-1)	-0.98425	0.072083	-13.6544
Trend	1.09E-05	1.20E-05	0.907824
D(RTUNISIA(-1))	0.004407	0.051477	0.085605
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.671488	Probability	0.511559
Obs*R-squared	1.359551	Probability	0.506731
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rTunisia)=c1+c2(rTunisia(-1))+c3(Trend)+ c4(D(rTunisia(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	**93.22542**		
Chi-square	186.4508		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (Kuwait Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RKUWAIT**)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.001189	0.004215	0.282076
RKUWAIT(-1)	-1.23358	0.129104	-9.55492
Trend	5.36E-05	4.67E-05	1.147885
D(RKUWAIT(-1))	-0.00881	0.082028	-0.10741
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.200512	Probability	0.818534
Obs*R-squared	0.416154	Probability	0.812145
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rKuwait)=c1+c2(rKuwait(-1))+c3(Trend)+ c4(D(rKuwait(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (Φ_1)	**45.65394**		
Chi-square	91.30787		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

Continued: Table 7.7 (MENA Return Index)

1) Determining the order of differenced terms included in the equations to achieve ADF test.			
LS // Dependent Variable is D(**RMENA**)			
Variable	Coefficient	Std. Error	t-Statistic
C	0.003046	0.00297	1.02541
RMENA(-1)	-0.84753	0.087883	-9.64383
Trend	-1.57E-05	2.21E-05	-0.71048
D(RMENA(-1))	-0.01195	0.066907	-0.17856
2)Serial Correlation LM Test (suggests no autocorrelated residuals)			
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.440942	Probability	0.643995
Obs*R-squared	0.902227	Probability	0.636919
3)Wald Test: $H_0 : (\alpha, \beta t, \phi^*) = (\alpha, 0, 0)$			
Equation: D(rMENA)=c1+c2(rMENA(-1))+c3(Trend)+ c4(D(rMENA(-1))			
Null Hypothesis:	C(2)=0		
	C(3)=0		
F-statistic (**Φ_1**)	**46.51988**		
Chi-square	93.03976		
Conclusion: The series is stationary without time trend or intercept at 5% significance level.			

7.5.3 Pair-Wise Cointegration between Jordan and other Markets

7.5.3.1 The Engle-Granger Two-Step Method

The Engle-Granger two-step method is conducted, before implementing the Johansen method, as a preliminary test for cointegration, as well as for comparative purposes before implementing the Johansen method. Table 7.8 presents some simple bivariate cointegration results between the ten price indices and the Jordan price index. The findings in this table suggest that the Jordan price index may only be cointegrated, according to the DF test at the 90% significance level and the ADF test at the 95%

significance level[24], only with the Bahrain and the MENA indices. Referring to the cointegration regressions with Bahrain and MENA,

$$Bahrain = 89.6 - 0.043 Jordan \quad \textbf{(7-21)}$$
$$\textit{t-statistic} \quad (30.90) \quad (-2.40)$$

$$Mena = 94.69 - 0.146 Jordan \quad \textbf{(7-22)}$$
$$\textit{t-statistic} \quad (30.18) \quad (-7.59)$$

the long –run coefficients are about -0.043 for Bahrain and -0.146 for MENA, which suggest small and negative long run adjustments between Jordan and Bahrain, and between Jordan and MENA[25].

[24] The Engle-Granger two-step multivariate estimates will not be used to test cointegration for more than two indices due to some problems inherent in the two-step methodology, such as that the critical values for systems of more than five variables are not available for the two-step procedure. The Johansen test will be employed.

[25] The coefficient of the cointegrating equation represents the *speed* of adjustment in stock prices in Jordan to the long-term relation they share with their counterparts.

Table 7-8: Engle-Granger Cointegration Test for Pair Indices for the Sample Countries:

$$Bahrain = 89.6 - 0.043 Jordan$$

t-statistic (30.90) (-2.40)

DW	0.089
DF	$\mathbf{3.312}^{*}$
ADF	$\mathbf{3.268}^{**}$

$$Egypt = 155.43 - 0.334 Jordan$$

t-statistic (5.71) (-2.01)

DW	0.006
DF	1.026
ADF	1.777

$$Greece = 89.9 - 4.36 Jordan$$

t-statistic (-0.63) (4.81)

DW	0.013
DF	1.133
ADF	1.018

$$Morocco = 136.03 + 0.298 Jordan$$

t-statistic (6.18) (2.22)

DW	0.010
DF	0.912
ADF	1.071

$$Turkey = 541.29 - 0.639 Jordan$$

t-statistic (5.31) (-0.994)

DW	0.035
DF	2.178
ADF	2.305

$$Oman = 94.14 - 0.074 Jordan$$

t-statistic (16.29) (-2.06)

DW	0.045
DF	1.853
ADF	1.475

$$Saudiarabia = 129.58 - 0.114 Jordan$$

t-statistic (10.66) (-1.53)

DW	0.012
DF	1.008
ADF	1.140

$$Tunisia = 170.23 - 0.69 Jordan$$

t-statistic (22.02) (-14.49)

DW	0.024
DF	2.691
ADF	2.507

$$Kuwait = -182.24 + 5.11 Jordan$$

t-statistic (-3.81) (17.17)

DW	0.085
DF	1.258
ADF	1.053

$$Mena = 94.69 - 0.146 Jordan$$

t-statistic (30.18) (-7.59)

DW	0.107
DF	3.072^{*}
ADF	3.260^{**}

DW, DF, and ADF denote respectively, Durbin Watson, Dickey Fuller and Augmented Dickey Fuller statistics on the residuals generated from the cointegrating equation. The critical values for these statistics as mentioned in Table II, Engle and Granger (1987), are as follows:

	Significance Levels		
	1%	5%	10%
DW	0.511	0.386	0.322
DF	4.070	3.370	3.030
ADF	3.770	3.170	2.840

If the values of DW, DF, and ADF from the regression are exceeding the critical values, the null hypothesis of no cointegration is rejected.

* *Significance at 5% level.

* Significance at 10% level.

7.5.3.2 Johansen Approach

The Johansen approach is applied to test the cointegration between the Jordan index and every other index separately, and then the Johansen multivariate approach is implemented to test cointegration using different groups of indices. As shown in Table 7.9, the trace statistic does not reject the hypothesis of no cointegration and rejects the hypothesis of one cointegrating relation for all tests performed. These results confirm the Engle-Granger two-step method except for Bahrain and MENA indices. This indicates that there is no long run relationship between the price series, that is, that the two price indices have no equilibrium condition that keeps them in proportion to each other in the long run. The overwhelming result is the total absence of any clear cointegrating vector between the Jordan index and the indices of other MENA countries indices, suggesting that no gains from regional arbitrage appear to persist long to allow any clear cointegration to be determined. It indicates that ASE does not share stochastic links with its regional counterparts and therefore it offers risk and returns profiles that are unique in the region.

Thus, investors seeking diversified portfolios may benefit from investing in Jordan and other MENA markets because they are not cointegrated. Such diversification would be effective since more country risk can be diversified away.

On the other hand, this result can be seen as an inference on the efficiency of these markets. Due to Granger (1986), if asset prices in different markets are cointegrated, this may indicate the existence of inefficiency in the asset markets, as the prices of two different assets, each priced in efficient markets, cannot be cointegrated.

Table 7-9: Johansen Cointegration Test for Jordan and Each Other Countries Price Indices (Jordan and Bahrain Price Indices)

Johansen Cointegration Test

Series: JORDAN BAHRAIN
Included observations: 156
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.074293	13.60308	15.41	20.04	None
0.009951	1.560203	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Egypt)

Johansen Cointegration Test

Series: EGYPT JORDAN
Included observations: 323
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.015712	8.071787	15.41	20.04	None
0.009111	2.956398	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Greece)

Johansen Cointegration Test

Series: JORDAN GREECE
Included observations: 518
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.015952	11.20957	15.41	20.04	None
0.005544	2.879893	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Kuwait)

Johansen Cointegration Test

Series: JORDAN KUWAIT
Included observations: 152
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.034032	5.777691	15.41	20.04	None
0.003381	0.51477	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and MENA)

Johansen Cointegration Test
Series: JORDAN MENA
Included observations: 225
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.04814	13.57664	15.41	20.04	None
0.010943	2.475802	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Morocco)

Johansen Cointegration Test
Series: MOROCCO JORDAN
Included observations: 323
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.010011	4.883166	15.41	20.04	None
0.005044	1.633364	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Oman)

Johansen Cointegration Test
Series: JORDAN OMAN
Included observations: 156
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.026025	5.07144	15.41	20.04	None
0.006121	0.957768	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Saudi Arabia)

Johansen Cointegration Test
Series: JORDAN SAUDIARAB
Included observations: 228
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.01802	4.656519	15.41	20.04	None
0.002236	0.510434	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Tunisia)

Johansen Cointegration Test

Series: JORDAN TUNISIA
Included observations: 376
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.019152	10.75904	15.41	20.04	None
0.009234	3.487938	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

Continued: Table 7-9(Jordan and Turkey)

Johansen Cointegration Test

Series: JORDAN TURKEY
Included observations: 521
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.012517	10.11884	15.41	20.04	None
0.006803	3.556506	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

The Table presents the trace test, using Eviews software, to determine the number of cointegration relations. The eigenvalues are presented in the first column, while the second column (Likelihood Ratio) presents the LR test statistic (trace statistic)[26]:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\lambda_i)$$

for r=0, 1, .. , n-1 (in this Table n=2 as tow series are used to perform the test) where λi is the i-th largest eigenvalue. To determine the number of cointegrating relations r, we can proceed sequentially from r=0 to r=n-1 until we fail to reject the null hypothesis of cointegration. The first row in the table tests the hypothesis of no cointegration, the second row tests the hypothesis of one cointegration relation, the third row tests the hypothesis of two cointegrating relations, and so on, all against the alternative hypothesis of full rank, i. e. all series in the VAR are stationary.

7.5.4 Granger Causality Test

Granger causality tests are used to examine the short run dynamics of the series and to investigate causality between each pair and its direction. The individual market returns are used rather than levels because the inferences based on the standard

[26] Refer to Appendix 5 for more details.

regression do not hold when the regressors are non stationary. Table 7.10 summarizes the results to test the null hypothesis that the first index series does not Granger cause the second; it appears that Jordan has not any links in the short run with other markets except for Bahrain and MENA and at the 10% significance level. The two indices impact on Jordan but not the other way around. This result corresponds with the Engle-Granger two-step test which indicates a cointegration relation between the Jordan index and the other two indices. Cointegration relation dictates at least a one direction Granger causality link. Past returns of the two indices help to predict returns in Jordan, which is considered a violation of the efficient market hypothesis since one of the markets can help forecast the other.

