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Market Efficiency and Volatility in an Islamic Financial Market Interpreted from a Behavioural Finance Perspective
A Case Study of the Amman Stock Exchange

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Market Efficiency and Volatility in an Islamic Financial Market Interpreted from a Behavioural Finance Perspective: A Case Study of the Amman Stock Exchange

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Abstract

The research undertaken aims to contribute to the debate about market efficiency and market volatility in an Islamic context. The research relates to the Amman Stock Exchange (ASE) and covers the period 1992 to 2007. It undertakes quantitative analysis involving two key elements: first, testing for random walk and calendar anomaly effects in market returns and, second, modelling volatility in market returns.

The thesis applies a series of standard econometric and statistical techniques to this issue. The key 'novel' contributions of this study relate to the focus on Islamic religious holiday effects and also the application of behavioural finance theoretical models to explain the findings in terms of the influence of social mood (mood misattribution) effects. These are approaches that have not been previously applied in the literature within an Islamic context.

The author argues that the econometric and statistical techniques applied are 'fit for purpose'. Standard methods are applied; however, these are applied in 'novel' ways in parts of the thesis. For example, moving-date calendar effects are modelled for the first time and the modelling of volatility makes use of interaction effects to explore the impact of interactions between different mood-influencing variables.

The study begins by identifying that the ASE index returns do not follow a Random Walk. It then goes on to identify day-of-the-week effects. First trading day of the week effects found in relation to the first trading day that follows the Muslim holy day of Friday. Monthly calendar effects were also found. January or turn-of-the-year effects were found in the ASE similar to those found previously in some Western markets. However, the largest monthly effects were found in relation to the holy month of Ramadan. Most significantly, Ramadan was found to be the only month where the average daily returns were both statistically

different from the other months in the year and also positive. This, it is argued in the thesis, is due to social mood (or mood misattribution) effects.

The research looks beyond informational efficiency and develops a number of 'novel' contributions to research in this area in terms of both the empirical findings and the behavioural finance-related interpretation of these findings, as well as the influence of Islamic ethics in Amman's stock market returns. The thesis also examines the relationship between seven behavioural mood-proxy variables and stock market returns. Fama (1991) argues that efficiency and volatility are unrelated. In this thesis, however, evidence is uncovered which suggests that this may not be the case. High levels of volatility were found at the start and at the end of the Ramadan holy festival; this volatility, it is argued, is related to social mood. This issue is examined further by exploring previously unstudied interactions between mood-related Ramadan effects and mood-related weather and biorhythmic effects.

The results of this thesis, the author believes, provide strong evidence for the existence of Muslim religion investment decision biases associated with social mood effects (mood misattribution). It is argued that these social mood effects in the case of Jordan relate mainly to Islamic ethics and cultural issues, as they are found predominantly during the Ramadan religious holiday.

Despite the existence of decision biases within the ASE, no profitable trading anomaly opportunities were identified. This may be due, in part, to Jordan having high trading transaction costs. It is possible, however, that profitable trading opportunities related to Islamic holidays may exist in countries that follow stricter religious observance. The author believes that there is an opportunity to extend this research to countries such as Bahrain.

"In The Name of God Most Gracious Most Merciful"

To the memory of my Lovely Father,
To my Beloved Mother, Sisters, Brothers and my Wife
Undiluted Support, Encouragement and Prayers has enabled me
Reach this Height of Academic Glory.

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Acronyms

ADF	Augmented Dickey–Fuller test
ADSM	Abu Dhabi Securities Market
AFM	Amman Financial Market
AIC	Akaike information criterion
AMF	Arab Monetary Fund
AR	Autoregressive
ARCH	Autoregressive conditional heteroscedasticity
ARIMA	Autoregressive integrated moving average
ASE	Amman Stock Exchange
ASM	Amman Stock Market
C	Celsius
CBOE	Chicago Board Options Exchange
CRSP	Center for Research in Security Prices
DEM	Dubai Financial Market
DJIA	Dow Jones Industrial Average
DSTC	Daylight saving time changes
ECM	Error correction model
EGARCH	Exponential general autoregressive conditional heteroscedasticity
EGARCHM	Exponential general autoregressive conditional heteroscedasticity in the mean
EMH	Efficient market hypothesis
FDoW	First trading day-of-the-week
FTI	Financial Times Industrial Ordinary Index
FTSE	Financial Times and London Stock Exchange Share Index
GARCH	General autoregressive conditional heteroscedasticity

GARCH-M	General autoregressive conditional heteroscedasticity in mean
GCC	Gulf Cooperation Council countries
GDP	Gross domestic product
GED	Generalized error distribution
GPH	Geweke and Porter-Hudak test
GTS	General-to-specific
GUM	General unrestricted model
H	Humidity
HT	High temperature
IID	Identical independent distribution
IMF	International Monetary Fund
Int. (10RDN.*H)	Interaction between the last 10 days of Ramadan and humidity
Int. (10RDN.*LP)	Interaction between the last 10 days of Ramadan and lunar phases
Int. (5RDN.*H)	Interaction between the last 5 days of Ramadan and humidity
Int. (RDN.*H)	Interaction between Ramadan and humidity
Int. (RDN.*HT)	Interaction between Ramadan and high temperature
Int. (RDN.*LP)	Interaction between Ramadan and lunar phases
Int. (RDN.*LT)	Interaction between Ramadan and low temperature
Int. (RDN.*SAD)	Interaction between Ramadan and seasonal affective disorder
Int. (RDN.*W)	Interaction between Ramadan and wind
ISE	Istanbul Stock Exchange
JD	Jordanian Dinar
JSC	Jordan Securities Commission
JSE	Jamaica Stock Exchange
KM	Kilometre
LLRT	Log likelihood ratio test

LOMAC	Lo and MacKinlay test
LP	Lunar phases
LT	Low temperature
MC	Marginal cost
ME	Market efficiency
MENA	Middle East and North Africa
MG	Marginal gain
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
R10 days	Last 10 days of Ramadan
R5 days	Last 5 days of Ramadan
RDN	The month of Ramadan
REH	Rational expectations hypothesis
RW	Random walk
RWH	Random walk hypothesis
S&P	Standard & Poor's
SAD	Seasonal affective disorder
SDC	Securities Depository Centre
TGARCH	Threshold general autoregressive conditional heteroscedasticity
TOM	Turn-of-the-month
UAE	United Arab Emirates
UK	United Kingdom
US	United States
VIX	Chicago Board Options Exchange Market Volatility Index

VR	Variance ratio
W	Wind speed
WB	World Bank
WFME	Weak form market efficiency

1. Chapter One: Introduction

1.1. Introduction and Aims

The stock market works as a focal point in a modern economy to reallocate capital in more effective ways. Its main function is to facilitate share trading more effectively. It brings sellers and buyers of shares together by creating links between them as participating partners in the economy. For an emerging market economy like Jordan, the Amman Stock Exchange (ASE) plays an important role in channelling and intermediating capital in the Jordanian economy, which currently depends significantly on the inflows of foreign capital.

Jordan has striven to improve the quality and flow of information into the stock market. Since the market's inception in 1978, the economic and legal foundations of the Jordanian capital market have been strengthened, while its products have been enhanced and its liquidity improved. This would be expected to increase the level of market efficiency; however, it should be noted that, despite the increasing number of listed companies, the Jordanian market has continued to be dominated by the banking sector. Whilst there have been a number of studies into Jordanian market efficiency, these have not taken into consideration the unique characteristics associated with an Islamic society. The impact these Islamic characteristics have on market efficiency is what this thesis focuses on.

The efficient market framework assumes that investors behave rationally in the sense that they analyse all relevant information in the most effective way with a view of achieving the best possible outcomes. This assumption has motivated scholars to test the validity of Efficient Market Hypothesis (EMH) in many stock exchanges all over the world. The studies undertaken on developed markets have found that, historically, even if stock markets are

predominantly efficient, anomalies have existed during certain times of the year or in certain countries. As an example, calendar anomalies were identified during the 1970s and 1980s in some developed markets. These anomalies resulted in many investors reconsidering their investment strategies in the 1980s. However, by the 1990s calendar anomalies started to disappear from Western markets. This has led many investors to look for calendar-related trading opportunities elsewhere in less developed emerging markets.

It should be noted that many emerging markets are significantly different from developed markets. Jordan, for example, has many of the characteristics of an emerging market in that historically, it has faced lower volumes and lower frequency of trading ('thin trading') and is vulnerable to manipulation by a small number of influential traders. Another dimension that needs to be considered is the fact that Jordan is an Islamic society with different ethics and a different attitude to investing to that found in Western markets.

Ergo, the research aims to contribute to the debate in relation to the market efficiency of one emerging market, namely the Amman Stock Exchange (ASE). The aim of the research is to examine whether or not the Islamic nature of Jordanian society has any specific influence on market efficiency. To do this, the thesis begins by examining whether or not the market process follows a random walk and looking for the standard calendar anomaly effects found in the literature. It then turns its attention to the specific issue of Islam-related effects. Particularly, it focuses on the impact that the holy month of Ramadan has on market efficiency. This research goes beyond informational efficiency to exploring the relation between risk and return by examining the volatility, again focusing specifically on the impact that the holy month of Ramadan has on volatility levels. As well as examining the ASE for inefficiencies, the thesis also applies behavioural finance and ethics theories, as alternative frameworks to market efficiency, in an attempt to explain why these inefficiencies occur.

This element of the thesis lays emphasis on the importance of the social mood in influencing investor behaviour.

1.2. Background

In the past two decades, the ASE has seen considerable growth in terms of trading volume and market value and, as it has grown, it has become a vital instrument for financing investment in Jordan. In a developing country like Jordan, the efficient allocation of scarce resources and encouragement of foreign private investment are both of crucial importance. This is especially important in terms of Jordan's objective of encouraging economic development through the expansion of the private sector, as this will only be achieved if the country has an active and efficient stock market.

It should be noted that emerging stock markets such as the ASE are not strictly comparable to those in well-developed markets. The ASE exhibits greater levels of volatility than, for example, are found in London. Investors are more concerned about issues such as speculative activities, market manipulation and government involvement. Hence, it can be argued that the Jordanian investment environment is significantly different from that faced by investors in well-developed markets.

Other issues also exist. For instance, the Muslim attitude to interest means that stock markets have a more significant role in relation to saving than occurs in Western countries, where banks play a fuller role in this respect. Another important issue is the central role that Ramadan plays in Muslim life; in fact, the *Qur'an* (Islamic holy book) mentions:

> "The month of Ramadan in which was revealed the Qur'an, a guidance for mankind, and clear proofs of the guidance, and the Criterion (of right and wrong). And whosoever of you is present, let him fast the month, and whosoever of you is sick or

on a journey, (let him fast the same) number of other days. Allah desireth for you ease; He desireth not hardship for you; and (He desireth) that ye should complete the period, and that ye should magnify Allah for having guided you, and that peradventure ye may be thankful."[1]

Furthermore, according to Bukhari (an influential Muslim scholar), "Allah's Apostle" said:

"Fasting is a shield (or a screen or a shelter). (Allah says about the fasting person), 'He has left his food, drink and desires for My sake. The fast is for Me. So I will reward (the fasting person) for it and the reward of good deeds is multiplied ten times.'"[2]

Therefore, if Muslim investors in ASE behave differently during the month of Ramadan, it would indicate that religious belief is a factor that influences investors' behaviour and has an impact in a financial market in countries like Jordan.

In practice, the assumption of efficient markets found in much of the academic literature has been built on the assumption that rational investors dominate the stock market; however, it does not require all individual investors to be rational (it requires that the rational investors outweigh the irrational ones). This view can be contrasted with psychological models, which suggest actions and performances of people are driven by what they think – thoughts that are heavily influenced by how people feel which in turn is partly determined by their interactions with others. If an investor is in a good mood, there will be a trend to be optimistic when evaluating an investment. Good moods may cause investors to be more likely to make risky investments (Redhead, 2008). Weather and the length of daylight are also factors that can

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[1] *Qur'an* Sura 2 – Al-Baqara (MADINA): Verse 185
[2] Bukhari: Book 3: Volume 31: *Hadith* 118

affect mood (Hirshleifer and Shumway, 2003; Kamstra et al., 2003). It is argued in this thesis that social mood effects are influenced not only by these biorhythmic effects but also, in the Muslim world at least, by the powerful impact that religious festivals such as Ramadan have on people's thought processes.

1.3. Objectives of the Thesis

The specific objectives of the full thesis are:

- To evaluate the market efficiency of the ASE by testing for the presence of a random walk in stock prices covering the period 1992–2007.

- To test for the presence of calendar anomaly inefficiencies associated with the Muslim religious holiday of Ramadan.

- To interpret market inefficiencies found from a behavioural finance perspective.

- To test the profitability of trading rules based on religious holiday calendar anomalies on the ASE.

- To examine the nature of price volatility on the ASE during religious holiday periods and to examine the nature of interaction between mood-related religious holiday effects and mood-related weather and human biorhythmic effects.

- To interpret any market volatility anomalies found from the ethics and behavioural finance perspectives.

1.4. Contribution of the Thesis to the Literature

Most of the research related to random walk and calendar effects has been undertaken in developed countries. Most recently, more studies have been undertaken in developing

countries. There are a number of studies that have looked specifically at the issue of market efficiency in Jordan.

The author of this thesis is unaware of other studies that have examined Muslim developing markets for market anomalies related to religious holidays. This study aims to make a novel contribution to the literature by addressing this issue and assessing whether or not mood-related factors, associated with the Muslim religious holiday, present any profitable trading opportunities.

A further novel contribution that this study makes is to provide an interpretation of the reasons for the anomalies found based on behavioural finance. This analysis centres on explaining how mood-related factors associated with the holiday of Ramadan influence investors' stock buying/selling behaviour.

It was noted during the research that there were considerable changes in volatility levels associated with specific periods within Ramadan. A further contribution that this thesis makes is to model the associated volatility using a GARCH analysis. Previous research had examined the relationship between mood proxies and returns or variance. The author of this thesis has not found any literature relating to the impact of the Muslim religious holiday on volatility. A further contribution that the thesis makes to the literature is to examine how the effects of religious holidays and social mood interact with the effects of weather and human biorhythms. The results from this analysis are again interpreted from the ethics and behavioural finance perspectives.

1.5. Overview of Methodology of the Thesis

This study develops a time series analysis of market efficiency and volatility using a quantitative approach. The principle data used relates to daily prices from the ASE market

index over the period 1992–2007. This index is a market capitalization weighted price index. Other data sources referenced are the International Monetary Fund (IMF), the Arab Monetary Fund (AMF) and the World Bank (WB).

The first key stage of the thesis (Chapters Five and Six) uses a series of tests to identify whether or not the ASE is efficient by following a random walk. A comprehensive review of the literature illustrates that even when one type of test (the serial correlation coefficient test, the run test, the variance ratio test, etc.) fails to reject the random walk hypothesis, others may actually reject it. Therefore, to help the robustness of this analysis, a series of tests (both parametric and non-parametric) are applied at that stage. These include the Wald-Wolfowitz (1940) runs test for the randomness of the series, the length-of-runs test, the serial correlation test of independence, and the variance ratio (VR) of Lo and MacKinlay (1988). Further tests of efficiency are also carried out. For example, using t-tests to examine for significance in any differences found in daily returns. Employing different testing procedures facilitates the reaching of a conclusion of consistency in the findings.

The second key stage of the thesis (Chapter Seven) models the nature of volatility in the ASE. This is undertaken using GARCH models (Bollerslev, 1986; Nelson, 1991) to examine the structure of the volatility for both religious holiday and human biorhythmic effects.

For both of the key stages identified above, the thesis attempts to explain the anomalies found through the application of theoretical models derived from ethics and behavioural finance theories.

1.6. Outline of Subsequent Chapters

The rest of the thesis is organized as follows:

Chapter Two, the literature review starts by presenting the alternative frameworks used by scholars to examine the performance of financial markets. Then a brief review of the main framework of this thesis is presented through a historically based discussion of the ways in which market efficiency has been examined in the literature. The efficient market hypothesis (EMH) and its classifications are then examined. The EMH remains the orthodox model for examining efficiency in financial markets. However, despite this being the orthodoxy, there are many anomalies identified in the literature. The chapter also explores the debate on the relationship between market efficiency and volatility and finally examines the influence of sentiment and behavioural finance in investor behaviour. The latter is a framework developed from the perspective of identifying the different behavioural biases that might be used to understand the inefficiency and volatility variations in the ASE from a psychological perspective.

Chapter Three presents an overview of the background of Jordan and identifies the key features of the Jordanian economy and financial markets. It also discusses recent developments in the Jordanian economy and the Amman Financial Market (AFM).

Chapter Four presents the theoretical framework and the hypotheses tested in this thesis. The statistical definition of market efficiency used in the research is provided, which is examined in the context of the random walk hypothesis (the original model of weak form efficiency is that the time series of stock prices follows a random walk). The random walk model presumes that successive prices in the time series are serially independent and that their

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probability distribution is identical through time. The design of the tests used in Chapters Five and Six is also presented in this chapter, as well as the justification for using these tests.

Chapter Five examines whether the ASE stock prices follow a random walk for the period 1992–2007 using the methods outlined above. Behavioural finance theory is then applied to the results.

Chapter Six tests the ASE for calendar anomaly effects. The chapter starts by looking for the standard effects described in Western literature. The main focus of the chapter is, however, on Islamic calendar effects in relation to the month of Ramadan. The Islamic anomaly effects found are then discussed in terms of behavioural finance theory.

Chapter Seven examines volatility in the ASE. It uses a number of mood-proxy variables relating to the weather and human biorhythms and identifies how these interact with an Islamic holiday mood-proxy variable. The relationships found are then discussed in terms of an ethical perspective and also behavioural finance theory.

Chapter Eight presents a summary of the research findings. The thesis contends that the Islamic religion (especially during the period centred on Ramadan) does have a significant impact on market efficiency and market volatility; however, the anomalies found did not present profitable trading opportunities due to high transaction costs in Jordan. The key recommendation of the thesis is that this study should be extended to identify whether similar results can be identified in other Islamic countries such as Bahrain.

2. Chapter Two: Literature Review

2.1. Introduction

The literature review begins in Section 2.2 a discussion of alternative theoretical frameworks through an examination of the different approaches used by scholars to examine the performance of financial markets. Section 2.3 identifies and provides a brief review of the main theoretical framework of this thesis. This is followed by Section 2.4, which examines the efficient market hypothesis (EMH) and its classifications. Although EMH remains the orthodox model for examining efficiency in the financial market, there are many anomalies identified in the literature. Section 2.5 outlines these anomalies with a primary focus on the calendar effects and their consequences for the validity of the weak form of market efficiency. The section focuses on differences between the findings in respect to developed and developing countries. It also examines the non-Gregorian calendar effects, specifically those related to the Muslim and Jewish religious calendars.

In Section 2.6, the literature in respect to the debated relationship between market efficiency and volatility is addressed. Some evidence is found that suggests it may be possible to add further potential material indicators related to stock market cycles that may be useful from an investment perspective. This is followed in Section 2.7 by an examination of behavioural finance theories. This is approached by identifying the different behavioural biases that might be utilized to help understand the inefficiency in the ASM from a psychological perspective. Finally, the concluding section identifies, within the context of the literature review, the areas that the research undertaken in this thesis focuses on.

2.2. Theoretical Frameworks to Examine the Performance of Financial Markets

Throughout the history of economic thought, scholars have examined the ways in which the theoretical frameworks used to study economic activity develop and evolve over time. Kuhn (1962) describes these theoretical frameworks as paradigms. They can possibly also be characterized as being 'world views' or the perspective from which an economic issue is examined.

The dominant paradigm in the Western academic world in respect to financial market behaviour can be described as the *market efficiency* approach. The origins of this approach go back to the 'Chicago school of economics' and work related to rational expectations by Muth (1961) and others. The paradigm was subsequently extended by financial economists, such as Fama (1970), in a financial markets context and by macroeconomic theorists, such as Friedman (1962), in a macroeconomic context.

We should not lose sight of the fact that financial market behaviour can also be examined from alternative perspectives; three distinctive paradigms or theoretical frameworks can be identified. In addition to the *market efficiency* approach, it can be argued that there is an *ethics* paradigm, as well as a *market sentiment* or *behavioural finance* paradigm. Although these latter frameworks have received less attention from scholars in the literature, it is important to consider them. For example, Petrochilos (2010) argues that, in light of the 2007 financial markets crash, an ethics-based approach may need to be reconsidered as a framework for managing and understanding financial markets.

In the next part of this section, the three frameworks outlined above are presented in more detail and this is used to draw conclusions about how the research topic examined in this thesis should be approached.

2.2.1. The Ethics, Responsibility and Regulation Framework

Both Western and Islamic scholars have argued that markets, market behaviour and the ways in which they operate should be examined from the perspective of the moral codes laid down by society. From a practical perspective, they argue that limits and regulations need to be imposed on markets to ensure that behaviour reflects society's relevant moral codes.

2.2.1.1. The Western Ethics Value System

The ethical perspective of examining financial markets found in Western scholarship can be traced back to the ancient Greek philosophers, who were the first to establish ethics (or the philosophy of morals) as a subject for study. This was through the ancient Greek philosophy that economics works together with other sciences in order to serve the body politic and improve the life of society. Ethics was seen as being related to what is morally good or bad, and also what is right or wrong. In effect ethics focuses on what is proper, right or obligatory to do or not to do.

Petrochilos (2004) identifies Greek ethics in terms of *Kalokagathia* or the character and conduct of *kalos Kagathos*. The latter element can be seen in terms of the perfect and just man and it can be interpreted as kindness, honesty, uprightness and just behaviour. *Kalos* has to do with beauty and harmony of the body, while *agathos* is the perfect, virtuous, just and good man. Clearly, in the context of this thesis, the emphasis is on *agathos*. *Agathoi* must display their *arête* (virtue) in public affairs if the *polis* (city-state) is to run efficiently.

According to ethics approach, of deontology, the actions of people are ethically right depending on the characteristics of the action itself rather than the goodness of its outcome. As a result, people act ethically because it is their duty to do so, irrespective of consequences. This implies that deontological ethics is the opposite of teleological ethics, i.e. utilitarianism,

which asserts that the fundamental paradigm of morality is the value (utility) of what the action brings about, and the three major monotheistic religions of Judaism, Christianity and Islam, support formalist ethics, since they all require people to obey God in their daily actions.

Kant (1724–1804) argues that people have to behave ethically out of respect for moral law rather than out of a natural tendency. Therefore, people should act honestly for the reason that honesty is the correct thing to do. If people behave honestly because honesty pays then honesty is cheapened. Therefore, if firms behave ethically out of fear of the law, then they are not behaving ethically at all. Kant's moral law was established in relation to human reason, based on the tenet: *"Act only on that maxim whereby thou canst at the same time will that it should become a universal law."* Kant's view has been criticized on the grounds that he was too concerned with the rational.

In fact, deontology relies on a categorization of rules, which makes it rigid. Petrochilos (2004) says, "Any ethical uncertainties can only be resolved by constructing even more complicated specific rules and ranking them hierarchically in order for conflict between them to be avoided." Therefore, the question of what is proper remains open, and it is quite difficult to identify what is good and what is bad, particularly in a business sense.

Another approach to ethics is provided by *utilitarianism*. This is the school of thought based on rationality, established by Hume (1711–1776)[3] and Bentham (1748–1832) and considered the cornerstone of neoclassical economics. According to Hume, moral decisions rely on

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[3] Hume is known today in most circles for his contributions to philosophy; during his own lifetime he was renowned for his moral, political and critical essays and for his *The History of England: From the Invasion of Julius Caesar to the Revolution in 1688* (1762), the vehicle that principally carried his name into the nineteenth century. Hume himself believed his thinking to be important and revolutionary; writing about his first philosophical work, *A Treatise of Human Nature: Being an Attempt to Introduce the Experimental Method of Reasoning into Moral Subjects* (1739), that its principles are *"so remote from the vulgar Sentiments on this Subject, that were they to take place, they wou'd produce almost a total Alteration in Philosophy."*

moral sentiments and their qualities, which are of importance due to their utility or their agreeableness. Hume's moral system aims to achieve happiness for both the person and the society simultaneously; however, his emphasis is with regard to society. The moral sentiment that Hume's moral system claims to find in man is altruism. He traces it to a sentiment for sympathy for one's fellow beings.