Table 7-10: Pairwise Granger Causality Test for the Jordan and each Other Return Indices of the Sample:

Null Hypothesis:	Obs	F-Statistic	Probability
RJORDAN does not Granger Cause RBAHRAIN	159	0.01784	0.89393
RBAHRAIN does not Granger Cause RJORDAN		2.84722	**0.0935***
RJORDAN does not Granger Cause REGYPT	326	0.00013	0.99102
REGYPT does not Granger Cause RJORDAN		0.5677	0.45172
RJORDAN does not Granger Cause RGREECE	521	0.06637	0.7968
RGREECE does not Granger Cause RJORDAN		2.61107	0.10673
RKUWAIT does not Granger Cause RJORDAN	155	0.67172	0.41373
RJORDAN does not Granger Cause RKUWAIT		0.01799	0.89348
RMENA does not Granger Cause RJORDAN	228	3.06915	**0.0811***
RJORDAN does not Granger Cause RMENA		0.52456	0.46965
RMOROCCO does not Granger Cause RJORDAN	326	1.48659	0.22364
RJORDAN does not Granger Cause RMOROCCO		0.00033	0.98556
ROMAN does not Granger Cause RJORDAN	159	1.81523	0.17984
RJORDAN does not Granger Cause ROMAN		0.7964	0.37355
RSAUDIARAB does not Granger Cause RJORDAN	231	2.1119	0.14753
RJORDAN does not Granger Cause RSAUDIARAB		0.04937	0.82436
RTURKEY does not Granger Cause RJORDAN	521	1.05869	0.30399
RJORDAN does not Granger Cause RTURKEY		0.00541	0.9414
RTUNISIA does not Granger Cause RJORDAN	383	0.0669	0.79604
RJORDAN does not Granger Cause RTUNISIA		2.57712	0.10925

*** Significant at 1% level
** Significant at 5% level
* Significant at 10% level

7.5.5 Group Cointegration

7.5.5.1 The Gulf Cooperation Council (GCC) Countries

The cointegration test was performed twice; including and excluding the Jordan price index.

- **Excluding Jordan price index**

As shown in Table 7.11 and in the case of excluding the Jordan index, the test indicates one cointegration equation at the 5% significance level. This means that the stock indices of the four countries in the GCC share one long-term equilibrium.

It is worth mentioning that the benefit of national diversification is limited when national equity markets are cointegrated because the presence of common factors limits the amount of independent variation and indicates stable long-run relations. Thus, cointegration among national equity markets implies that there are fewer assets available to investors than a simple count of the number. Different reasons may interpret the long-run relationship among different countries' stock prices.[27] Chen et. al. (2002) suggested that the presence of strong economic ties and policy coordination between the relevant countries can indirectly link their stock prices over time. These strong ties and policies are present in the case of GCC group. All the countries belonging to this group are oil-producing countries; moreover, these financial markets have traditionally discriminated against non-GCC investors and privileged the GCC nationalities. The removal of the restrictions and barriers to the flow of capital in the GCC region's financial markets is expected to, as the experience of the developed economies shows, increase allocative efficiency within MENA and provide MENA

[27] Many of the empirical studies, e.g. Kasa (1992), Joen and Chiang (1991). Arshanapalli et al. (1995) and Ghosh et al (1999), detected the statistical dependencies across stock markets without identifying or discussing the economic reasons for such dependencies.

investors with greater opportunities to diversify their portfolios and reduce risks. In other words, MENA investors will have access to a variety of risk adjusted rates of return to enhance the efficiency of portfolio allocation and diversification, which will foster the efficiency of MENA's financial markets.

- **Including Jordan price index**

The result is interesting when including the Jordan price index to the GCC group. The test rejects any cointegration equation at the 5% significance level. This lack of cointegration suggests that such series have no long-run link, and that series can wander arbitrarily far away from each other. The theoretical implication of this result is that diversifying across the GCC and Jordan markets allows investors to reduce portfolio risk while holding expected return constant[28]. On the other hand, this result confirms the results of pair-wise cointegration that there is no long term relationship between the Jordan index and other market indices.

[28] Ajayi and Mehdian (1995) and Bowman and Comer (2000) conclude that adding stocks from emerging markets to a portfolio of stocks from developed markets will benefit the efficient diversification of the portfolio.

Table 7-11: Johansen Cointegration Test for the Price Indices of GCC Countries and Jordan

Johansen Cointegration Test

Series: BAHRAIN OMAN KUWAIT SAUDIARABIA

Included observations: 152
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.139553	49.26396	47.21	54.46	None *
0.1264	26.41794	29.68	35.65	At most 1
0.034775	5.877745	15.41	20.04	At most 2
0.00327	0.497888	3.76	6.65	At most 3

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating equation(s) at 5% significance level

Continued: Table 7-11 Johansen Cointegration Test for the Price Indices of GCC Countries without Jordan

Johansen Cointegration Test

Series: BAHRAIN OMAN KUWAIT JORDAN SAUDIARABIA

Included observations: 152
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.153087	62.60271	68.52	76.07	None
0.143693	37.34675	47.21	54.46	At most 1
0.052823	13.76754	29.68	35.65	At most 2
0.031216	5.518625	15.41	20.04	At most 3
0.004583	0.698187	3.76	6.65	At most 4

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration equation(s) at 5% significance level

7.5.5.2 The African Countries: Egypt, Tunisia, and Morocco

- **Excluding Jordan price index**

The results in Table 7.12 indicate one cointegrating equation at the 5% significance level. This indicates that a long-run relation links these markets. As mentioned in Economic Trends in the MENA Region, 2000[29], Egypt, Morocco, and Tunisia have committed themselves to letting the private sector lead growth. In addition to reform on the macroeconomic front, these countries are making the business environment friendlier. They are reducing direct government involvement in the economy through privatization, encouraging private sector participation in infrastructure and reforming their institutions to make them more hospitable to private investment. Gelos and Sahay (2000) stated that with technological and financial innovation, the advance of international finance and trade, and deliberate regional and global co-operation, the geographical divide among various national stock markets are less obvious. Also, Jeon and Chiang (1991) cite deregulation and market liberalization measures, rapid developments in communication technology and computerized trading systems, and increasing activities by multinational corporations as factors contributing to such integration.

- **Including Jordan price index:**

As present in Table 7.12, the test rejects any cointegration equation at the 5% significance level after adding the Jordan index. This result is similar to the previous case of the GCC group, indicating that the series in this group plus Jordan do not have a long-run link. Considering Jordan when investing in the GCC markets or Egypt,

[29] Economic Research Forum, Economic Trends in the MENA Region, 2000.

Tunisia, and Morocco markets would provide MENA investors with greater opportunities to diversify their portfolios and reduce risks.

Table 7-12: Johansen Cointegration Test for the Price Indices of Egypt, Morocco, and Tunisia

Johansen Cointegration Test
Series: EGYPT MOROCCO TUNISIA

Included observations: 323
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.060659	31.36419	29.68	35.65	None *
0.031147	11.15179	15.41	20.04	At most 1
0.002879	0.931201	3.76	6.65	At most 2

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating equation(s) at 5% significance level

Continued: Table 7-12 Johansen Cointegration Test for the Price Indices of Egypt, Morocco, Tunisia, and Jordan

Johansen Cointegration Test
Series: EGYPT JORDAN MOROCCO TUNISIA

Included observations: 323
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.070539	44.25619	47.21	54.46	None
0.041597	20.62867	29.68	35.65	At most 1
0.017345	6.905485	15.41	20.04	At most 2
0.003875	1.253925	3.76	6.65	At most 3

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. rejects any cointegration at 5% significance level

7.5.5.3 The European countries: Turkey and Greece

The results in Table 7.13 indicate one cointegration equation at the 1% significance level between the Greece and Turkey indices. However, after including the Jordan index the results also indicate one cointegration equation, but at the 5% significance level. It is worth mentioning that this group has the longest available data, covering the last 10 years, and has one of the most well established markets in the region. The result may indicate that the Jordan market could be integrated with other non-Arab international markets since Jordan is considered a liberated market and could be affected by the price movement of developed countries.[30]

[30] The extensive literature which deals with equity market liberalization and world market integration is beyond the scope of this study. (see for example, Bekaert et. al. 2003)

Table 7-13: Johansen Cointegration Test for the Price Indices of Grecce and Turkey

Johansen Cointegration Test

Series: GREECE TURKEY

Included observations: 518
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.036815	21.93024	15.41	20.04	None **
0.004815	2.49995	3.76	6.65	At most 1

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating equation(s) at 5% significance level

Continued: Table 7-13 Johansen Cointegration Test for the Price Indices of Grecce, Turkey and Jordan

Johansen Cointegration Test

Series: GREECE JORDAN TURKEY

Included observations: 518
Test assumption: Linear deterministic trend in the data
Lags interval: 1 to 4

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.037247	31.55797	29.68	35.65	None *
0.015241	11.89564	15.41	20.04	At most 1
0.007577	3.939996	3.76	6.65	At most 2 *

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating equation(s) at 5% significance level

7.6 Conclusion

The first part of this study, Chapters 5 and 6, employed traditional tests, i.e. runs test, tests of autocorrelation and regression-based tests, in order to test the weak form of the EMH (or price-predictability, Fama 1991). These tests were based on the examination of time-series structure. This method of analysis is based on the requirement that in an efficient market, returns are serially independent. An alternative formulation of the weak form of the EMH is the random walk hypothesis which states that share prices in an efficient market follow a random walk. This suggests an extension to the set of tests just listed by adding tests for stationarity in the price process, which is conducted in Chapter 6, where the unit root test was applied for testing stationarity. In this chapter, the cointegration tests, as an extension of unit root tests, are applied to investigate financial integration and the comovement of stock prices. The finding of the existence of such cointegration relations is considered a clear violation of market efficiency since it suggests information in past prices could have been used to improve the forecasts of the current prices.

The cointegration methodology is applied to test Jordanian market efficiency from a domestic point of view, by using the five sub-indices prices, and from a national point of view, by using price indices of ten Middle Eastern countries. Additionally, the Granger causality test is used to assess any causal relationship between indices. The cointegration test is performed for each pair of Jordan indices by the two techniques: the Engle-Granger two step method and the Johansen approach. The results of the two techniques are very close, suggesting no cointegration equation between each pair. The cointegration test is also applied for a group that contains all the indices; the result confirmed the previous results indicating no long term relationship among the indices. On the other hand, the Granger causality test shows a short run relationship between all pairs of Jordan indices. In general, these findings contradict the findings in the last chapters which had suggested that the Jordan market is not weak form efficient. However, some studies were skeptic about using the cointegration method in testing market efficiency. Stock and Watson (2001) examine empirical evidence of the forecasting ability of asset prices and conclude that some asset prices are predictable in some countries in some periods. Which series predicts what, when and where is, however, is itself difficult to predict. Most empirical evidence, as summarized in Stock and Watson (2001), shows that a significant Granger causality statistic contains little or no information about whether the indicator has been a reliable predictor. Hence, the predictability inferred from cointegration and causality tests does not necessarily mean a violation of market efficiency.

Cointegration and Granger causality testing was then applied to ten Middle Eastern countries' price indices. The unit root tests are performed firstly for these indices to investigate the stationarity and to detect the order of integration. All indices are found to be I(1), and the cointegration results indicated no long relationship between Jordan price index and any other price index in the sample, except for Bahrain and MENA. The Granger causality tests also suggest a short relation only between the Jordan price index and Bahrain and MENA indices.

After that, the ten indices are divided into three groups; GCC, Africa, and Europe, and the cointegration tests are employed twice for each group; once including the Jordan index, and once excluding the Jordan index. The results for the first two groups indicate one integration equation whilst the Jordan index is not included, and reject any cointegration equation once the Jordan index is included. The third group has one cointegration equation whether the Jordan index is included or not. These results suggest that considering Jordan when investing in GCC markets or Egypt, Tunisia, and Morocco markets would provide MENA investors with greater opportunities to diversify their portfolios and reduce risks.

CHAPTER 8

Conclusions

Contents:

8.1 Introduction

The Jordanian stock market was established in 1976. Its most important function, as specified by the Securities Law, is to provide the proper environment to secure the interaction of supply and demand forces for listed securities by establishing proper, clear and fair trading rules necessary to achieve price discovery and trade. The Amman Stock Exchange (ASE) contributes to the economic development of Jordan by mobilizing local savings and attracting foreign investments. The broad objective of this research, as set out in the introduction, is to investigate the stochastic properties and efficiency of the ASE, and whether the prices fully reflect all available information. Another objective for the thesis is to investigate the issue of internationalization of the ASE, examining the possibility of earning arbitrage profits by trading in more than one national market.

Section 8.2 seeks to summarize and draw out the main conclusions regarding ASE efficiency, and Section 8.3 presents recommendations and suggestions for further research.

8.2 Summary and Main Findings of the Study

The core of the thesis examines ASE efficiency, specifically focusing on the concept of market integration and comovements between the five indices of the ASE, and between different market indices in the region.

Apart from the Introduction and Conclusion chapters, the thesis is structured around six chapters. In Chapter 2, different definitions for market efficiency, which have developed throughout time, are presented. The theory of market efficiency, its development and the main concepts it relied on, such as, martingales and random walk, equilibrium model, rational expectations and arbitrage concept, were presented. The idea of testing for market efficiency in the context of cross market integration was highlighted. The last part of this chapter addressed the main characteristics of emerging financial markets that distinguish them from developed markets.

Numerous studies suggest that many emerging equity markets do not behave like developed markets; some studies document that emerging market equity returns have a higher serial correlation than developed market returns, and this serial correlation is symptomatic of infrequent trading and slow adjustment to current information (Harvey, 1995 and Kawakatsu and Morey, 1999). It is also argued that emerging market returns are also less likely to be impacted by company-specific news announcements than developed market returns (Bhattacharya and Daouk, 2002). The evidence suggests that insider trading occurs well before the release of information to the public. Moreover, some literature on stock selection in emerging markets suggests that relatively simple combinations of fundamental characteristics can be used to develop portfolios that exhibit considerable excess returns to the benchmark (Fama and French, 1998, Rouwenhorst, 1999).

These findings suggest that emerging markets are relatively less informationally efficient than developed markets. Bekaert and Harvey (2003) have also suggested that standard models are often ill suited for dealing with the specific circumstances arising in these markets, and therefore, in the next chapters, review of the empirical studies is divided (when applicable) into two sections: developed and emerging markets.

The third chapter gives a general overview of the development of the ASE, and considers the objectives, properties, and the legislation environment for this market. A comparison of the ASE with other markets in the region is also presented. It concludes that the ASE has developed greatly since its establishment and has succeeded in accomplishing several of its goals by mobilising capital into the productive sectors of the economy. The ASE appears to be well organised, attractive, and well managed with much potential for growth when compared with other emerging markets. It ranks among the leaders of emerging markets. Despite the accomplishments so far, the ASE has much room for improvement, in order to become a regional financial market in the future. There are several comparative advantages in this market which should be further developed in order to improve its efficiency and to attract international investments, thereby increasing the depth of the market and enabling it to better compete at emerging markets' level.

Chapter 4 delves into the conventional tests used in literature to examine market efficiency, focusing on the autocorrelation and runs tests. The first part of this chapter presents empirical studies conducted in developed markets, followed by empirical studies conducted in developing markets, and ends with studies conducted in the ASE[1]. Empirical literature suggests that price behavior in developed markets can be characterized as random walk. However, it is still controversial in the case of developing countries. Much work must be conducted to investigate price dynamics in emerging markets. The empirical results obtained in this chapter for the ASE suggests that it is not weak form efficient. The ASE reflects a high degree of positive temporal dependency patterns, violating the assumption of random walk model, and runs tests showed that the null hypothesis of randomness can not be rejected.

To investigate whether the previous results, i.e. the significant positive dependency patterns in stock prices, could be exploited to outperform the simple buy and hold policy, Chapter 5 applied the technical analysis rules[2] by employing filter rules and moving average rules. A large number of surveyed studies indicated that filter rules and moving average rules do not generate superior returns to the buy and hold strategy. The empirical results, for ASE, showed that the filter rules produced, to some extent, higher profits than the buy and hold strategy. The breakdown of return by filter rules for long and short transactions showed that the long positions returns outperform the short positions, which

[1] Some studies investigating the ASE efficiency were found in literature. However, these studies used the conventional tests and didn't proceed to use recent econometric procedures. Moreover, they didn't use the five indices daily prices for the ASE as conducted in this study.

[2] Technical analysis forecasts future price trends through the identification of recurring patterns in historical prices, and claims it is capable of exploiting the trends that it discovers. Hence, the general goal of technical analysis is to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data.

is consistent with the results of the moving average techniques. The moving average techniques are used to study the extent to which alternative moving average trading rule forecast future prices and hence can be profitable. The results of this part of the study generally suggest that technical analysis helps predict stock price changes in the ASE. In common with previous studies, it was found that returns during buy periods are larger than returns during sell periods. This chapter also studied the performance of the moving average trading rule under alternative specifications for the underlying generating process (namely, random walk, AR1, GARCH-M). In each case, the model was fitted to the original data, and the residuals from that model used as the basis for a bootstrap study. The bootstrap technique[3] was used to generate trading rule returns for each given model for the underlying generating process. The comparison between returns generated by the bootstrap and those for the actual series reveals that actual trading profits are consistent, to a certain limit, with those that would be generated using any of the three fitted models (random walk, an AR(1), or a GARCH-M model).

The previous results suggest that the daily returns for the five indices of the ASE do not follow the random walk model, as the first order autocorrelation coefficients are high and significant for all the indices, and since the random walk hypothesis is not equivalent to market efficiency. Chapter 6 employed recent econometric procedures to investigate some behaviour properties of ASE indices, and to identify patterns in time series data.

[3] Whilst, for stock returns, there are several well-known deviations from normality, stationarity and time-independence, such as leptokurtosis, autocorrelation, and conditional heteroskedasticity the bootstrap is a method for estimating the distribution of an estimator or test statistic by resampling one's data or a model estimated from the data.

The Box-Jenkins (ARMA)[4] methodology, which considers the statistical dependence of observations from one time period to the next, is used. The results presented in this chapter are consistent with Chapter 4. Different models with high prediction validity, implying the existence of deviations from market efficiency in the pricing of equities, are produced. Hence, ASE is not weak form efficient, and prices do not adjust fully and instantaneously for new information.

The results of the analysis differ from the findings of an idealized efficient market. As mentioned in Chapter 4, the results of the runs test and auto-correlation coefficient tests indicate the non-random nature of the series and violate the assumption of the null hypothesis that the market is weak-form efficient. Predictability, using dynamic time series statistical techniques such as the Auto regression model and ARIMA model, confirms the previous findings, and the results are consistent in all the indices.

Furthermore, this chapter investigates the stationary and the random walk process for the indices' series. If a series displays non-stationarity, this implies that the series has a unit root, and thus a series generated by such a process has no tendency to return to a mean value. That is, its behaviour is not mean-reverting and unpredictable. One model of non-stationarity is the random walk model (Pindyck and Rubinfeld, 1993). Hence, if a unit root is found in the series, the null hypothesis of a unit root is therefore not rejected, and the series is a random walk. The unit-root test also confirmed previous results, as the return series for all indices did not exhibit unit root and all processes were stationary.

[4]The Box-Jenkins method of forecasting is different from other methods in that it does not assume any particular pattern in the historical data of the series to be forecast. Instead, it uses an iterative approach to identify the underlying pattern.

The last part of Chapter 6 highlighted the questions of stock market volatility, persistence of volatility, and risk premia in the stock market as the ASE tries to attract foreign investment and achieve economic growth. The interest to test the return-volatility behaviour in emerging markets has risen from the increased globalization and integration of the world economies in general, and that of the financial markets in particular. The GARCH-M(1,1)[5] model is estimated, and the results support the existence of a significant link, to a certain limit, between conditional volatility measures and three indices of stock returns. The risk-return parameter is positive and statistically significant. On the other hand, the conditional variance is found to change over time as a result of volatility clustering effects. The clustering could represent the arrival of information in clusters, or delays in the market adjustment process as traders try to measure its content, breaching the efficient market conditions. Unlike ARMA estimations, the GARCH-M(1,1) prediction validity is low, which lessens the importance of the GARCH effect, especially that the GARCH-M(1,1) parameters are not significant for all indices.