Bentham argues that the purpose of the law is to reach the *"greatest happiness of the great number"*. Furthermore, he proposed three different options that are still accepted today, which are:

(a) Individual well-being ought to be the end of moral actions.

(b) Each individual is to "count for one and no more than one".

(c) The object of social action should be to maximize general utility or, in Bentham's terms, to promote the greatest happiness of the greatest number.

In fact, happiness and pleasure are equal in Bentham's view, although some modern utilitarians may reject that. Although the influence of utilitarianism on economics and as a moral theory cannot be ignored, it is also important to look beyond the theory and to determine the usefulness of its consequences. Therefore, according to utilitarian theory, any action is considered right if it creates the maximum achievable happiness for all those who are part of it compared with any alternative action.

2.2.1.2. Corporate Governance and Financial Regulation

One of the practical consequences of an ethical approach to markets in Western philosophy can be seen in relation to corporate governance and financial regulation.

A number of ethical considerations are utilized in practice through corporate governance codes that represent the system and sets of rules by which firms are directed and controlled and which may also incorporate aspects of social responsibility. The Organisation for Economic Co-operation and Development (OECD, 1999) states that: *"The corporate governance structure specifies the distribution of rights and responsibilities among different participants in corporations, such as, the board, managers, shareholders and other stakeholders, and spells out the rules and procedures for making decisions on corporate affairs."*

After the Asian financial crises in 1997, the OECD launched the *OECD Principles of Corporate Governance* to help rebuild investor confidence. The principles set and modify a number of standards of management, based on analysis, and specify the practices for various countries subject to country-specific characteristics, such as cultural norms and legal rules. Its main areas of concern were the rights of shareholders, equitable treatment of shareholders, the role of the other stakeholders in corporate governance, disclosure, transparency, and the responsibilities of the board of directors (Petrochilos, 2004).

In 2004, the principles were reviewed to take into account the new developments in the principles-based approach, which highlights the need to adapt and adjust implementation to varying legal and cultural circumstances across borders. Thus, they can be used as a reference point by various policy makers in government as they formulate legal and regulatory frameworks and by the private sector as they develop their own practices. This could help develop a culture of values for professional and ethical behaviour on which well-run markets depend.

Regulation:

The various ethical considerations mentioned above are applied in practice through the regulation that represents the system and set rules by which firms are directed and controlled; therefore, the regulation of the financial system can be viewed as a particularly important case of public control over the economy. The accumulation of capital and the allocation of financial resources constitute essential aspects in the process of the economic development of a nation. The peculiarities of financial intermediation and of the operators who perform this function justify the existence of a broader system of controls with respect to other forms of economic activity. Various theoretical motivations have been advanced to support the opportunity of a particularly stringent regulation for financial markets, banks and other financial intermediaries. Such motivations are based on the existence of particular forms of market failure in the credit and financial sectors (White, 1996).

According to Di Giorgio et al. (2000), the primary objective of financial market regulation is the pursuit of macroeconomic and microeconomic stability. Safeguarding the stability of the system translates into macro-controls over the financial exchanges, clearing houses and securities settlement systems.

A second objective of financial regulation is transparency in the market and in intermediaries and investor protection. This is linked to the more general objective of equity in the distribution of the available resources and may be mapped into the search for *"equity in the distribution of information as a precious good"* among operators (Di Giorgio et al., 2000).

At the macro level, transparency rules impose equal treatment (for example, rules regarding takeovers and public offers) and the correct dissemination of information (insider trading, manipulation and, more generally, the rules dealing with exchanges microstructure and price-

discovery mechanisms). At the micro level, such rules aim at non-discrimination in relationships among intermediaries and different customers (conduct of business rules).

A third objective of financial market regulation, linked with the general objective of efficiency, is the safeguarding and promotion of competition in the financial intermediation sector. This requires rules for control over the structure of competition in the markets and, at the micro level, regulations in the matter of concentrations, cartels and abuse of dominant positions.

By contrast, in the 1980s the UK government introduced a policy of deregulation of markets in an effort to unleash the *"animal spirits"* of entrepreneurship. This resulted in, for example, the London Stock Exchange abolishing the distinction between stockjobbers and stockbrokers and changing from open outcry to electronic screen-based trading, which was called the 'Big Bang' or deregulation of the financial market in London in 1986 (Petrochilos, 2010).

2.2.1.3. The Islamic Ethics Value System and Economic Activity

Islamic economics, in its modern usage, came into existence in the early 1970s, mainly as a critique of both the capitalist and communist systems. The pioneering figures opined that the failure of economic development in Muslim society was capitalist economic development strategies that ignored the importance of societal well-being. Therefore, the objective of Islamic economics was to develop an economic system that would develop a human-centric development strategy.

Kahf (2003) indicates that Islamic economics cannot be considered outside the main discipline of economics; that perspective neglects the most important aim of an Islamic economics paradigm with its own values, rules and institutions, and its politically orientated 'systemic' understanding. The foundational principles of the Islamic economic paradigm are

to achieve the creation of human-centric economics. Ahmad (1980), Chapra (1992), El-Ghazali (1994) and Sirageldin (2002) have presented works that use, in varying degrees, an axiomatic approach to rationalize the existence of an Islamic political economy by treating Islamic ethos as an ideal through which social and economic policies are assessed.

An example of these principles is unity, which indicates the vertical dimension of the Islamic ethical system. God says: "O mankind, we have created you from a male and a female, and made you into races and tribes, so that you may identify one another" (Qur'an, 49:13). Another principle is justice equilibrium, which provides for the horizontal dimension of equity. A third principle is free will, which provides individual opportunities in the economic system to choose between. Additionally, there is the principle of responsibility, which implies that individuals and society need to uphold public good.

The *zakat* and *tazkiyah* principles (meaning both 'purification' and 'growth') are pillars of Islam. The Islamic system aims at eliminating poverty from society, rather than managing the poor. One of the companions of the Prophet Mohammad and also one of the Guided Successors of Him, Ali Bin Abi Talib stated: *"If poverty were a man, I would certainly kill him."* Practically, after few years of implementing Islam in Islamic society, the notion of poverty was gone altogether. It is narrated in history that during the era of the Khalifah Omar Bin Adel Aziz there was not a single poor person within the Islamic State who would accept the charity of the *zakat.* Prophet Muhammad said: *"Allah breaks covenant with any group of people living in close vicinity, whereby one of them goes to bed while hungry."*

Together, these principles define the foundational Islamic economics framework, in which economic and financial activity is intended to take place while incorporating intra- and inter-generational social justice. Moreover, it reveals itself in the methodological framework of the Islamic economic system. In comparing the methodologies of Islamic economics and

conventional economics, the points of contrast are unambiguously understood. To highlight those points of contrast, the methodological framework of neo-classical economics is first summarized as follows:

(i) Methodological individualism

(ii) Behavioural postulates: *self-interested individuals* who:

    (a) seek their own interests,

    (b) act in a rational way, and

    (c) try to maximize their own utility.

(iii) Market exchange.

Hence, a conventional economic system is based on a *one-dimensional utility function,* which leads to *homo economicus* or the economic individual in a market system.

The methodological postulates of Islamic economics, on the other hand, can be summarized as follows (Asutay, 2007):

(i) *Socio-tropic individualism*: not only individualism but also social concern is a prerequisite.

(ii) Behavioural postulates: socially concerned God-conscious individuals who:

    (a) in seeking their interests are similarly concerned with the social good,

    (b) conduct economic activity in a rational way in accordance with the Islamic constraints regarding social environment and hereafter, and

    (c) in trying to maximize their utility seek to maximize social welfare as well by taking into account the hereafter.

(iii) *Market exchange* is the main feature of economic operations in the Islamic system; however, this system is filtered through an Islamic process to produce a socially concerned and environmentally friendly system. In this process, socialist and welfare-state orientated frameworks are avoided to prevent curbing of incentives in the economy.

Hence, in Islamic economics we have the *two-dimensional utility function*, which leads to *homo Islamicus* or, as Arif (1989) names it, *tab'ay* (obedient) human being, where *"to be a Muslim is a necessary but not a sufficient condition to be tab'ay"* (Arif, 1989). Hence, as an implication, to qualify as *tab'ay*, one needs to apply Islamic principles in every aspect of one's life.

Therefore, Islamic economics aims at a world order where the ontological and epistemological sources, the *Qur'an* and *Hadith*, determine the framework of the ethics and economic value system, its foundational and operational dimensions, and the behavioural norms of individual Muslims. Islamic economics, thus, is an:

> *"approach to* [and process of] *interpreting and solving the man's economic problems based on the values, norms, laws and institutions found in, and derived from all sources of knowledge* [in Islam]" (Haneef, 2005).

This, however, implies both a systemic understanding and a political dimension.

Finally, Islamic economics, like neoclassical economics, suggests an implicit social welfare function, and expects Islamic finance to work towards that objective. However, neoclassical economic theory's implicit social welfare function was undermined by the discourse and analysis developed by the new political economy and public choice (see Mueller, 2003), which still follows the utility maximizing individual. The very idea that there is a social welfare function, which is assumed to be maximized by a benevolent authority, is no longer a

norm. This is so, since each government with its institutions is perceived to consist of individuals who attempt to maximize their own individual utilities in various capacities. In other words, the organic state with the social welfare function objective is no longer a reliable maxim.

2.2.2. Market Efficiency Framework

It can be argued that the *market efficiency* paradigm has only come to dominate Western academic thought relatively recently. After the inflation-related economic crises of the 1970s and the collapse of the Soviet Union and the Warsaw-Pact-related socialism in the world, capitalism became the main economic paradigm in the world. The arguments of Friedman and his fellow monetarists succeeded in influencing politicians such as Reagan in the US and Thatcher in the UK. Simultaneously, models related to market efficiency such as the rational expectations hypothesis (REH) and the efficient market hypothesis (EMH) began to develop a dominant role in academia. Petrochilos (2010) states:

> *"People in authority liked their political message. Firstly, both REH and EMH were cast in neat mathematical models which however upon testing were found wanting, but that did not lead to their abandonment."*

One of the consequences has been that mathematical models have been used extensively to examine market efficiency. For example, we see the widespread use of tools such as runs tests, serial correlation, variance ratio and GARCH models to examine the level of market efficiency.

The implication of the EMH was that, because investors behave rationally and competitively, financial markets would constantly set prices reflecting *all available information* and so markets were efficient. Accordingly, the market price would constantly reflect more perfect

information than was available to any one individual and, therefore, no one could expect to *"beat the market"*. This included any regulators. This provided extra academic support to monetarist thought, which was also accepted by many governments, particularly in the UK. Constant market price fluctuations were dismissed as meaningless random fluctuations, akin to a *random walk*. Even though EMH failed to explain five major crises in the financial markets; in stock markets in 1987, bank lending in emerging markets in 1994, currencies in 1998, the new economy dot-com bankruptcies of 2003-2007 and credit markets in 2008 (Petrochilos, 2010), it is still the most accepted theory in the field.

2.2.3. Sentiment and Behavioural Finance Framework

Relatively recently, the sentiment and behavioural finance framework was developed in the Western academic world. This questions whether or not we should examine markets in the context of market efficiency. This is not questioning this model from an ethical perspective; it questions it from the perspective of examining how individuals actually make financial decisions in practice. The influences on their decisions may partly be ethics related (their moral code, such as Muslims' attitude to interest) but there are also other important factors, such as investor psychology. Werner and Thaler (1985) label this approach *behavioural finance*. Its origins can be traced back to earlier work on market sentiment.

When psychological thinking is applied to financial markets, it is in search of explanations for behaviour that apparently deviates from what is expected. On the basis of economic theory, and efficient market theory in particular, the applications are often referred to as behavioural finance. While there are several ways of delimiting the field, Statman (1999) clarifies the difference between standard finance and behavioural finance. He says that market efficiency has two meanings. To some, it means that there is no systematic way to

beat the market. To others, it means that security prices are assumed to be rationally derived. If rational, price reflects only *fundamental* or *utilitarian* characteristics, which include *risk*. They do not comprise psychological or *value-expressive* characteristics such as sentiment. The psychological characteristics include many aspects of forms from cognitive psychology such as *heuristics*, *biases* and *mental accounting*.