The last part of the thesis investigated the relation among the five indices of the Jordan market and analyzed the behavior of the Jordan equity market in relation to another ten emerging markets in the Middle East. The cointegration methodology is applied to test the Jordan market efficiency from a domestic point of view, by using the five indices' prices, and from a national point of view, by using the price indices of the ten Middle Eastern countries. Additionally, the Granger causality test is used to indicate any causal

[5]The GARCH approach incorporates volatility clustering characteristics in the estimation process by allowing for time variation and temporal dependence of conditional second order moments (conditional on the information set at time t-1). In turn, this is consistent with excess kurtosis in the unconditional distribution of returns, as shown by Campbell, Lo and MacKinley(1997).

relationship between indices. The cointegration test is performed for each pair of Jordan indices by two techniques: the Engle-Granger two step method and the Johansen approach. The results of the two techniques are very close, in each case suggesting no cointegration equation between each pair of market indices. The cointegration test is also applied for a group that contains all indices; the result confirmed the previous results indicating no long term relationship among the indices. On the other hand, the Granger causality test shows a short run relationship between all pairs of Jordan indices.

Cointegration and Granger causality tests are also applied for price indices of ten Middle Eastern countries. The unit root tests are performed firstly for these indices to investigate the stationarity and to detect the order of integration. All indices are found to be I(1), and the cointegration results indicate no long relationship between the Jordan price index and any other price index in the sample, except for Bahrain and MENA. The Granger causality tests also suggest a short run relation only between the Jordan price index and the Bahrain and MENA indices.

After that, the ten indices are divided into three groups: GCC, Africa and Europe, and the cointegration tests are employed twice for each group, once including and once excluding the Jordan index. The results for the first two groups indicate one integration equation whilst the Jordan index is excluded, and reject any cointegration equation once the Jordan index is included. The third group has one cointegration equation whether or not the Jordan index is included. These results suggest that considering Jordan when investing in

GCC markets or Egyptian, Tunisian, and Moroccan markets would provide MENA investors with greater opportunities to diversify their portfolios and reduce risks.

The ASE, as an emerging market, is relatively illiquid, highly concentrated, and exhibits thin trading effects. Although the ASE strives to attract local and foreign investment, these characteristics may repel investors and adversely affect market performance. Sufficient liquidity is important to facilitate price equalization. Calculated ratios for ASE showed a low trading volume and turnover ratio, and also a low dividend ratio and market to book ratio. As mentioned in literature, the ASE shares the same low ratios with other emerging markets, in addition to the deviation from normal distribution for the return series. The return series for the ASE indices showed different trends which indicated that the sectors of economy are affected by different factors, hence, diversification within the same market is efficient.

The return series for the market indices exhibited statistically significant autocorrelation coefficients when daily data is used. However, weekly data produced lower autocorrelation coefficients with less significance. It is obvious that some of the autocorrelation refers to the effect of thin trading which can be reduced by increasing data frequency. As the ASE index contains the majority of ASE stocks, a non-negligible fraction of them is relatively illiquid and therefore stable prices (due to stocks which are not traded every day) could explain the larger first-order autocorrelation.

Campbell et al. (1997) showed that large stocks tend to lead smaller stocks, which suggests that non-trading may be a source of autocorrelation. However, they also found that the magnitudes for the autocorrelations imply an implausible level of non-trading and therefore led them to the conclusion that non-trading is only responsible for some of the autocorrelation.

The technical rules were applied to the ASE index and indicated that some rules could outperform a buy and hold strategy. However, and in addition to the limitation of these tests[6], it is still remarkably hard to profit from exploiting these rules (see Chapter 5). It has been demonstrated that superior in-sample performance often fails to translate into superior out-of-sample performance (Roll, 1994).

Other main issues also investigated regarding the ASE index are stock market volatility, persistence of volatility, and risk premia.[7]. It is expected that the ASE exhibits ARCH and GARCH effects as most financial data usually exhibit volatility clustering due to

[6] For example, the computation of the index ignores the payment of dividends on the component stocks. Ignoring dividends yield leads to underestimation of the buy-and-hold return. The trading rule returns are also underestimated, but to a lesser extent. The transaction cost is considered another limitation for interpreting the results. Although the transaction cost in ASE considers low comparing with other markets in the region, it is still expected to affect the results once it taken into consideration. Other limitations are comprised of the ability of practical implementation of the filter rules for different reasons. As there is no market maker who provides offers prices for buying and selling stocks and the bid-ask spread, and as the ASE suffers from thin trading and a non-negligible fraction of the index stocks is relatively illiquid, it is unrealistic to hold and trade the same equities in the same amount as the index. Hence, tracker funds are not available in the ASE and it's not easy to imitate the performance of the stock market index or sector index.

[7] As Jordan tries to attract foreign investment and achieve economic growth, volatility and market efficiency are two important features which will ultimately determine the effectiveness of the stock market in economic development. For example, in a stock market which is informationally inefficient, investors face difficulty in choosing the optimal investment as information on corporate performance is slow to materialise or simply not available. The resulting uncertainty may induce investors either to withdraw from the market until this uncertainty is resolved or discourage them from investing funds over the long term.

increased uncertainty from new information arrival and time delays for traders to adjust to it. Beside that, there is a yearly pattern in stock dividend payments in the ASE, where dividends tend to be concentrated in April and May, and the clustering of dividends could produce GARCH effects. Also, the existence of noise traders may also affect volatility in assets prices.

The results showed a low ARCH coefficient and a high GARCH coefficient. Non-trading effects may cause spurious autocorrelation into the conditional volatility process which produce a high GARCH coefficient and also non-trading may produce shocks for the volatility process as the return for non-trading days is considered equal and zero. Regarding the volatility and return, the results of the estimated parameter capturing the influence of volatility on stock returns is positive for all indices, confirming a positive relation between risk and return, which is consistent with the basic postulate of the portfolio theory, and indicates that, on average, investors trading stocks were compensated with higher returns for bearing risk.

The extent of integration of the ASE and other major stock markets in the region has been assessed. A range of factors could strengthen the linkages among stock markets in different parts of the world: the presence of strong economic ties and policy coordination between relevant countries, the removal of controls on capital movements, deregulating financial markets and allowing freely floating prices, technological advances and increasing in the number of multinational companies and international trade.

If asset prices in different markets are cointegrated, then this may indicate the existence of inefficiency in the asset markets. Granger (1986) has demonstrated that the prices of two different assets, each priced in efficient markets, cannot be cointegrated. On the other hand, Dwyer and Wallace (1992) argue that there is no general equivalence between market efficiency and cointegration, or a lack of co-integration, and demonstrate that co-integration in financial markets can be consistent with market efficiency. Engle (1996) also discusses predictability in an efficient market, and concludes that co-integration has nothing to do with EMH. Caporale and Pittis (1998) argue that whatever concerns one might have about the identification of a cointegrating relationship with market inefficiency, cointegration tests can still be usefully employed to investigate the predictability of asset prices.

Results suggest that the Jordan stock market does not exhibit a long run relationship with most other markets, and there is an advantage for investors looking for diversification in the Middle East markets to include the Jordan market in their portfolios. However, the interpretation of these results must consider the possible effect of thin trading. The law of one price is expected to hold to a greater degree for stocks that are heavily traded in different markets, because each market offers sufficient liquidity to facilitate price–equalizing trades.Hence, trading for more actively traded stocks is expected to exhibit stronger integration and the thinner market is expected to display deviations from the law of one price.

8.3 Recommendations and Suggestions for Further Research

An examination of the efficiency of the ASE has been conducted in this thesis. It is believed that this study has drawn an over-all picture for the time series properties of the ASE. Such a study provides a number of suggestions for investors, and to academics and researchers interested in emerging equity markets. These are discussed in more detail below.

8.3.1 For Investors

- Investors who seek diversified portfolios are recommended to invest in the ASE as well as other Middle-eastern markets since the ASE does not exhibit a long run relationship with most other markets, and there is an advantage for investors looking for diversification in the Middle-eastern markets to include the ASE in such portfolios. Such a diversification would be effective because country risk can be diversified.
- The ASE may be considered, by investors, as one of the available emerging markets to invest in. Its characteristics are similar to that of most emerging markets as described in literature.

8.3.2 For Academics and Researchers

- Since amongst the results reported in this thesis is the finding that the ASE price index is not cointegrated with most of the Middle-eastern markets' price indices.

portfolio analysis could examine whether these findings indicate benefits from diversification. Portfolio Optimization and Efficient Frontier could be used to examine the gains that might be had from incorporating and excluding ASE stocks into portfolios with other Middle-eastern stocks.

- The period of the study witnessed major political events[8], and it would be argued that the results were affected by these temporary events. Further, work could usefully examine the relationship between politics and market efficiency. One difference between emerging and developed markets is the much more prominent role of politics in emerging markets. Perotti and Oijen (2001) suggested that political risk is priced in many emerging markets.
- It is easy to reject market efficiency, but much more difficult to discern the nature of the inefficiency. Since most of the results in this thesis indicated inefficiency of the ASE, carrying out research in behavioural finance (the study of human fallibility in competitive markets (Shleifer, 2000)), could help to explain the nature of the inefficiency. Behavioural finance theory rests on two major foundations. The first is limited arbitrage, that is, arbitrage in real world securities' markets is far from perfect. This happens for different reasons: many securities do not have perfect substitutes, as the arbitrage theory presumes, and arbitrage may be limited and risky because prices do not converge to fundamental values instantaneously. Limited arbitrage thus may explain why prices do not necessarily react to information by the right amount, and why markets may

[8] For example: elections of Parliament was resumed after 40 years of banning, the peace treaty in the Middle East was unleashed, King Hussein's death after 45 years in leadership, the Iraqi crisis, and more recently the 2001/2002 uprising in the Palestinian territories.

remain inefficient when perturbed by noise traders. The second foundation of behavioural finance is investor sentiment: the theory of how real world investors actually form their beliefs and valuations, and more generally their demands, for securities. Combined with limited arbitrage, a theory of investor sentiment may help generate precise predictions about the behaviour of security prices and returns (Shleifer, 2000).