The field of economic psychology covers these phenomena and many more. This does not imply that behavioural finance is necessarily a subdivision of economic psychology. Some differences as well as similarities between the two approaches should be pointed out. In economic psychology, notably financial psychology, more attention is paid to the psychological intricacies of financial behaviour and attempts are made to relate the problems to psychological theory.

Furthermore, there has been steadily increasing interest among psychologists in the problems of financial behaviour. In *cognitive* psychology, judgments and decisions under uncertainty form an important area of study. The problems studied are often close to financial psychology and are sometimes directly relevant to it. The work by Kahneman and Tversky (1973, 1979, 1984 and 1996) has drawn special attention to it and these authors have themselves applied their thinking to financial behaviour. Their ideas of *loss aversion*, *framing* of decision situations and the use of *heuristics* have flowed into economists' attention span in the search for explanations for irrational behaviour, and practitioners have also eagerly seized upon the ideas.

Shefrin (2000), who deals primarily with investment in stocks, discusses behavioural finance as an alternative to efficient market theory and notes that, while it is useful for the practitioners to be well versed in cognitive psychology, there is still much truth in efficient market theory at the aggregate level. He reports on many cognitive psychological concepts

developed in the Kahneman-Tversky approach and used in behaviour finance. Fama (1998) downplays behavioural finance as an alternative to efficient market theory and demands a clearly formulated alternative, for example based on the *representativeness heuristic*, before accepting the challenge.

2.3. Historical Perspective of the Market Efficiency Framework

The general implication of stock market efficiency is that stock markets receive new information about all aspects that impact stock prices, which in turn adjusts stock prices with such speed that market investors are not capable of realizing above-average trading profits by trading on that information. Hence, in efficient market hypothesis, stock prices are always rational. The notion of rationality in stock market behaviour was introduced in 1874 by classical economists like Walras, who wrote that the *"stock market exchange of a large investment center like Paris or London"* is an illustration of *"how competition works in a well-organized market"* (cited in Raines and Leathers, 2000).

Concurrently, investors looked at the issue of market inefficiency in terms of the impact of speculation on the stock market. David Ricardo is cited as the first stock market speculator in around the 1800s, in different sources such as Weatherall (1976); he was known by his *"golden rules"* for trading such as *"cut short your losses"* and *"let your profits run on"*.

2.3.1. Rational Markets Traders and the Neoclassical View

The rational markets perspective of the economic functions of the stock market argues that existing capital should be efficiently reallocated into the most precious uses and promotes the investment of capital rather than saving (Lionel, 1922). In order to achieve these functions, markets must present perfect and accurate corporate share prices, including all the elements

that are necessary to consider when share prices are determined. The main idea is that the share prices must be produced through a different process of market activity based on rational expectations.

By the early 1900s, stock markets, like other competitive markets from a neoclassical point of view, had many social functions and were described as:

- Assisting and promoting capital growth through encouraging the conversion of short-term savings into long-term investments.
- Allocating the limited supplies of capital to beneficial uses.

The main theme in the neoclassical view is that the prices of companies' shares formulated in stock market trading activities became rational estimations offering useful information. This is necessary for rational investment decisions relating to the use of capital and encourages companies to use capital in a more efficient way (Baumol, 1965; West and Tinic, 1971; Pratten, 1993).

On the other hand, it has been argued that the stock market will function in the most efficient way as long as the conditions for perfect competition prevail. In fact, in the early 1900s this was not the case. At that time, the stock market suffered from lack of competition and was controlled by insider traders and speculators who manipulated shares prices to the extent that governments were pushed to regulate the stock markets in order to protect the participants/shareholders. For example, in the NYSE, in the post-World War II period, concern continued to be expressed over plausible inefficiencies resulting from institutional imperfections, in particular the guild-like arrangements of stock exchanges and the role of specialists on the NYSE (Baumol, 1965; West and Tinic, 1971).

2.3.2. Manipulation, Speculation and the Rational Market View

However, Bagehot (1880) discusses the speculation in stock market. He mentions that speculators of the stock market trade, expecting stock prices to increase in the near future, would incite intentions to sell the stock as the prices became higher. These predictions come from watching a company's performance. If they expect a company's performance to grow, then by investing they will increase their money over time. Another deciding factor is influenced by a psychological phenomenon, which is predicting the behaviour of other market participants. These ideas are the key of Galbraith's (1955) work to explain the 1929 crash. He states that it was during the crash that the psychological characteristics and behavioural patterns were quite clear in the stock market.

There are opposing opinions among the rational market view's economists about the large volatility and period of instability in stock prices that has continued throughout the history of stock markets. Baumol (1965) declares that:

> *"one has come to look upon the stock market as the allocator of capital resources par excellence, and aside from some uneasiness about the untoward effects of speculation, one is readily inclined toward the view that the stock market constitutes an allocative mechanism of remarkable efficiency."*

Since the 1900s, speculation has been partially acceptable for the majority of economists, even the rational market view extends back to there. For instance, Lavington in 1913 discussed 'The Social Interest in Speculation in the Stock Exchange' in *The Economic Journal*. In 1915, a meeting of the American Economic Association referred to stock market speculation. Additionally, both Lavington (1913) and the American Economic Association meeting focused on manipulation (Untermeyer, 1915; Emery, 1915). The views of many

economists on the rational market have contributed to highlighting the importance of speculation, as it impacts significantly on stock market behaviours, while a few economists have formed a view that speculation is part of gambling.

Furthermore, the character of the stock market became suspicious due to the character of the market's participants. To illustrate, in 1715, the London Stock Market was described as:

> *"a complete system of knavery, founded in fraud, born of deceit and nourished by trick, cheat, wheedle, forgeries, falsehoods and all sorts of delusions; covering false news, whispering imaginary terrors, and preying upon those they have elevated or depraved"* (Weiner, 1964, p. 177).

After more than a century, in 1817, the speculators had become more involved in stock market activity, such as in the NYSE when the number of shares traded increased, the volume of trades expanded. Furthermore, throughout the 1800s and early 1900s, the stock market was broadly viewed as being manipulated to some extent by unethical practices. Speculation and manipulation had always been linked together as one, until the formation of the rational market view. At this point, manipulation became more active than before (Werner and Smith, 1991).

By the end of the 1900s, the level of manipulation had increased in the stock market as a result of: a boost in the number of shares traded, an increase in the volume of trading, the improvement in the technology used in communications, and the development of the organization of large trusts. The amplification of the power of manipulation in the stock market encouraged the manipulators to influence the stock markets in order to gain more profit by trading large amounts of shares at prices higher than those determined by the true market values of the underlying assets (Werner and Smith, 1991).

Although Shiller (1984) agrees with the rational market view that the stock market has many social functions, he put forward the question of *"whether the stock market could be relied upon to achieve those functions"*. Anomalies have been discovered in stock market prices, which means that the efficient market theories and rational expectations are not reliable. When the stock price is set irrationally, the stock market will not allocate capital in an efficient way.

2.3.3. Neoclassical Economists on Rational Markets and Speculation

The challenge facing the neoclassical economists is the view of speculation and manipulation on the stock markets, as it affects the explanations of how stock prices are determined. In real-world stock markets, speculation and manipulation are noticeable and cannot be ignored.

The latest development in the neoclassical view of stock markets is the efficient market theory, indicated by competitive markets. Bernstein (1992) points out that Bachelier (1900) and Kendall (1964) notice that share prices move in a random way, meaning that share prices are unpredictable. Samuelson (1965) suggests that the best estimates of shares' intrinsic value are the current share prices. Furthermore, Fama (1970), in his breakthrough neoclassical view, presented his *efficient market hypothesis*, which assumes that the market will be efficient if the market participants cannot produce more profit than the rate of return based on all information available in the markets.

Even the efficient markets have revealed an intense concern about levels of stock prices that appear to challenge the degree of 'rational'. The meaning of 'rational' is subject to different explanations. The rational expectations theory states that each participant in the stock market works rationally because their expectations are completely correct. While, in a practical sense, that expectation has been limited by an argument that each participant works rationally

in response to what he assumes is true information, in fact the expectation itself might be the most important factor. This led to studies in the stock market trying to explain irrational prices within the rational expectations model. In the first case, the market findings will be rational. But in the second case, the market findings will not be rational if the 'information' is not true.

2.4. Efficient Market Hypothesis

As stated earlier in this chapter, the dominant paradigm in the Western academic world in respect to financial market behaviour can be described as the *market efficiency* approach. The origins of this approach go back to the 'Chicago school' and work related to *rational expectations* by Muth (1961) and others. The paradigm was subsequently extended by financial economists, such as Fama (1970), in a financial markets context and by macroeconomic theorists, such as Friedman (1962), in a macroeconomic context.

Fama (1970) provided affirmative clarification of the mechanism of equity prices by introducing the efficient market hypothesis (EMH). The EMH states that *"A market in which prices always 'fully reflect' available information is called 'efficient'."* The EMH divided the level of market efficiency into three stages:

- *Weak level efficiency*: at this level, all historical information is reflected in current prices, so there is no possible way to gain more profit by knowing any past information.
- *Semi-strong efficiency*: the second level of efficiency, in which all public information has already been impounded in share prices, and the market mechanism works rapidly when new information is released so no one can beat the market.

- *Strong level efficiency*: at this level, the stock market will be in perfect competition as all information – historical, current and even inside information – is already reflected in the market prices.

Moreover, Fama (1991) later modified the EMH because of the increasing number of anomalies in the stock market, by changing the three levels of efficiency to *return predictability*, *event studies* and *private information*. Nonetheless, tests of *return predictability* are similar to the tests of weak form efficiency and anomalies, tests of *event studies* are similar to the tests of semi-strong efficiency and tests of *private information* are similar to tests of strong form efficiency.

2.4.1. Definition of an Efficient Stock Market

In his initial work, Fama (1970) identifies an efficient stock market as a market in which the stock prices reflect, perfectly, all information on hand at any time. A stock market is identified as efficient if:

- Stock market participants can access the information set without difficulty.
- Stock market participants trade stocks on the basis of this information.

Therefore, the information is incorporated into the stock prices, and every stock price is adjusted to be equal to its intrinsic market value. Consequently, no one can beat the market by monopolizing information to achieve a competitive advantage over other participants, and no one can determine a regular pattern in stock prices to obtain abnormally high profits.

The efficient stock market requires stock prices to respond to new information immediately. In practice, this means that when new information is released in the market, it should be fully reflected in the stock prices immediately. The stock prices should be reorganized to a new

equilibrium level by the new information. If the market mechanism handles the new information slowly, the stock prices will not respond to the new information immediately and there will be a trading rule in the stock market that could allow traders to use this information in order to generate abnormal profits. In this case, some stocks traders will buy stocks immediately after a company announces unanticipated 'good' news, or they will sell the stocks immediately after a company announces unanticipated 'bad' news. After a period, stock prices will eventually fully reflect the news, allowing stock traders to trade in the opposite way to gain profits.

An efficient stock market also requires stock prices to respond to new information without bias. In practice, this means that when new information is released in the market, it should be reflected in the stock prices correctly. The stock prices should be reorganized to a new equilibrium level by the new information by moving to an appropriate level, and should be balanced until further information is released. Otherwise, it will have overreacted to the information and the stock prices will be above the equilibrium level, or it will have underreacted to the new information, making the prices lower than the equilibrium level. Both overreaction and underreaction allow profitable trading strategies.

If prices always overreact to positive news after the announcement, stock traders could sell the stocks immediately and buy them back when the stock prices decrease to their equilibrium level. In a similar way, stock traders could buy the stocks that have underreacted to the positive news, and sell them when their prices increase to the equilibrium level.

2.4.2. Conditions of a Perfectly Efficient Stock Market

The vital assumption for a perfectly efficient stock market is that the market equilibrium prices should be independent of the distribution of existing information between market

participants. Thus, all factors that drive market participants to value stocks differently are treated as insignificant issues, as all participants have the same information and all of them are trying to maximize their profit according to the information set.

Under this assumption, there are several conditions, according to Fama (1970):

- The transaction costs of trading in the stock market must be negligible or close to zero, which means that the transaction costs will not affect the market participants' trading decisions.

- No matter whether the market participants are large or small investors, a financial institution or an individual investor, all of them receive the same information. In other words, all relevant information is freely and easily available to all market participants. This implies that the wealth and social positions of investors do not provide admission to secret information.

- All market participants are the same in their preference for profit maximization, risk aversion and appropriate knowledge of the market. Then all of them will agree on the current stock market prices as well as on the distribution of future prices of each stock.

In a practical sense, the reality is different. For example, in most stock markets the transaction costs have declined but they still affect stock trading. Therefore, market participants have to bear in mind the transaction costs before they trade the stocks, mainly when trading fees are higher than the expected returns of stock trading. In addition, not all information is freely offered and not all market participants are completely informed. Commonly, financial institutions have more power than individual investors in terms of gaining information. They also decrease the average cost of information per stock by bulk trading.

In fact, Grossman (1976) and Grossman and Stiglitz (1980) claim that a perfectly informational efficient market has never been achieved. Furthermore, they argue that, if all the conditions of perfect efficiency are achieved in the stock market, the expected returns will be divided between market participants according to their investment value only and there will be no profit to be made in gathering information in the markets. Therefore, there will be little motivation for market participants to gather information about market activities, which will lead the market to collapse. Conversely, an imperfectly efficient market motivates market participants to gather and trade on information. Hence, market participants expect to make their profit from gathering information and analysing it, to know the equilibrium of future prices before other participants.

2.4.3. Determinants of an Efficient Stock Market

It is understandable that an efficient market is essential but also that a perfectly efficient market will not survive. Hence, market efficiency is comparative efficiency rather than complete efficiency. Even if some markets are stated as efficient and others as inefficient, this status depends on the statistical tests used in examining the efficiency, so the difference between them is merely comparative.

The level of efficiency in the market is determined by the degree of accuracy, as analysed through statistical testing. Moreover, if the market participants made less effort gathering and analysing the market information, the stock prices would not reflect the accurate prices, resulting in a reduction in the level of efficiency in the market (Boudreaux, 1975).

Figure 2.1: Relationship between Information Employed and Level of Market Efficiency[4]

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Figure 2.1 illustrates the relationship between the information employed by market participants and the level of market efficiency. The vertical axis measures the market efficiency, whereas the horizontal axis shows the level of information immediately and correctly being employed by the market participants. The ME curve demonstrates that, if correct information employed in the market increases, the market efficiency will increase. The break phase in the ME curve denotes that there is a long distance to point P, which represents the point of perfect market efficiency. Nevertheless, the market is comparatively efficient around point C, and the market is comparatively inefficient around point D. On the

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[4]Shiguang, M. (2004), *The efficiency of China's stock market*, UK: Ashgate Publishing Limited. http://books.google.co.uk/books [3February 2008]

other hand, the equilibrium point of information is determined by the equilibrium of the marginal gain of possessing and the marginal cost of gathering and processing information.

Market participants are seeking to maximize wealth in the stock market. Hence, each share trader is willing to gather and analyse information up to the point where cost of information is equal to the return obtained from it. Boudreaux (1975) states that, when the market is competitive, each share trader will not increase expenditure on the information because they would not gain more profit from trading, and so the total gain is equal to the total cost and market equilibrium occurs.

Panel B of the graph above demonstrates the structure of the market equilibrium. The horizontal axis shows the total expenditure on information; the vertical axis shows the marginal gain (MG) and marginal cost (MC) of expenditure on the information. Point E is where the MC curve crosses the MG curve, where MC=MG, which is equilibrium of the market. Where MG exceeds MC to the left of point E, the market participants prefer to spend more on information. In contrast, where MG is less than MC to the right of point E, market participants prefer to spend less on information.

In the graph above, the market equilibrium, occurs at point E that is illustrated by a dotted vertical line drawn from point C of panel A to point E of panel B. The level of market efficiency relies upon the equilibrium of the market gain and marginal cost of gathering and analysing information. Furthermore, the vertical line from point P of panel A to point Y of panel B shows that, if the stock market is a perfectly efficient market, the MG of gathering and analysing information is under the MC of gathering and analysing information. However, from an economic point view, the MC curve is never less than or equal to zero. Therefore, the MC of gathering and analysing information will never equal the MG at point Y. In conclusion, the perfectly efficient market can be approached but can never be reached.

2.4.4. Information Sets and Classifications of Market Efficiency

Fama (1970) initially explains three degrees of market efficiency (weak form, semi-strong form and strong form), taking into account three types of information (historical, public and private) impacting stock prices. He introduced the well-known efficient market hypothesis (EMH).

According to the EMH, the information set of each level is cumulative. Therefore, weak form efficiency includes all the historical information of prices, semi-strong form efficiency includes all the historical information and all the current publicly available information, and strong form efficiency includes all the historical information, all the current public information and all privately held information. Hence, if the stock market is semi-strong form efficient, it must also be weak form efficient and, if the market is strong form efficient, it must also be weak form efficient and semi-strong form efficient. Figure 2.2 illustrates the three sets of information and three classifications of market efficiency.

Figure 2.2: Three Levels of Information and Three Classifications of Market Efficiency[5]

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According to the ME curve above, the stock market is weak form efficient only when all historical information is available in the market. The second level, the semi-strong form efficient market, occurs when all historical and current public information is utilized in the market. The third level, the strong form efficient market, occurs when all the historical information, and current public and private information is utilized in the market. On the contrary, if a market is not weak form efficient, it will be neither semi-strong form nor strong form efficient. Moreover, if a market is not semi-strong form efficient, only the historical information is fully utilized in the market.

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[5]Shiguang, M. (2004), *The efficiency of China's stock market*, UK: Ashgate Publishing Limited. http://books.google.co.uk/books [3 February 2008]

2.4.4.1. Weak Form Efficient Market Hypothesis

The weak form efficient market hypothesis emphasizes that the current stock prices completely reflect the information included in the historical stock prices. Any knowledge from historical information has already been incorporated in the current market prices, and is already known by market participants. Therefore, market participants of the stock market cannot predict future price changes by analysing past price patterns. Any effort to develop a trading strategy based on past price information to gain higher returns will be fruitless. Furthermore, technical analysis, based on graphs drawn of data from past price information, will be useless to gain higher returns than the market's average return under the weak form market efficiency.

Samuelson (1965) claims that, if information flows are unrestricted and there are no transaction costs in the stock market, then today's price change reflects only today's news and is independent of yesterday's price change. Mandelbrot (1966) supports the same idea, that if the market is weak form efficient, then historical information has already been integrated into the prices. Consequently, the new change in the stock prices will depend only on the new information released. By definition, the forthcoming information is unpredictable and, as a result, the next movement in the stock prices cannot be predicted as no one will know the new information before it is released to the public.

The original model of weak form efficiency is that the time series of stock prices follows a random walk. The strict random walk model presumes that the successive increases of a time series are serially independent and that their probability distribution is identical through time. However, this assumption is not essential to prove that a market is weak form efficient. The weak form efficient market would benefit if past price information could not influence market participants in gaining abnormally high returns.

Typically, empirical studies of weak form efficiency have two approaches:

- Testing the random walk of stock prices. If the stock prices move in a random walk, which means there are no trading patterns in the stock prices and therefore participants cannot gain abnormally high profits, the market is interpreted as a weak form efficient market. Otherwise, if the statistical tests reject the random walk hypothesis, the market will not be interpreted as a weak form efficient market.

- Testing whether trading rules based on past price movements can earn abnormally high returns. If market participants can earn high returns from applying trading rules in terms of past price movements, the test rejects the weak form efficiency hypothesis.

2.4.4.2. Semi-Strong Form Efficient Market Hypothesis

The semi-strong form efficient market hypothesis states that the current stock prices not only reflect the historical price information but are also completely responsive to all current public information immediately without bias. Therefore, analysis based on new publications of microeconomic information concerning the listed companies or relevant to the country's economic policies will not help the market participants to gain abnormally high returns. Additionally, under the semi-strong hypothesis, the fundamental analysis, which is based on current available information, will not be helpful to market participants in building their trading strategies.

Figure 2.3: Example of Abnormal Returns Associated with New Releases in Public Information[6]

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A semi-strong form efficient market can be examined in order to determine whether there are abnormal returns associated with new releases in public information. As an example, in Figure 2.3 above, assume that the initial price of a share is X. The publication of company profit is more than the market expectation; according to a perfectly efficient market, the share price could increase to match the surplus of the good news immediately up to Y, which is the new equilibrium price, and then it should be stable until a new announcement is released. However, if the price underreacts to that information, the share price will go to Y1, which is more than the initial price and less than the new equilibrium price $(X \prec Y1 \prec Y)$. Subsequently, the price will increase gradually up to Y where it fully reflects the information. Under this case, the market speculators can make abnormal returns by purchasing shares directly following the announcement, and selling them when the price is fully adjusted to the

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[6]Shiguang, M. (2004), *The efficiency of China's stock market*, UK: Ashgate Publishing Limited. http://books.google.co.uk/books [3 February 2008]

correct level of Y. Conversely, if the price overreacts to the information, the price rises to Y2 immediately following the announcement, which is more than the initial price and also more than the equilibrium price ($X \prec Y2 \succ Y$). Subsequently, the price will decrease gradually to Y, where it fully reflects the information. In this case, market speculators can also make abnormal returns by selling the shares shortly following the announcement and buying them back when the price has adjusted to the correct level of Y.

2.4.4.3. Strong Form Efficient Market Hypothesis

The strong form efficient market hypothesis states that the current prices fully reflect all types of information, including historical information, public information and private (inside) information. Hence, all information is available to any market participant, and market participants cannot make superior profits by monopolizing any information. For instance, a listed firm in the stock market has found a new way to reduce its costs. Some market participants may have access to this information before this news is published, and buy the shares in this company. When the firm releases this information to the public, the market participants sell their shares in this firm because the share price has increased in response to the good news. In this example, the market does not reflect strong market efficiency because there are some market participants who have access to information before others, which is known as insider trading.

In general, corporate insiders, security analysts and portfolio managers are recognized as groups having access to private information. An indirect test to examine if there have been accesses to private information in the stock markets is called an audit, which detects whether there was bulk buying or selling carried out by any group before the information was publicized. Both the purchasing of a large number of shares prior to a 'good' news release

and the selling of a large number of shares before a 'bad' news release imply that private information has been employed, which means the stock market is not strong form efficient

However, empirical testing of strong form efficiency is more complicated than the tests for weak form efficiency or semi-strong form efficiency because:

- To identify the date at which the insiders access the private information is either very difficult or impossible.
- The difference between an abnormal return made by rational analysis of public information (which indicates semi-strong form efficiency) and an abnormal return made using private information is indistinguishable.
- Insiders hide the abnormal returns obtained by employing private information.

2.4.5. Evidence from Tests of Weak Form Efficiency

2.4.5.1. Evidence from Tests in Developed Countries

Kendall (1964) examined the weekly price changes in nineteen British securities. He found a near-zero serial correlation of price changes. This finding came to be labelled the 'random walk model' or 'random walk theory'. If prices wander randomly, then this creates a major challenge to market participants who try to predict future security prices. Roberts (1959) studied the weekly change in the Dow Jones Industrial Average (DJIA). He examined whether the familiar stock price pattern could be replicated using the assumption that the price follows a random walk. He concludes that the weekly change to the index has the same appearance as a time series generated from a sequence of random numbers.

The mid-1960s was a turning point in research on the random character of stock prices. Fama (1965) assumed that if the autocorrelation is significantly large enough, share traders could

formulate a profitable trade strategy using past returns. He examined the autocorrelation of daily returns for each of the thirty stocks in the DJIA in the period 1957–1962. The results show that the correlation coefficients between the returns on day t and day t-1, day t-2, through to t-10 are very small and nearly zero. This means that speculators cannot earn an abnormal return based on such series of past returns.