APPENDIX 1

Index Sample, 2003

Banks & Financial Companies Sector
ARAB BANK
INDUSTRIAL DEVELOPMENT BANK
JORDAN KUWAIT BANK
JORDAN INVESTMENT & FINANCE BANK
JORDAN NATIONAL BANK
EXPORT AND FINANCE BANK
UNION BANK FOR SAVING &INVESTMENT
PHILADELPHIA INVESTMENT BANK
BANK OF JORDAN
THE HOUSING BANK
JORDAN ISLAMIC BANK FOR FINANCE & INV.

Insurance Sector
JORDAN INSURANCE
YARMOUK INSURANCE AND REINSURANCE
JERUSALEM INSURANCE
OASIS INSURANCE
JORDAN FRENCH INSURANCE
THE HOLY LAND INSURANCE
ARAB LIFE & ACCIDENT INSURANCE
ARAB OREINT INSURANCE
UNION ARAB INTERNATION INSURANCE
ARABIAN SEAS INSURANCE

Services Sector
JORDAN ELECTRIC POWER
AL-DAWLIA FOR HOTELS & MALLS
JORDAN PRESS FOUNDATION / AL-RA'I
IRBID INDUSTRIAL ELECRICITY
SPECIALIZED INVESTMENT COMPOUNDS
THE ARAB INTERNATIONAL FOR EDUCATION & INV.
THE UNIFIED FOR ORGANIZING LAND TRANSPORT
AL-ZARQA EDUCATIONAL & INVESTMENT
ZARA INVESTMENT
UNION INVESTMENT CORPORATION
JORDAN TELECOM
ARAB INTERNATIONAL HOTELS
JORDAN INVESTMENT TRUST
UNITED ARAB INVESTORS

Industrial Sector
JORDAN CEMENT FACTORIES
JORDAN PHOSPHATE MINES
ARAB POTASH
JORDAN PETROLEUM REFINERY
THE INDUSTRIAL COMMERCIAL & AGRICULTURAL
THE JORDAN WORSTED MILLS
THE ARAB PHARMACEUTICAL MANUF.
JORDAN CERAMIC INDUSTRIES
PEARL SANITARY PAPER
MIDDLE EAST COMPLEX FOR ENG., ELECTRONICS
ADVANCED PHARMACEUTICAL INDUSTRIES
MIDDLE EAST PHARMACEUTICAL INDUSTRIES
DAR AL- DAWA DEVELOPMENT & INV.
ARAB ALUMINUM INDUSTRY/ARAL
JORDAN PAPER & CARDBOARD FACTORIES
UNION TOBACO & CIGARETTE INDUSTRIES
RUM METAL INDUSTRIES
ARAB ELECTRICAL INDUSTRIES
NATIONAL CABLE & WIRE MANUFACTURING
NATIONAL STEEL INDUSTRY
ARAB CENTER FOR PHARM. & CHEMICALS
AL-EKBAL PRINTING AND PACKAGING
NUTRI DAR
INTERNATIONAL CERAMIC INDUSTRIES
UNIVERSAL MODERN INDUSTRIES
JORDAN INDUSTRIAL RESOURCES
NATIONAL CHLORINE INDUSTRIES
JORDAN NEW CABLE
EL-ZAY READY WEAR MANUFACTURING
INTERNATIONAL TOBACCO & CIGARETTES
UNION CHEMICAL & VEGETABLE OIL INDUSTRIES
JORDAN STEEL
NATIONAL ALUMINUM INDUSTRIAL
NATIONAL POULTRY
JORDAN PIPES MANUFACTURING

APPENDIX 2

Calculation of Runs Test and Runs by Length

Excel software is used to calculate the number of sign changes, the actual total number of runs and the actual positive, negative, and zero runs. The TSP software is also used to calculate the actual number of runs and the distribution of runs by length. Table (4.8) gives an example of the programme in Excel. In column B the difference between each two successive daily prices ($P_t - P_{t-1}$) is calculated, then the sign of the difference is located in column C (positive if $P_t - P_{t-1}$>0, negative if $P_t - P_{t-1}$<0, and 0 if $P_t - P_{t-1}$=0). After that, the results of each sign are separated into three columns: D for positive, E for negative, F for zero. The sum of each column presents the number of price changes of each sign (n_i), which is used to calculate the expected number of runs. The total number of actual runs is determined in column G. The current price is considered as a new run if the sign of the price differences, calculated in column C, differs from the sign of the previous day. The results of the total runs are classified as positive, negative, and zero runs in columns: H, I, and J.

The runs test and runs by length are also calculated by the TSP programme as it is shown below.

Table A1: Calculation Runs Test (Formula)

	B	C	D	E	F	G	H	I	j
[illegible]es	Δ price	Sign	Number of sign changes			Total runs	Numbers of runs of each sign		
[illegible]321			(+)	(-)	(0)		(+) run	(-) run	(0) run
[illegible]343	=A3-A2	=IF(B3>0,"+",IF(B3<0,"-",0))	=IF(C3="+",1,0)	=IF(C3="-",1,0)	=IF(C3=0,1,0)				
[illegible]406	=A4-A3	=IF(B4>0,"+",IF(B4<0,"-",0))	=IF(C4="+",1,0)	=IF(C4="-",1,0)	=IF(C4=0,1,0)	=IF(C4=C3,0,1)	=IF(AND(C4="+",G4=1),1,0)	=IF(AND(C4="-",G4=1),1,0)	=IF(AND(C4=0,G4=1),1,0)
[illegible]018	=A5-A4	=IF(B5>0,"+",IF(B5<0,"-",0))	=IF(C5="+",1,0)	=IF(C5="-",1,0)	=IF(C5=0,1,0)	=IF(C5=C4,0,1)	=IF(AND(C5="+",G5=1),1,0)	=IF(AND(C5="-",G5=1),1,0)	=IF(AND(C5=0,G5=1),1,0)
101.298	=A6-A5	=IF(B6>0,"+",IF(B6<0,"-",0))	=IF(C6="+",1,0)	=IF(C6="-",1,0)	=IF(C6=0,1,0)	=IF(C6=C5,0,1)	=IF(AND(C6="+",G6=1),1,0)	=IF(AND(C6="-",G6=1),1,0)	=IF(AND(C6=0,G6=1),1,0)
101.257	=A7-A6	=IF(B7>0,"+",IF(B7<0,"-",0))	=IF(C7="+",1,0)	=IF(C7="-",1,0)	=IF(C7=0,1,0)	=IF(C7=C6,0,1)	=IF(AND(C7="+",G7=1),1,0)	=IF(AND(C7="-",G7=1),1,0)	=IF(AND(C7=0,G7=1),1,0)
101.891	=A8-A7	=IF(B8>0,"+",IF(B8<0,"-",0))	=IF(C8="+",1,0)	=IF(C8="-",1,0)	=IF(C8=0,1,0)	=IF(C8=C7,0,1)	=IF(AND(C8="+",G8=1),1,0)	=IF(AND(C8="-",G8=1),1,0)	=IF(AND(C8=0,G8=1),1,0)
102.648	=A9-A8	=IF(B9>0,"+",IF(B9<0,"-",0))	=IF(C9="+",1,0)	=IF(C9="-",1,0)	=IF(C9=0,1,0)	=IF(C9=C8,0,1)	=IF(AND(C9="+",G9=1),1,0)	=IF(AND(C9="-",G9=1),1,0)	=IF(AND(C9=0,G9=1),1,0)
103.723	=A10-A9	=IF(B10>0,"+",IF(B10<0,"-",0))	=IF(C10="+",1,0)	=IF(C10="-",1,0)	=IF(C10=0,1,0)	=IF(C10=C9,0,1)	=IF(AND(C10="+",G10=1),1,0)	=IF(AND(C10="-",G10=1),1,0)	=IF(AND(C10=0,G10=1),1,0)
103.964	=A11-A10	=IF(B11>0,"+",IF(B11<0,"-",0))	=IF(C11="+",1,0)	=IF(C11="-",1,0)	=IF(C11=0,1,0)	=IF(C11=C10,0,1)	=IF(AND(C11="+",G11=1),1,0)	=IF(AND(C11="-",G11=1),1,0)	=IF(AND(C11=0,G11=1),1,0)
103.655	=A12-A11	=IF(B12>0,"+",IF(B12<0,"-",0))	=IF(C12="+",1,0)	=IF(C12="-",1,0)	=IF(C12=0,1,0)	=IF(C12=C11,0,1)	=IF(AND(C12="+",G12=1),1,0)	=IF(AND(C12="-",G12=1),1,0)	=IF(AND(C12=0,G12=1),1,0)
104.118	=A13-A12	=IF(B13>0,"+",IF(B13<0,"-",0))	=IF(C13="+",1,0)	=IF(C13="-",1,0)	=IF(C13=0,1,0)	=IF(C13=C12,0,1)	=IF(AND(C13="+",G13=1),1,0)	=IF(AND(C13="-",G13=1),1,0)	=IF(AND(C13=0,G13=1),1,0)
Total		=SUM(C3:C14)	=SUM(D3:D14)	=SUM(E3:E14)	=SUM(F3:F14)	=SUM(G3:G14)	=SUM(H3:H14)	=SUM(I3:I14)	=SUM(J3:J14)

Table A2: Continued (Numbers)

A	B	C	D	E	F	G	H	I	J
Prices	Δ price	Sign	Number of sign changes			Total runs	Numbers of runs of each sign		
101.321			(+)	(-)	(0)		(+) run	(-) run	(0) run
101.843	0.522	+	1	0	0				
101.406	-0.437	-	0	1	0	1	1	0	0
101.018	-0.388	-	0	1	0	0	0	0	0
101.298	0.280	+	1	0	0	1	0	1	0
101.257	-0.041	-	0	1	0	1	1	0	0
101.891	0.634	+	1	0	0	1	0	1	0
102.648	0.757	+	1	0	0	0	0	0	0
103.723	1.075	+	1	0	0	0	0	0	0
103.964	0.241	+	1	0	0	0	0	0	0
103.655	-0.309	-	0	1	0	1	1	0	0
104.118	0.463	+	1	0	0	1	0	1	0
Total			7	4	0	6	3	3	0