Solnik (1973) tested 234 shares from March 1966 to April 1971 of serial correlation coefficients, shares selected from eight major European markets: France, the UK, Germany, Italy, Netherlands, Belgium, Switzerland and Sweden. The results showed that the average serial correlation coefficients of the returns for each market were more than in the United States market. This indicates that European markets are less efficient. However, the serial correlation coefficients were still statistically insignificant and support the random walk hypothesis. Jennergren and Korsvold (1975) examined the daily stock price changes of relatively small European stock markets such as Austria, Denmark, Greece, Norway and Sweden. The results showed that these markets have serial correlation in price changes, which implies that these markets deviate from a random walk and the weak form.

Fama and French (1988) concluded that autocorrelations may reflect market inefficiency or time-varying equilibrium. Hudson et al. (1996) reported that the technical trading rules have predictive power but not enough to enable excess return in the UK market. Similarly, Nicolaas (1997) also reported that past returns have predictive power in the Australian market but the degree of predictability of return is insufficient. Overall, the empirical studies on developed markets show no profitability from using past records of price series and support the weak form efficiency of the EMH in general.

Lo and MacKinlay (1988, 1989) suggest that the variance ratio (VR) is a more robust model to test the predictability of stock markets prices than unit root. They found evidence of mean

reversion in stock prices for the US. Since then, many researchers have employed VR to test the validity of the RWH for different countries. Blasco et al. (1997) found evidence of strong serial correlation for stocks traded on the Madrid Stock Exchange using VR tests. Mookerjee and Yu (1999) rejected the RWH for both the Shanghai and Shenzhen Stock Exchanges using VR tests. Lima and Tabak (2004) found that liquidity and market capitalization play a significant role in explaining results from VR tests for China, Hong Kong and Singapore.

Worthington and Higgs (2003) examined market efficiency in European equity markets for daily returns for sixteen developed markets (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom) and four emerging markets (Czech Republic, Hungary, Poland and Russia). The results of the tests of serial correlation are in broad agreement and conclusively reject the presence of random walks in daily returns for all markets save Germany, Ireland, the Netherlands, Portugal and the United Kingdom. The multiple variance ratio procedure rejects the random walks in most European markets; only Germany, Ireland, Portugal, Sweden and the United Kingdom are random walk markets. Among the emerging markets, only Hungary is a random walk market. The results of this analysis are consistent with the view that emerging markets do not follow the random walk hypothesis, which is required for the assumption of weak form market efficiency.

2.4.5.2. Evidence from Tests in Developing Countries

Review of previous studies show that developed markets are usually weak form efficient. On the other hand, developing markets are more tentative. In these markets, a number of theoretical arguments reject the weak form efficiency due to the following:

- Their thin traded markets, low level of competition and dominance of some players may allow individual traders to set stock prices above or below their intrinsic value (Mobarek and Keasey, 2000).

- The scarcity and uncertain validity of corporate information, the lack of auditing experience, and the weaknesses of regulations and disclosure requirements lead to shortages in fundamental information (Blavy, 2002).

- A number of structural and institutional specificities, such as the fragmentation of capital markets and the presence of political and economic uncertainties, may also account for departure from efficiency (El-Erian and Kumar, 1995).

Moreover, the principal tools for examining the RWH in less developed stock markets (developing countries) are the Lo and MacKinlay (1988) variance ratio (VR) test, the Chow and Denning (1993) VR test, the unit root, ARIMA, GARCH, artificial neural network tests, and the bootstrap test. Hoque et al. (2007) reported that, of eighteen published studies on the RWH in emerging stock markets, sixteen use the Lo and MacKinlay or Chow and Denning VR tests along with other tests. Recent studies use Wright's (2000) rank and sign nonparametric VR test along with other tests (Bugak and Brorsen, 2003; Belaire-Franch and Opong, 2005).

Errunza and Losq (1985) examined nine less-developed markets (Argentina, Brazil, Chile, Greece, India, Jordan, Mexico, Thailand and Zimbabwe). The results from runs tests and serial correlation coefficient tests show that these markets are more correlated than those in developed markets. Campbell (1995) examined twenty emerging markets in Latin America, Asia, the Middle East, Europe and Africa. He found that returns in these emerging markets are more predictable than returns in developed markets and returns are influenced by local rather than global information.

In the emerging European market, Dockery and Vergari (1997) used VR test to examine the random walk hypothesis for the Budapest Stock Exchange and concluded that it follows a random walk. Chun (2000) used the augmented Dickey-Fuller (ADF) test and the Lo and MacKinlay (1988) variance ratio method to examine weak form efficiency for Hungarian, Czech and Polish markets. The results show that only the Hungarian market is weakly efficient. Moreover, Gilmore and McManus (2003) examined the same three markets (Czech Republic, Hungary and Poland) for the period of July 1995 to September 2000, and found that uni-variate and multi-variate tests provide some evidence that stock prices in these exchanges exhibit a random walk, which constitutes evidence for weak form efficiency. This differs in some cases from studies using data for the initial years of these markets. The variance ratio test of Lo and MacKinlay (1988) yields somewhat mixed results concerning the random walk properties of the indices. A model comparison test compares forecasts from ARIMA and GARCH models. Results from the model-comparison approach are consistent in rejecting the random walk hypothesis for the Czech Republic, Hungary and Poland markets.

Nivet (1997) examined the performance of the Warsaw Stock Exchange using daily and weekly index data from the WIG for the period 1991–1994. On the basis of autocorrelation coefficients, he concludes that the model of a random walk for the Warsaw stock market cannot be supported for those years. Recently, Abrosimova et al. (2005) examined the Russian stock market by considering the predictability of Russian Trading System index time series. The results rejected the random walk hypothesis using daily and weekly data, but not for monthly data.

Panagiotidis (2003) examined the efficiency level of the Athens Stock Exchange. Linear and nonlinear models were used; simple uni-variate linear models (RW and AR), various conditional volatility models (GARCH, EGARCH and TGARCH) and multi-variate models (ECM, ACM, and NECM) were estimated. Batteries of tests for randomness were estimated

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in each case. Bootstrap values as well as asymptotic values were generated. The preferred model (TGARCH) is the one that produced a unanimous verdict of Identical Independent Distribution (IID) residuals. The results show that leverage effects exist and the news impact is asymmetric. Furthermore, strong form efficiency is found to exist in the period after the introduction of the common currency. Even though Panagiotidis (2003) stated that ASE is semi-strong form efficient, he said *"we can reject the hypothesis that the series follows a random walk"* (p. 6). Fama (1970) stated that the market could not be semi-strong unless it is weak form efficient. Therefore, it seems that Panagiotidis' finding is not adequate.

On the other hand, Filis (2006) examined Athens Stock Exchange for the period 2000–2002. The results showed evidence of weak form efficiency as it followed a random walk pattern, although it was not shown to be semi-strong form efficient. Additionally, he found evidence that there is volatility clustering in the Athens Stock Exchange, as GARCH effects were significant in both years. Filis justified that by stating that the Athens Stock Exchange is one of the emerging markets that can be described as having 'country effects'. Country effects create a high correlation between the listed stocks because of the correlation fundamentals (Serra, 2000). Furthermore, Filis explained high correlation of listed stocks by the political situation surrounding emerging markets, where an event can cause the rise or fall of the whole market, rather than specific sectors; therefore, the Athens Stock Exchange is affected by fewer pricing factors and tend to be more volatile than developed markets. This creates opportunities for investors who take advantage of the volatility. Nevertheless, the Athens Stock Exchange is less liquid, as most traders are reluctant to write calls (Alexander, 1999), causing inefficiency in the Athens Stock Exchange. Thus, Filis' (2006) findings are more convincing than those of Panagiotidis (2003).

For Latin American stock markets, Urrutia (1994) examined the efficiency level of the Argentinean, Brazilian, Chilean and Mexican market indices. The variance ratio test rejected the RWH for these markets, whereas the runs test indicated weak form efficiency. Robinson (2001) found no evidence of return predictability on the Barbados Stock Exchange, while Singh (1995) found returns on the Trinidad and Tobago Stock Exchanges to be predictable. Koot et al. (1989) rejected the random walk hypothesis for the Jamaica Stock Exchange (JSE) index during the period 1969–1986. Grieb and Reyes (1999) examined the random walk of the Brazil and Mexico stock markets. The results from the variance ratio tests show that Mexico exhibits mean reversion and there is a tendency toward a random walk in Brazil. These conflicting inferences could possibly be attributed to the effect of cross-sectional and temporal variations in the degree of infrequent trading in these markets. Recently, Robinson (2005) examined the weak form efficiency and the seasonal patterns for the JSE. An analysis of daily returns on all stocks listed on the JSE over the period from 2 January 1992 to 31 December 2001 rejects the weak form efficiency of stocks listed on the JSE. However, seasonal patterns, such as day of the week and month of the year, are absent from the JSE.

In Asian markets, Huang (1995) examined Korea, Malaysia, Hong Kong, Singapore and Thailand. The results demonstrate that none of these markets follows the RWH. Liu et al. (1997) examined Shanghai and Shenzhen stock exchanges in China. The results show that both markets are individually efficient and are random-walk processes. Alam et al. (1999) examined Bangladesh, Hong Kong, Malaysia, Sri Lanka and Taiwan stock markets; the results illustrate that all these markets follow the RWH with the exception of Sri Lanka. Darrat and Zhong (2000) examined A shares in the Shanghai and Shenzhen exchanges,[7]

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[7] By December 1997 China had 720 A-share listed stocks, of which 372 traded on Shanghai and 348 traded on Shenzhen, and 101 B-share listed stocks, of which 50 traded on Shanghai and 51 traded on Shenzhen. A shares are traded among Chinese citizens and B share stocks are traded among non-Chinese citizens or overseas Chinese citizens (Lee et al., 2001).

using weekly data from 1990 to 1998 for Shanghai and from 1991 to 1998 for Shenzhen to avoid biases due to bid-ask spreads and non-trading days. Their results reveal that neither stock exchange follows the random walk hypothesis. They justified that non-synchronous effects as well as other explanations for inefficiency found may lie behind market imperfections that are common in emerging markets due to their ineffective legal structures and lack of transparency that prevent the smooth transfer of information.

Furthermore, Lee et al. (2001) examined Chinese stock exchanges using A and B shares in both Shanghai and Shenzhen exchanges from 1992 to 1997 (although for Shanghai A shares they used data from 1990 to 1997). Using variance ratio tests and GARCH models (which had been used in Darrat and Zhong's (2000) study). They found that neither A nor B shares in the two exchanges follow the random walk hypothesis. Their findings are convincing because if A shares do not follow the random walk, then B shares are not expected to follow the random walk as A shares are more liquid than B shares.[8]

Chang and Ting (2000) examined the Taiwan Stock Exchange; the results show that the RWH cannot be rejected for the Taiwan Stock Exchange with monthly, quarterly and annual data, but it is rejected with weekly returns. Ryoo and Smith (2002) examined the Korean stock market; the results show that it cannot reject the RWH. Lima and Tabak (2004) examined China, Hong Kong and Singapore stock markets using variance ratio tests, robust to heteroscedasticity, and employing a recently developed bootstrap technique. The results demonstrate that Class A shares for Chinese stock exchanges and the Hong Kong equity markets are weak form efficient. However, Singapore and Class B shares for Chinese stock exchanges do not follow the random walk hypothesis. Recently, Hoque et al. (2007)

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[8] Darrat and Zhong (2000) mentioned that the B-share market is relatively very small compared to the A-share market in terms of market capitalization and level of activity. Established research has shown that low-volume, thinly traded markets are inappropriate for testing efficiency since the lack of liquidity and poor provision of smooth transfer of information cause inefficiency in these markets.

examined the RWH for Hong Kong, Indonesia, Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand. They used two new variance ratio tests, Wright's and Whang-Kim's sub-sampling tests, as well as the conventional Lo and MacKinlay and Chow and Denning tests. The results show that the stock prices of the eight Asian markets do not follow the random walk hypothesis, with the possible exceptions of Taiwan and Korea.