TSP program

```
? This program determine the total number of runs
?divided into three groups(positive runs,
?negative runs, zero runs) for the index price
?changes of amman financial market for the period
?from 1/1/92 to 30/7/2001 on a daily basis
?then each group analyzed to the lengths of days.
options crt;
freq n;
options limwarn=0;
smpl 1 2350;
read(file='\latest.xls')banks insurance
services industry general;
dot banks insurance
services industry general;
smpl 1 2350;
A=.;
B=.(-1);
D=.(-2);

E=.(-3);
F=.(-4);
G=.(-5);
H=.(-6);
I=.(-7);
J=.(-8);
K=.(-9);
L=.(1);
run=1*(A>B & B<=D) + 2*(A<B & B>=D) + 3*(A=B&B^=D);
title 'number of total runs';
select run;
title 'number of positive runs';
select run=1;
title 'number of negative runs';
select run=2;
title 'number of zero runs';
select run=3;
smpl 1 2350;
length=8*(A>b &b>d&d>e&e>f&f>g&g>h&h>i&I>J&J<=K&A>=L) + 7*(A>b
&b>d&d>e&e>f&f>g&g>h&h>i&I<=J&A>=L) + 6*(A>b
&b>d&d>e&e>f&f>g&g>h&h<=i&A>=L) + 5*(A>b &b>d&d>e&e>f&f>g&G<=h&A>=L)
+ 4*(A>b &b>d&d>e&e>f&f<=g&A>=L) + 3*(A>b &b>d&d>e&e<=f&A>=L) +
2*(A>b &b>d&d<=e&A>=L) + 1*(a>b&b<=d&A>=L);
title 'number of oneday length for positive runs';
select length=1;
title 'number of 2day length for positive runs';
select length=2;
title 'number of 3day length for positive runs';
select length=3;
title 'number of 4day length for positive runs';
select length=4;
title 'number of 5day length for positive runs';
select length=5;
title 'number of 6day length for positive runs';
select length=6;
title 'number of 7day length for positive runs';
select length=7;
title 'number of 8day length for positive runs';
```

```
select length=8;
SMPL 1 2350;
length=8*(A<b &b<d&d<e&e<f&f<g&g<h&h<i&I<J&J>=K&A<=L) + 7*(A<b
&b<d&d<e&e<f&f<g&g<h&h<i&I>=J&A<=L) + 6*(A<b
&b<d&d<e&e<f&f<g&g<h&h>=i&A<=L) + 5*(A<b &b<d&d<e&e<f&f<g&G>=h&A<=L)
+ 4*(A<b &b<d&d<e&e<f&f>=g&A<=L) + 3*(A<b &b<d&d<e&e>=f&A<=L) +
2*(A<b &b<d&d>=e&A<=L) + 1*(a<b&b>=d&A<=L);
title 'number of oneday length for negative runs';
select length=1;
title 'number of 2day length for negative runs';
select length=2;
title 'number of 3day length for negative runs';
select length=3;
title 'number of 4day length for negative runs';
select length=4;
title 'number of 5day length for negative runs';
select length=5;
title 'number of 6day length for negative runs';
select length=6;
title 'number of 7day length for negative runs';
select length=7;
title 'number of 8day length for negative runs';
select length=8;
SMPL 1 2350;
length=8*(A=b &b=d&d=e&e=f&f=g&g=h&h=i&I=J&J^=K&A^=L) + 7*(A=b
&b=d&d=e&e=f&f=g&g=h&h=i&I^=J&A^=L) + 6*(A=b
&b=d&d=e&e=f&f=g&g=h&h^=i&A^=L) + 5*(A=b &b=d&d=e&e=f&f=g&G^=h&A^=L)
+ 4*(A=b &b=d&d=e&e=f&f^=g&A^=L) + 3*(A=b &b=d&d=e&e^=f&A^=L) +
2*(A=b &b=d&d^=e&A^=L) + 1*(a=b&b^=d&A^=L);
title 'number of oneday length for zero runs';
select length=1;
title 'number of 2day length for zero runs';
select length=2;
title 'number of 3day length for zero runs';
select length=3;
title 'number of 4day length for zero runs';
select length=4;
title 'number of 5day length for zero runs';
select length=5;
title 'number of 6day length for zero runs';
select length=6;
title 'number of 7day length for zero runs';
select length=7;
title 'number of 8day length for zero runs';
select length=8;
enddot;
```

APPENDIX 3

Calculating Filter Rule

Table A2 explains how the 0.1% filter size is calculated. Column A is a counter, column B is the daily prices for the index, and columns C and D specify the new positions to be opened (long [peak] and short [through]). If the price (B column) increases or decreases more than the filter size, then a new position is opened and the price of that day is fixed in the corresponding cell, in either the C (long) or D (short) column; otherwise the corresponding cell is filled by 0.

In columns E and F, the possible reference price, for peak and trough, respectively, is updated. After determining the open positions days for long and short, all the possible closing days for both positions are determined, each open position day is matched with the suitable closing day. Regarding the long reference, if the current price exceeds the reference price, then a new peak has been attained, and the cell in E column is filled by the current price as a new reference. On the other hand, if the current price is less than [(1- filter size) *reference price], then the current price is considered as a possible new reference for a long position because, in this case, the long position is closed and the current price could be a possible new long reference. Otherwise, when the current price is less than the reference price and higher than [(1- filter size) *reference price], the reference price doesn't change. The same applies for the short position, keeping in mind the change in direction. The possible ends for long positions are calculated in column G.

If the current price is less than [(1- filter size) *reference price], then the current price is a possible end for a long position, otherwise the cell is filled by 0 (again, the same applies for the short position, keeping in mind the change in direction).

So far, the days to open long and short positions are determined in columns C and D, respectively, and the days that could be possible ends for the long and short positions are determined in columns G and H, respectively. The next step is to match each position with an appropriate closing date, and to calculate the number of days during which the position was opened, and calculate the position's profit. To achieve this task, the match function is used (the long position will be used as an example). First, the rows that contain zeros in the C column are hid by using the Autofilter command from the data menu; the rows that haven't been hidden (which do not equal zero) contain the open long positions' days. The A column, which represents the serial number of the all trading days, is copied while the zero rows of column C are hid and pasted in column J. Column J represents the serial number of the open long position days. The same procedure is done to remove the zero values and copy the corresponding serial days for the nonzero days for the possible ends for long positions (column G) and to paste them into column K. Column K represents the serial number of the possible ends for the long position. The values in this column are placed in a descending order to fulfill the MATCH command.

To match between each open long position day and its suitable end, the MATCH command is then used in column L. This command returns the relative position of an item in an array [1] (the serial numbers of days of possible ends for long positions [K column]), which matches a specified value or finds the smallest value that is greater than the specified value(the serial number of the open long position day [J column]). That is, each open position day will be matched by the first next possible end day. Since the MATCH command returns the relative position of the items, column I is a counter started from number 1 to determine the relative positions for values in column K. The results now in column L are the relative positions of the suitable ends for the corresponding open days in column J. To replace the relative positions by the serial number of the trading day, the VLOOKUP command is used in column M. It searches for a value in a specified column (L) of a table, and then returns a value in the same row from another specified column (I). Column M represents the serial number of the end position days. In column N, the duration in terms of total trading days for the long position ($n_{l,i}^{(j)}$) is calculated as a difference between the serial number of the end day (M column) and the serial number of the open day (J column). The profit for the position ($I_{l,i}^{(j)}$) is calculated in column O as the difference between the end position price and the open position price.

To match each serial number of the open and the end positions with its price, the VLOOKUP command is used. The end price is divided by the open price, which is considered as $[1 + r_{l,i}^{(j)}]^{n_{l,i}^{(j)}}$. In column Q the return is calculated by using P cells rising to the power (1/n), and then deducting 1. $T_i^{(j)}$ refers to the total number of transactions initiated is the number of cells in column J, $N_i^{(j)}$ is the summation of column N, and

[1] Array is a contiguous range of cells containing possible lookup values.

$(n_{t,i}^{(j)}).[1+r_{t,i}^{(j)}]^{n_{t,i}^{(j)}}$ is the product of the cells in column P. The daily return is calculated by the following equation: $r_i^{(j)} = \left\{ \prod_{t=1}^{T_i^{(j)}} \left[1+r_{t,i}^{(j)}\right]^{n_{t,i}^{(j)}} \right\}^{1/N_i^{(j)}} - 1$, and the annual return is calculated by the following equation: $R_i^{(j)} = 260 r_i^{(j)}$.

TableA2: Calculation 0.1% Filter

A	B	C	D	E	F	G	H
1	prices	Open Long (Peak)	Open Short (Through)	Update possible Long Reference	Update possible Short Reference	Possible ends for Long Position	Possible ends for Short Position
2	100.648						
3	100.904	=IF(B3>1.001*B2,B3,0)	=IF(B3<0.999*B2,-B3,0)	=IF(OR(B3>E2,B3<0.999*E2),B3,E2)	=IF(OR(B3<F2,B3>1.001*F2),B3,F2)	=IF(B3<0.999*E2,B3,0)	=IF(B3>1.001*F2,B3,0)
4	100.757	=IF(B4>1.001*B3,B4,0)	=IF(B4<0.999*B3,-B4,0)	=IF(OR(B4>E3,B4<0.999*E3),B4,E3)	=IF(OR(B4<F3,B4>1.001*F3),B4,F3)	=IF(B4<0.999*E3,B4,0)	=IF(B4>1.001*F3,B4,0)
5	100.691	=IF(B5>1.001*B4,B5,0)	=IF(B5<0.999*B4,-B5,0)	=IF(OR(B5>E4,B5<0.999*E4),B5,E4)	=IF(OR(B5<F4,B5>1.001*F4),B5,F4)	=IF(B5<0.999*E4,B5,0)	=IF(B5>1.001*F4,B5,0)
6	103.077	=IF(B6>1.001*B5,B6,0)	=IF(B6<0.999*B5,-B6,0)	=IF(OR(B6>E5,B6<0.999*E5),B6,E5)	=IF(OR(B6<F5,B6>1.001*F5),B6,F5)	=IF(B6<0.999*E5,B6,0)	=IF(B6>1.001*F5,B6,0)
7	102.641	=IF(B7>1.001*B6,B7,0)	=IF(B7<0.999*B6,-B7,0)	=IF(OR(B7>E6,B7<0.999*E6),B7,E6)	=IF(OR(B7<F6,B7>1.001*F6),B7,F6)	=IF(B7<0.999*E6,B7,0)	=IF(B7>1.001*F6,B7,0)
8	102.964	=IF(B8>1.001*B7,B8,0)	=IF(B8<0.999*B7,-B8,0)	=IF(OR(B8>E7,B8<0.999*E7),B8,E7)	=IF(OR(B8<F7,B8>1.001*F7),B8,F7)	=IF(B8<0.999*E7,B8,0)	=IF(B8>1.001*F7,B8,0)
9	103.407	=IF(B9>1.001*B8,B9,0)	=IF(B9<0.999*B8,-B9,0)	=IF(OR(B9>E8,B9<0.999*E8),B9,E8)	=IF(OR(B9<F8,B9>1.001*F8),B9,F8)	=IF(B9<0.999*E8,B9,0)	=IF(B9>1.001*F8,B9,0)

A	B	C	D	E	F	G	H
1	prices	Open Long (Peak)	Open Short (Trough)	Update Long Reference	Update Short Reference	Possible ends for Peaks	Possible ends for Through
2	100.648						
3	100.904	100.904	0	100.904	100.904	0	100.904
4	100.757	0	-100.757	100.757	100.757	100.757	0
5	100.691	0	0	100.757	100.691	0	0
6	103.077	103.077	0	103.077	103.077	0	103.077
7	102.641	0	-102.641	102.641	102.641	102.641	0
8	102.964	102.964	0	102.964	102.964	0	102.964
9	103.407	103.407	0	103.407	103.407	0	103.407

Table A2: Continued

I	J	K	L	M	N	O
Counter	Open peak	Possible End peak	Match	End peak	No. days ($n_{t,i}^{(j)}$)	Profit ($I_{t,i}^{(j)}$)
1	3	2343	=MATCH(B5,$K$5:$K$1032,-1)	=VLOOKUP(D5,$I$5:$K$1032,3,FALSE)	=E5-B5	=VLOOKUP(E5,$A$1:$B$2344,2,FALSE) – VLOOKUP(B5,$A$1:$B$2344,2,FALSE)
2	6	2339	=MATCH(B6,$K$5:$K$1032,-1)	=VLOOKUP(D6,$I$5:$K$1032,3,FALSE)	=E6-B6	=VLOOKUP(E6,$A$1:$B$2344,2,FALSE) – VLOOKUP(B6,$A$1:$B$2344,2,FALSE)
3	8	2336	=MATCH(B7,$K$5:$K$1032,-1)	=VLOOKUP(D7,$I$5:$K$1032,3,FALSE)	=E7-B7	=VLOOKUP(E7,$A$1:$B$2344,2,FALSE) – VLOOKUP(B7,$A$1:$B$2344,2,FALSE)
4	9	2335	=MATCH(B8,$K$5:$K$1032,-1)	=VLOOKUP(D8,$I$5:$K$1032,3,FALSE)	=E8-B8	=VLOOKUP(E8,$A$1:$B$2344,2,FALSE) – VLOOKUP(B8,$A$1:$B$2344,2,FALSE)
5	13	2332	=MATCH(B9,$K$5:$K$1032,-1)	=VLOOKUP(D9,$I$5:$K$1032,3,FALSE)	=E9-B9	=VLOOKUP(E9,$A$1:$B$2344,2,FALSE) – VLOOKUP(B9,$A$1:$B$2344,2,FALSE)
6	18	2330	=MATCH(B10,$K$5:$K$1032,-1)	=VLOOKUP(D10,$I$5:$K$1032,3,FALSE)	=E10-B10	=VLOOKUP(E10,$A$1:$B$2344,2,FALSE) – VLOOKUP(B10,$A$1:$B$2344,2,FALSE)
7	19	2325	=MATCH(B11,$K$5:$K$1032,-1)	=VLOOKUP(D11,$I$5:$K$1032,3,FALSE)	=E11-B11	=VLOOKUP(E11,$A$1:$B$2344,2,FALSE) – VLOOKUP(B11,$A$1:$B$2344,2,FALSE)
8	23	2319	=MATCH(B12,$K$5:$K$1032,-1)	=VLOOKUP(D12,$I$5:$K$1032,3,FALSE)	=E12-B12	=VLOOKUP(E12,$A$1:$B$2344,2,FALSE) – VLOOKUP(B12,$A$1:$B$2344,2,FALSE)
9	24	2318	=MATCH(B13,$K$5:$K$1032,-1)	=VLOOKUP(D13,$I$5:$K$1032,3,FALSE)	=E13-B13	=VLOOKUP(E13,$A$1:$B$2344,2,FALSE) – VLOOKUP(B13,$A$1:$B$2344,2,FALSE)
.	.	.	.	.	.	
.	.	.	.	.	.	
904					=SUM(N5:N903)	

I	J	K	L	M	N	O
Counter	Open peak	Possible End peak	Match	End peak	No. days ($n_{t,i}^{(j)}$)	Profit($I_{t,i}^{(j)}$)
1	3	2343	1030	4	1	-0.147482128670973
2	6	2339	1029	7	1	-0.435720418914485
3	8	2336	1028	12	4	-0.0731894784359923
4	9	2335	1028	12	3	-0.515927300635539
5	13	2332	1027	15	2	-0.448641469699339
6	18	2330	1025	20	2	0.132439044306395
7	19	2325	1025	20	1	-0.12118797149958
8	23	2319	1023	27	4	-0.0449417615807164
9	24	2318	1023	27	3	-0.158275588664736
.	.	.	.	.	.	
.	.	.	.	.	.	
904					2589	

Table A2: Continued

P	Q	R	S
$(1+r_t^i)^n$	r_t^i		LONG
=VLOOKUP(E5,$A$1:$B$2344,2,FALSE) / VLOOKUP(B5,$A$1:$B$2344,2,FALSE)	=H5^(1/F5)-1	T=	=I904
=VLOOKUP(E6,$A$1:$B$2344,2,FALSE) / VLOOKUP(B6,$A$1:$B$2344,2,FALSE)	=H6^(1/F6)-1	N=	=N904
=VLOOKUP(E7,$A$1:$B$2344,2,FALSE) / VLOOKUP(B7,$A$1:$B$2344,2,FALSE)	=H7^(1/F7)-1	$(1+r_t^i)^n=$	=P978
=VLOOKUP(E8,$A$1:$B$2344,2,FALSE) / VLOOKUP(B8,$A$1:$B$2344,2,FALSE)	=H8^(1/F8)-1	$r_i=$	=R4^(1/R3)-1
=VLOOKUP(E9,$A$1:$B$2344,2,FALSE) / VLOOKUP(B9,$A$1:$B$2344,2,FALSE)	=H9^(1/F9)-1	R_i (filter)=	=260*R5
=VLOOKUP(E10,$A$1:$B$2344,2,FALSE) / VLOOKUP(B10,$A$1:$B$2344,2,FALSE)	=H10^(1/F10)-1		
=VLOOKUP(E11,$A$1:$B$2344,2,FALSE) / VLOOKUP(B11,$A$1:$B$2344,2,FALSE)	=H11^(1/F11)-1		
=VLOOKUP(E12,$A$1:$B$2344,2,FALSE) / VLOOKUP(B12,$A$1:$B$2344,2,FALSE)	=H12^(1/F12)-1		
=VLOOKUP(E13,$A$1:$B$2344,2,FALSE) / VLOOKUP(B13,$A$1:$B$2344,2,FALSE)	=H13^(1/F13)-1		
.	.		
.	.		
=PRODUCT(P5:P903)			

P	Q	R	S
$(1+r_t^i)^n$	r_t^i		LONG
0.998538404688345	-0.0014615953116	T=	902
0.995772889308765	-0.0042271106912	N=	2589
0.999289176571612	-0.0001777532458	$(1+r_t^i)^n=$	216.247537490483
0.995010716690577	-0.0016658680117	$r_i=$	0.00207879879331729
0.995652719164483	-0.0021760079229	R_i (filter)=	0.540487686262496
1.0012884919892	0.00064403860173		
0.998823871188107	-0.0011761288118		
0.999563231466457	-0.0001092100223		
0.998463483944881	-0.0005124345627		
.	.		
.	.		
216.247537490483			

APPENDIX 4

Time Series and Box-Jenkins Analysis

Contents:

3A.1 Time Series Analysis

The aim of time-series analysis is to study the dynamics or temporal structure of the data. The stationary and non-stationary stochastic processes for the series should be investigated.

3A.1.1 Stationary and Non-stationary Stochastic Processes

A time series X_t is said to be stationary if it's mean, variance and covariance remain constant over time (Greene, 1997). In other words, it must satisfy the following requirements:

- $E(X_t) = \text{constant}$ *for all t* **(3A-1)**
- $Var(X_t) = \text{constant}$ *for all t* **(3A-2)**
- $Cov(X_t, X_{t+k}) = \text{constant}$ *for all t and all k ≠ 0* **(3A-3)**

Otherwise, if the series fails to satisfy any of the above requirements, it is considered a non-stationary series. Stationary implies that autocovariances may be a function of k, but not of t (depending on (3A-3)). In what follows, the autocovariance at lag k is defined as:

$$\lambda_k = \text{cov}(X_t, X_{t-k}) \tag{3A-4}$$

1. Autocorrelation function:

The autocorrelation function, or ACF, is obtained by dividing the autocovariance function by variance λ_0 to obtain the following equation:

$$P_k = \lambda_k / \lambda_0, \quad -1 < P_k < 1 \tag{3A-5}$$

The ACF is useful for describing a time-series process, since the moments are used to describe the distribution of a random variable. The stationary stochastic process has an autocorrelation function that eventually tapers off to zero.

2.Partial autocorrelations of a stationary stochastic process:

The autocorrelation function ACF (k) gives the gross correlation between X_t and X_{t-k}. However, the correlation between X_t and X_{t-2} could arise because both variables are correlated with X_{t-1}. The partial autocorrelation between X_t and X_{t-2} measures the correlation between X_t and X_{t-2} net of the intervening effect of X_{t-1}. It is the simple correlation between X_{t-k} and X_t minus that part explained linearly by intervening lags. That is:

$$PP_k = Corr\left[X_t - E\left(X_t \mid X_{t-1}, \ldots\ldots\ldots, X_{t-k+1}\right), X_{t-k}\right] \tag{3A-6}$$

where:

$E\left(X_t \middle| X_{t-1}, \ldots\ldots, X_{t-k+1}\right)$ = the best linear prediction of X_t by X_{t-1}, …., X_{t-k+1}

The next section deals with stationarity in more detail.