Dickinson and Muragu (1994) examined the weak form efficiency of the Nairobi Stock Exchange. The results show that the Nairobi Stock Exchange is following the random walk using serial correlation test. These results were robust for both weekly and monthly returns. Olowe (1999) tested the weak form efficiency of the Nigerian stock market. Using correlation analysis and monthly stock returns data over the period from January 1981 to December 1992, the results show that the Nigerian stock market is weak form efficient. On the other hand, Ryoo and Smith (2002) examined eight emerging stock markets in Africa (Egypt, South Africa, Zimbabwe, Morocco, Kenya, Nigeria, Botswana and Mauritius) and concluded that none of these markets follows the RWH except for the South African market.

In Middle East and North Africa (MENA) markets, Azzam (1997), Darrat and Hakim (1997) and El-Erian and Kumar (1995) suggest that these markets have three main characteristics:

- Stock markets in these countries are sensitive to the country's political changes.
- Stock markets in these countries have considerable growth potential.
- These markets need to develop structural relations with major foreign and regional stock markets. For example, in the Asian crisis of 1997, many emerging markets suffered from the South East Asian crisis, while in the MENA countries, the effect was very small. For this reason, these countries have the possibility of offering unique risk-return characteristics to investors who are looking for international diversification.

Furthermore, Harvey (1995) reported that developing markets have high average returns, low overall volatility, low exposure to world risk factors, and little integration. He concludes that these markets are less efficient than developed markets. Nevertheless, Darrat and Zhong (2000) mentioned that established research has shown that low-volume, thinly traded markets are inappropriate for testing efficiency since the lack of liquidity and poor provision of smooth transfer of information cause inefficiency in these markets.

Balaban (1995a) examined the efficiency for the Istanbul Stock Exchange (ISE) for the period 1988–1994, using parametric (simple ordinary least squares (OLS) regression) and nonparametric (runs test) random walk tests. The results from both tests show that the ISE is not weak form efficient. Furthermore, Buguk and Brorsen (2003) examined ISE, using its composite, industrial and financial index weekly closing prices, for the period 1992–1999, using the ADF test to test the null hypothesis of a unit root, GPH fractional integration test (a semi-nonparametric procedure), LOMAC single variance ratio test and Wright's (2000) rank- and sign-based variance ratio tests. The outcomes from the first three tests indicate that all three series follow the RWH, but not when the VR test was used. The different findings from Balaban's (1995a) study and Buguk and Brorsen's (2003) study can be attributed to both the different time spans and different tests used.

Butler and Malaikah (1992) examined the weak form efficiency of Saudi Arabia and Kuwait stock markets, using serial correlation and runs tests. The results show that neither market follows the RWH. Dahel and Laabas (1998) examined the efficiency in four GCC markets: Bahrain, Kuwait, Oman and Saudi Arabia. The data consisted of weekly stock price indices from September 1994 to April 1998. They used unit root and variance ratio tests to test the hypothesis that returns follow a random walk and regression tests for autocorrelation of returns. The results show that all markets are weak form efficient; only one of the tests

(regression of returns) rejects the weak form of the EMH when the total period is considered for Kuwaiti markets. Abraham et al. (2002) examined the Kuwait, Saudi Arabia and Bahrain stock markets, using runs and variance ratio tests. The results show that all three markets follow the RWH. Hassan et al. (2003) examined the weak form efficiency for the Kuwait Stock Exchange (KSE). They used a methodology that included nonlinearity and infrequent trading and they employed EGARCH and GARCH-M to account for time-varying risk premia in the KSE. The results show that the KSE is weak form inefficient. Moustafa (2004) examined the efficiency of the United Arab Emirates (UAE) stock market. Using daily prices of the 43 stocks included in the Emirates market index from 2 October 2001 until 1 September 2003, he employed the nonparametric runs test. The results indicate that the returns of 40 stocks out of the 43 are random at a 5% level of significance.

Civelek (1991) examined the random walk hypothesis and weak form efficiency of the Amman Stock Market (ASM), using daily data for the industrial sector of the ASM. He employed autocorrelation and runs tests; the results show that return in the industrial sector is positively serially correlated and the sector is weak form inefficient. El-Erian and Kumar (1995) confirm these results for daily and weekly data of the general index and found returns to be positively serially correlated and the market to be weak form inefficient.

Omet et al. (2002) examined the random walk hypothesis and weak-form efficiency of the Amman Stock Exchange, for the period 1992–2000, using the AR(1)-GARCH(1,1)-M model. The results indicate that the Amman Stock Exchange is not weak form efficient. On the other hand, Karemera et al. (1999) examined the random walk hypothesis and weak form efficiency of several emerging markets including the Amman Stock Exchange. Using multiple variance ratio and runs tests, the results show that the Amman Stock Exchange follows the RWH and weak form efficiency. The difference in findings between Omet et al.'s

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(2002) study and Karemera et al.'s (1999) study can be attributed to both the different time spans and different tests used. A comprehensive review of the literature illustrates that, even when one sort of test (serial correlation coefficient test, runs test, variance test, GARCH test, etc.) fails to reject the random walk hypothesis, the others may actually reject it. When the main sample data follow the random walk hypothesis the sub-samples may not follow the random walk hypothesis. Therefore, applying a variety of tests to different types of data and comparing the results on the bases of similar sorts of data and tests implemented improves the accuracy of a study. Thus, this research follows this approach to provide more accurate results regarding the Amman Stock Exchange (for more details see Chapter Four).

Furthermore, Smith (2004) examined the RWH for Israel, Jordan and Lebanon. He used a variance ratio methodology; the results show that all three markets follow the RWH. Lagoarde-Segot and Lucey (2005) examined the weak form efficiency for seven Middle East and North Africa stock markets (Morocco, Tunisia, Egypt, Jordan, Lebanon, Turkey and Israel) using daily data returns. They employed unit-root analysis, individual and multiple variance ratio, wild bootstrapping and nonparametric tests based on ranks. The results show that only Israel and Turkey are weak form efficient. Al-Khazali et al. (2007) examined the random walk in eight emerging markets in the Middle East and North Africa (Bahrain, Egypt, Jordan, Kuwait, Morocco, Oman, Saudi Arabia and Tunisia) for the period 1994–2003. They employed Wright's (2000) rank and sign VR tests; the results indicate that the eight MENA stock markets do not follow a random walk; however, after accounting for data problems from thinly and infrequently traded stocks, the random walk hypothesis cannot be rejected for the eight emerging markets.

2.5. Stock Market Anomalies

Schwert (2002) identified that anomalies are empirical results that seem to be inconsistent with maintained theories of asset-pricing behaviour. They indicate either market inefficiency (profit opportunities) or inadequacies in the underlying asset-pricing model.

Furthermore, before the 1970s, there was evidence about the difficulty of beating the equity markets; for instance, Cowles (1933) found that there was no discernable evidence of any ability to outguess the market. Despite the emerging evidence of the randomness of stock price changes, there have been occasional instances of anomalous price behaviour, where certain series have appeared to follow predictable paths. For instance, Cowles (1944) provided corroborative results for a large number of forecasts over a much longer sample period.

Schwert (2002) stated that; the growth in the amount of data and computing power available to researchers, along with the growth in the number of active empirical researchers in finance since Fama's (1970) survey article, have created an explosion of findings that raise questions about the first simple models of efficient capital markets, and many anomalies have begun to appear in the stock market prices that are not consistent with the EMH. Earnings surprises, the size effect, value investing and calendar effects are anomalies that were found and documented in the stock market.

Nevertheless, it is also important to consider the economic relevance of a presumed anomaly. Jensen (1978) stressed the importance of trading profitability in assessing market efficiency. In particular, if anomalous return behaviour is not definitive enough for an efficient trader to make money trading on it, then it is not economically significant. This definition of market efficiency directly reflects the practical relevance of academic research into return behaviour.

It also highlights the importance of transaction costs and other market microstructure issues for defining market efficiency.

2.5.1. Earnings Surprises

Earnings announcements are related to the market response. Although some early studies of price reactions to earnings announcements concluded that the price changes were executed rapidly, later research suggested that part of the price response was subject to a significant time lag. If a lag occurs, investors have the opportunity to make profits from knowledge of the earnings announcement. They would have time to adjust and undertake trades that could take advantage of resulting price trends. Latane and Jones (1979) developed the concept of standardized unexpected earnings, defined as:

(actual earnings - predicted earnings) / (standard deviation of earnings)

The division by the standard deviation of earnings reflects the fact that the element of surprise or news on a particular difference between actual and predicated earnings depends upon its relationship to previous differences.

Doyle et al. (2006), whilst confirming the earnings surprise effect, made an observation about the stocks with the greatest earnings surprises. They tended to have lower analyst coverage, small volumes, high trading costs, and a high variation of analyst forecasts. Thus, the stocks offering the greatest apparent profits tended to be the most difficult and costly to trade, with the largest risk of being mispriced. However, the authors concluded that there was still value from following investment strategies based on earnings surprises, even if the most extreme surprises are excluded from the strategy.

2.5.2. The Size Effect

Another anomaly has been referred to *the size effect*. Banz (1981) found that small firms, in terms of market capitalization, provided much greater investment returns than large firms. However, Dimson et al. (2004) questioned the continued existence of the size effect by citing evidence that the small firm advantage was reversed during the 1980s. The shares of small companies are often traded infrequently. The absence of trades could mean that their prices do not move while the market as a whole is moving. Consequently, their betas are underestimated. In addition, small firms would include those that have recently encountered difficulties and borrowed heavily as a result. The increased gearing might have raised their betas so that the betas based on past data are underestimates. If the estimated betas are too low, the expected returns would be too low. The observed high returns on small company stocks, relative to expected returns, could be the result of low expectations rather than high returns.

2.5.3. Value Investing (Ratio Effects)

The main ratios that have been researched and used in stock selection are the: price-earnings ratio, the dividend-price ratio (dividend yield), and the book-price ratio (book-to-market ratio). Shares exhibiting one or more of a low price-earnings ratio, a high dividend yield and a high book-to-market ratio are often referred to as value stock. Value investing is an investment style that weights portfolios towards such shares (Redhead, 2008).

The price-earnings ratio effect has been investigated by Basu (1977) and Reinganum (1981) among others. They both found that the shares of firms with low price-earnings ratio tended to yield abnormally high returns. Levy and Lerman (1985) found that, after adjusting for the transaction costs necessary to rebalance a portfolio in order to maintain the low price-

earnings ratio as prices and earnings change over time, the superior performance of portfolios of low price-earnings ratio stocks no longer held. Fama and French (1992) found that two variables, firm size and price-to-book ratio, between them captured the cross-sectional variation in average stock returns during the period 1963–1990.

2.5.4. Calendar Effects

Calendar effects indicate that returns behave regularly in accordance with calendar time. The returns are usually high or low, on average, at some specific times of the week, the month, the year and so forth. The calendar regular pattern in returns is perhaps the most common anomaly to challenge the EMH. The fact that the calendar effects are reliable implies a degree of predictability in returns, and market participants can take advantage of this to earn abnormally high returns (Shiguang, 2004).

2.5.4.1. Evidence from Tests of Calendar Effects in Developed Countries

The *day-of-the-week effect* (or the *weekend effect*) refers to the abnormally high returns to common stocks on Fridays and negative returns to common stocks on Mondays. Fama (1965) reports Monday's variance to be 20% greater than other daily returns. French (1980) notes that the average returns on the Standard and Poor's (S&P500) composite portfolio was significantly negative over weekends from 1953–1977. Lakonishok and Smidt (1988) identified weekend effects.

Furthermore, Ariel (1987), Lakonishok and Smidt (1988), Kohers and Kohli (1991) and Sias and Starks (1997) provided evidence of day-of-the-week effects in the US stock market. Furthermore, Brown et al. (1983) found evidence for it in the Australian stock market, Tinic and West (1987) and Berges et al. (1984) found evidence for the Canadian market, and

Reinganum and Shapiro (1987) identified evidence for the UK stock market. In yet further support for day-of-the-week effects, Gultekin and Gultekin (1983) and Agrawal and Tandon (1994) supplied international evidence of the phenomenon, and Bubak and Zikes (2004) confirmed the existence of the effect in Central European markets, while Fantazzini and Rossi (2005) provided evidence of calendar anomalies in both specifications for the S&P500 and NASDAQ 100 futures indices.