3A.1.2Models of Time Series:

Several types of stochastic processes could be used in modelling time series (Maddala, 2000). These include:

1. Purely random walk process
2. Random walk
3. Moving average (MA) process
4. Autoregressive (AR) process
5. Autoregressive moving average (ARMA) process
6. Autoregressive integrated moving average (ARIMA) process

1-Purely Random Walk Process (White Noise):

This is achieved when a discrete process $\{X_t\}$ consisting of a sequence of mutually independent identically distributed random variables has a constant mean and a constant variance and the autocovariance function is:

$$\lambda_k = \operatorname{cov}(X_t, X_{t-k}) = 0 \quad for\, k \neq 0 \qquad \textbf{(3A-7)}$$

The autocorrelation coefficient is given by

$$\begin{aligned} P_k &= 0 \quad for\ k \neq 0 \quad and \\ P_k &= 1 \quad for\, k = 0 \end{aligned} \qquad \textbf{(3A-8)}$$

2-Random Walk:

A process $\{X_t\}$ is said to be a random walk if

$$X_t = X_{t-1} + \varepsilon_t \qquad \textbf{(3A-9)}$$

And $\{\varepsilon_t\}$ is a purely random walk series with mean μ and variance σ^2

3-Moving Average Process:

A process $\{X_t\}$ is defined as a moving average process of order *m*, and is denoted by MA (*m*) if:

$$X_t = \beta_0\varepsilon_t + \beta_1\varepsilon_{t-1} + \ldots\ldots + \beta_m\varepsilon_{t-m} \qquad \textbf{(3A-10)}$$

And $\{\varepsilon_t\}$ is a purely random walk series with a mean zero and a variance σ^2

4-Autoregressive Process:

The process $\{X_t\}$ given by:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + ... + \alpha_p X_{t-p} + \varepsilon_t \qquad \textbf{(3A-10)}$$

And $\{\varepsilon_t\}$ is a purely random walk series with a mean zero and a variance σ^2. This process is called an autoregressive process of order p and is denoted by AR(p). It is called regressive because it is like a multiple regression equation. It is a regression of X_t on its own past values, hence it is autoregressive.

5-Autoregressive Moving Average Process:

It is a combination of the AR and MA models. An autoregressive moving average model ARMA(p,q) is defined as:

$$X_t = \alpha_1 X_{t-1} ...... + \alpha_p X_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + ... + \beta_q \varepsilon_{t-q} \qquad \textbf{(3A-11)}$$

Where $\{\varepsilon_t\}$ is a purely random process with a mean zero and a variance σ^2.

6-Autoregressive integrated moving average process:

When successive differencing $(\Delta^d X_t)$ is used to convert a nonstationary series to a stationary series then the series is said to be integrated.

Considering $\Delta X_t = X_t - X_{t-1}$, $\Delta^2 X_t = (X_t - X_{t-1}) - (X_{t-1} - X_{t-2})$, and so on, then the $(\Delta^d X_t)$ is integrated to d degree. If the $(\Delta^d X_t)$ is a stationary series that can be represented by an ARMA (p,q) model, then X_t can be represented by an autoregressive integrated moving average model ARIMA (p,d,q).

3A.2 Modelling Univariate Time Series and Box-Jenkins Analysis:

No theory states why a compact ARMA(p,q) representation should adequately describe the movement of a given series, unless it is a methodology for building forecasting models. Box and Jenkins (1984) have pioneered a forecasting framework. The basic steps in their methodology are:

1- Differencing the series so as to achieve stationarity, which can be obtained by studying the graph of the correlogram of the series. Stationary series correlogram drops off as k, the number of lags, becomes large. Differencing must continue till the correlogram dampens.

2- Identification of a model after the differencing procedure is used to get a stationary time series. The correlogram is examined in order to decide on the appropriate orders of the AR and MA components. Judgmental procedure is involved in this stage rather than clear-cut rules.

3- The estimation of the ARMA model:

- AR--autoregressive terms: first order or additional higher order terms could be used. Each AR term corresponds to the use of a lagged value of the residual in the forecasting equation for the residual.
- MA--the moving average term: A moving average forecasting model uses lagged values of the forecast error to improve the current forecast. A first-order moving average term uses the most recent forecast error; a second-order term uses the forecast error from two periods ago, and so on.
- The kind of ARMA model that should be used is decided as follows: if the autocorrelation function dies off smoothly at a geometric rate, and the partial autocorrelations were zero after one lag, then a first-order autoregressive model would be suggested. Alternatively, if the autocorrelations were zero after one lag and the partial autocorrelations declined geometrically, a first-order moving average process would come to mind.
- ARMA analysis is considered as a parsimonious representation of the process governing the residual. Enough AR and MA terms to fit the properties of the residuals should be used. After fitting a candidate ARMA specification, it should be checked that there are no remaining autocorrelations not accounted for by the model.

4- Diagnostic checking to check the adequacy of the model. In order to test the goodness of fit, there are two criteria often used to reflect the closeness of fit and the number of parameters estimated. These are the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC).

3A.2.1 Akaike Information Criterion

The Akaike Information Criterion, or AIC, is a guide to the selection of the number of terms in an equation. It is based on the sum of squared residuals, but places a penalty on extra coefficients. Under certain conditions, the chosen length of a lag distribution should be specified with the lowest value of the AIC.

$$AIC(p) = n \log \hat{\sigma}_p^{\,2} + 2p \qquad \text{(3A-12)}$$

where p is the number of parameters estimated, and n is the sample size (Maddala, 2001)

3A.2.2 Schwarz Criterion

The Schwarz criterion is an alternative to the AIC with basically the same interpretation but a larger penalty for extra coefficients.

$$SIC(p) = n \log \hat{\sigma}_p^{\,2} + p \log n \qquad \text{(3A-13)}$$

where p is the number of parameters estimated, and n is the sample size (Maddala, 2001). Additionally, the serial correlation pattern of the residuals must be checked to be sure that there is no serial correlation. The serial correlation LM test is an alternative test for general serial correlation. It uses the Breusch-Godfrey large sample test for autocorrelated disturbances. It is applicable whether the disturbances follow an AR(p) or MA(p) process, where p can be specified as any positive order.

5- The final step is forecasting, where the k-period ahead forecast is used. K-period ahead forecast is to forecast the x_{n+k} when n observations were used to estimate the model.

APPENDIX 5

Johansen Approach

The hypotheses about cointegration can be tested within a framework established by Johansen (1991). If there are N endogenous variables, each of which is first-order integrated (that is, each has a unit root or stochastic trend or random-walk element), up to N-1 linearly independent cointegrating vectors could exist. The number of cointegrating equations is called the cointegrating rank. If there is one cointegrating equation, the VAR will need an error correction term involving levels of the series, and this term will appear on the right-hand side of each of the VAR equations, which otherwise will be in first differences. Each additional cointegrating equation contributes another error correction term.

Each cointegrating equation adds the parameters associated with the term involving levels of the series which needs to be added to each equation. The Johansen test procedure computes the likelihood ratio statistic for each added cointegrating equation. The test statistic does not have the usual χ^2 distribution.

The series may have means and deterministic trends as well as stochastic trends. Similarly, the cointegrating equations may have intercepts and deterministic trends. Johansen's framework considers five combinations of these ingredients:

1. Series have means but the cointegrating equations do not have intercepts,
2. Series have means and the cointegrating equations have intercepts,
3. Series have means and linear trends but the cointegrating equations have only intercepts,

4. Series have means and linear trends and the cointegrating equations have intercepts and linear trends, or
5. Series have means, linear, and quadratic trends but the cointegrating equations have only intercepts and linear trends.

These five cases are nested from the most restrictive to the least restrictive, given any particular cointegrating rank.

A vector error correction VEC model is a VAR that builds in cointegration. For example, a two-variable system with one cointegrating equation which is

$$X_{2,t} = \beta X_{1,t} \qquad \textbf{(4A-1)}$$

then there is a pair of vector error correction models of the following form:

$$\Delta X_{1,t} = \gamma_1 \left(X_{2,t-1} - \alpha X_{1,t-1} \right) + \varepsilon_{1,t} \qquad \textbf{(4A-2)}$$

$$\Delta X_{2,t} = \gamma_2 \left(X_{2,t-1} - \alpha X_{1,t-1} \right) + \varepsilon_{2,t} \qquad \textbf{(4A-3)}$$

The cointegrating equation will have a zero intercept, but the two endogenous variables $X_{1,t}$ and $X_{2,t}$ will have nonzero means. It is an example of the first case in the list. To keep the example simple, there are no lagged differences on the right-hand side, but normally, there would be several lagged differences as well as the cointegration term. For the second in the list above, if the series have means and the cointegrating equations have intercepts, then the cointegration equation is

$$X_{2,t} = \mu + \beta X_{1,t} \qquad \textbf{(4A-4)}$$

and VEC becomes :

$$\Delta X_{1,t} = \gamma_1 \left(X_{2,t-1} - \mu - \alpha X_{1,t-1} \right) + \varepsilon_{1,t} \qquad \textbf{(4A-5)}$$

$$\Delta X_{2,t} = \gamma_2 \left(X_{2,t-1} - \mu - \alpha X_{1,t-1} \right) + \varepsilon_{2,t} \qquad \textbf{(4A-6)}$$

If the intercepts in the equations, outside the parentheses, correspond to a linear trend in the levels of the series.(the third model in the list), the VEC becomes:

$$\Delta X_{1,t} = \delta_1 + \gamma_1 (X_{2,t-1} - \mu - \alpha X_{1,t-1}) + \varepsilon_{1,t} \quad \textbf{(4A-7)}$$

$$\Delta X_{2,t} = \delta_2 + \gamma_2 (X_{2,t-1} - \mu - \alpha X_{1,t-1}) + \varepsilon_{2,t} \quad \textbf{(4A-8)}$$

If there is a trend in the cointegrating equation, but no separate trends in the two VEC equations, the fourth case applies. And if there is a separate linear trend outside the parentheses in each VEC equation, there is an implicit quadratic trend in the series, the fifth case in the list.

The Johansen test use the maximum likelihood approach which gives consistent ML estimates of the whole cointegrating matrix and produces a likelihood ratio statistic for the maximum number of distinct equilibrium vectors in the matrix. Thus it is possible to identify the whole set of cointegrating relationships using this method.
Eviews software provides tests for the five possibilities mentioned above; Eviews also tabulates the critical values for the reduced rank test as given by Osterwald-Lenum (1992).

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