Christos et al. (2006) examined day-of-the-week effects for fifteen European countries (Germany, the UK, France, Spain, Italy, Portugal, Luxembourg, Greece, Finland, Belgium, Austria, the Netherlands, Switzerland, Denmark and Norway) for the period 1993–2005. The result showed that day-of-the-week effects are present in all stock markets, except the UK.

However, the day-of-the-week effects display two major patterns in the international markets. In the US, UK, Canada and some European stock markets, the mean returns on Mondays are negative and the lowest of the week, while the mean returns on Fridays are positive and highest of the week, on average. On the other hand, in the stock markets of Japan, Australia and some Asian countries, the mean returns on Tuesdays are negative and lowest of the week. Although many investigators have put forward several hypotheses, including the time-zone hypotheses and settlement hypothesis, to interpret the implication of the return pattern, none of the hypotheses is generally applicable for all markets.

In an effort to search for a satisfactory explanation for the weekend effect;

- Lakonishok and Levi (1982) presented the settlement effect explanation. They attribute 17% of the effect to the delay between trading and settlements in stocks and clearing checks.
- Keim and Stambaugh (1984) consider the bid-ask spread bias as another explanation.

- Penman (1987) and Damodaran (1989) noticed the information release assumption as a possible explanation.

- Gibbons and Hess (1981) and Rogalski (1984) considered measurement error as an explanation.

- Lakonishok and Maberly (1990), Sias and Starks (1997) and Kamara (1995) said that trading behaviour, particularly selling activity, tends to increase trading activity on Mondays.

- Sias and Starks (1997) documented that the weekend effect returns and volume patterns are more pronounced in securities in which institutional investors play a great role.

- Finally, Wang et al. (1997) introduced the measurement error hypothesis.

Boudreaux, et al. (2010) re-examined the weekend effect in the Dow Jones Industrial Average (DJIA), the S&P500 and the NASDAQ. Data used for the DJIA and S&P500 was for the period 1976–2002, whereas for the NASDQ it was for the period 1984–2002. This study examined the distribution of daily stock returns during bear and non-bear markets in an attempt to determine the robustness of the weekend effect. In a bear market, the study compared the average daily return for weekends with that for non-weekends. Contrary to prior expectations, no significant difference was found between the weekend and non-weekend average daily returns in any of the three indices. This study then tested the average percent daily returns for weekends against non-weekends during non-bear markets. The results show that there is no significant difference between average percent daily returns for non-weekends and weekends during non-bear markets, except for the NASDAQ.

Boudreaux, et al. (2010) suggested that human behaviour and the wealth effect might explain the weekend effect being present only in non-bear market orientations. Hence, when the

value of stock portfolio rises, investors are more confident, encouraged and secure about their wealth and financial well-being. They spend or consume more of their disposable income. This wealth effect stimulates the economy during bull or non-bear markets. Poor stock prices in bear markets hurt economic confidence and thus discretionary spending.

The *monthly effect* refers to higher returns in a certain month. Since January is the month with higher returns, the month effect is also commonly known as the *January effect*.

Rozeff and Kinney (1976) first examined the January pattern using New York Stock Exchange (NYSE) stocks for the period 1904–1974 and found that the average return for the month of January was 3.48% compared to only 0.42% for the other months. Keim (1983) employed the same data set for the period 1963–1979 and found that nearly 50% of the average magnitude of risk-adjusted premiums of small firms relative to large firms is due to the January abnormal returns. Furthermore, more than 50% of the January premium is attributable to large abnormal returns during the first week of trading in the year. Kato and Shallheim (1985) examined excess returns in January and the relationship between size and the January effect for the Tokyo Stock Exchange. They found no relationship between size and return in non-January months. However, they found excess returns in January and a strong relationship between return and size, with the smallest firms returning 8% and the largest 7%. Fama (1991) reports the results of the S&P500 for the period 1941–1981. In this period, small stocks averaged a return of 8.06% in January. Large stocks managed a return of 1.342%. Outside the UK and US, a substantial January return pattern has been uncovered. Boudreaux (1995) employed the global stock indices (indices reported by Morgan Stanley Capital International) to investigate the monthly seasonality in seven countries. The results indicate a positive monthly effect for Denmark, Germany and Norway stock markets.

Chen et al. (2007) examined monthly seasonal returns for the UK during the period 1955–2003. They identified four distinct tax regimes during which both the incentive and ability to make tax-loss sales varies. In support of the tax-loss selling hypothesis, they found that the relationship between past losses and both January and April returns is strongest during tax regimes in which the incentive to offset tax is high and weakest during regimes in which the incentive is low. Furthermore, they show that neither the January nor April effects appear to be driven by the size effect.

The explanation of the January effect can be summarized by three strands of thought:

The first explanation of this effect was provided by the tax-loss selling hypothesis (Branch, 1977; Dyl, 1977). According to this hypothesis, investors wait until the tax year-end to sell their common stock 'losers', in order to realize capital losses to be set against capital gains in order to reduce tax liability. Furthermore, Keim (1983) and Reinganum (1983) showed that much of the abnormal return to small firms (measured relative to the capital asset pricing model[9]) occurs during the first two weeks in 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 re-establish their investment positions.

The second explanation of the January effect suggests that abnormal returns in January are due to new information provided by the firms at the end of the fiscal year (Rozeff and

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[9] Sharpe (1964) introduced the capital asset pricing model (CAPM) to determine a theoretically appropriate required rate of return of an asset, if that asset is to be added to an already well-diversified portfolio, given that asset's non-diversifiable risk. The model takes into account the asset's sensitivity to non-diversifiable risk (also known as systematic risk or market risk), often represented by the quantity beta (β) in the financial industry, as well as the expected return of the market and the expected return of a theoretical risk-free asset.

Kinney, 1976). Note that, for many firms, announcements of the previous year's financial performance are made in January.

The third explanation is based on the existence of a positive January risk-return trade-off. For example, Corhay and Michel (1987) report in their study that, in the US and Belgium, there is a significant positive relationship between risk premium and average portfolio returns in the month of January.

During the 1980s the calendar effect in stock markets had been documented in the developed markets, but by the 1990s this effect started to disappear. The reason for the calendar effect disappearing might be that investors became aware of this anomaly and acted accordingly.

2.5.4.2. Evidence from Tests of Calendar Effects in Developing Countries

A review of the previous studies showed that the developed markets in recent years became more weak form efficient. Conversely, the developing markets became more tentative. In these markets, a number of theoretical arguments reject the weak form because of their thin traded markets (Mobarek and Keasey, 2000). The scarcity and uncertain validity of corporate information (Blavy, 2002) also remains questionable. A number of structural and institutional specificities, such as the fragmentation of capital markets and the presence of political and economic uncertainties, may also account for departure from efficiency (El-Erian and Kumar, 1995).

In Middle East markets, Omran and Farrar (2006) investigated the calendar effects in five major Middle Eastern emerging markets (Egypt, Jordan, Morocco, Turkey and Israel) for the period 1996–2000. Their findings suggest that Jordan and Morocco show significant differences in returns on their first day of trading (Sunday and Monday, respectively), although these returns are positive for Jordan and negative for Morocco. For Egypt, Morocco

and Turkey they exhibit a positive return on Thursday. However, there is little evidence of a relationship between the beginning or end of the week and the existence of abnormal returns.

Syed and Perry (2006) investigated the day-of-the-week effect in twenty-one emerging stock markets (Argentina, Brazil, Chile, Colombia, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Pakistan, Peru, the Philippines, Poland, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela and South Africa) for the period 1992–2003. The results indicate that, while the day-of-the-week effect is not present in the majority of emerging stock markets studied, some emerging stock markets do exhibit strong day-of-the-week effects, even after accounting for conditional market risk (such as the Philippines, Pakistan and Taiwan)

Alagidede (2007) investigated the day-of-the-week anomaly in Africa's largest stock markets. The result shows that for Egypt, Kenya, Morocco and Tunisia there is no day-of-the-week effect. However, there is significant daily seasonality in Zimbabwe, Nigeria and South Africa. The Friday average return is found to be consistently higher than other days in Zimbabwe.

In terms of the monthly effect, Nassir and Mohammad (1987) and Balaban (1995) provide evidence that in Malaysia and Turkey the average January returns were significantly positive and higher than in other months. Ho (1999), using daily returns for the period 1975–1987, found that six out of eight Asia Pacific stock markets exhibit significantly higher daily returns in January than in other months. Fountas and Segredakis (2002) and Koutianoudis and Wang (2003) investigated month-of-the-year effects in the Athens Stock Exchange, and found very significant January effects in this market. In fact, Fountas and Segredakis (2002) examined January effects in the Greek stock market for the period 1987–1995. They found that the average January return exceeded the average returns for the other months. However, they indicated that the tax-loss selling hypothesis cannot explain the January effect in Greece as

there is no tax on capital gains. In addition, Koutianoudis and Wang (2003) found January effects in the Greek stock market during the period from January 1992 to December 2001. Furthermore, this was not the case when the market was going down. On the other hand, they examined whether the January effect can be utilized as a profitable investment strategy, and they found that the January strategy clearly outperforms the 'buy-and-hold' strategy, even after the transaction costs.

As there is no tax on capital gains in Greece, it is intriguing that they cannot attribute the January effect to the tax-loss selling hypothesis. Thus, the January effect in the Greek stock market can be attributed to alternative explanations, such as the trading activity of international funds in the Greek stock market, the portfolio-rebalancing hypothesis, the 'liquidity' hypothesis and the accounting information hypothesis (Koutianoudis and Wang, 2003).

Yakob et al. (2005) examined the issue of stock market seasonality in the Asia Pacific stock market. They studied the day-of-the-week and month-of-the-year effects in ten Asia Pacific countries (Australia, China, Hong Kong, Japan, India, Indonesia, Malaysia, Singapore, South Korea and Taiwan) for the period 2000–2005. Overall, evidence to support the presence of day-of-the-week effect is documented in five countries, the month-of-the-year effect is detected in eight countries. In most cases, the calendar effects cannot be associated with conditional risk. Moreover, McGuinness (2006) demonstrates evidence of a 'turn-of-the-month' (TOM) effect for small-cap stocks in Hong Kong during the period 2000–2005.

Moreover, Chen et al. (2010) examined the possible January effect on some Asian stock markets (Singapore, Taiwan and Hong Kong) using daily data for the period 1990–2007. The results supported the existence of monthly seasonality effects in these Asian markets. Ogunca et al. (2009) investigated day-of-the-week and January effects in the Shanghai and Shenzhen

stock markets over the period 1990–2006 for both the A and B indices. The results indicated that the Shanghai A index is prone to higher volatility and also shows some January and weekend effects.

Mlambo and Biekpe (2006) investigated seasonal effects in seventeen indices on nine African stock markets (Cote d'Ivoire, Mauritius, Ghana, Botswana, Namibia, Tunisia, Egypt, Morocco and Zimbabwe) for the period 1998–2002. Significant Monday effects were found on the Botswana and Morocco indices. Significant *Turn-of-the-Month* effects (TOM) were also found on the Botswana, Egyptian and Mauritian indices. However, the January effects are considerable only for the Egypt and Zimbabwe indices.

In Arab countries, Al-Saad and Moosa (2005) investigated the general index of the Kuwait Stock Exchange. Monthly return data used for the period 1984–2000. The results indicate that seasonality takes the form of a 'July effect' rather than a 'January effect' that was widely observed in other studies. One possible explanation for the July seasonal effect is the summer holiday effect. Since the majority of investors take their holiday during August, they exploit the month of July to invest idle cash and rebalance their portfolios. Thus July witnesses abnormal stock market activity, pushing stock prices higher. Furthermore, Al-Deehani (2006) investigated the general index of the Kuwait Stock Exchange and its various sectors for the period 1996–2004. The results indicate the existence of positive pre-summer seasonal factors for the market and most of the sectors, which can be explained by the summer holiday effect.

Kamaly and Tooma (2009) investigated the day-of-the-week effect in twelve major Arab stock markets in eleven different countries (Bahrain, Egypt, Jordan, Kuwait, Lebanon, Morocco, Oman, Palestine, Qatar, Saudi Arabia and UAE (Abu Dhabi and Dubai)) from 2002 to 2005. The results reveal that Egypt, Jordan and Kuwait have a day-of-the-week effect for both the opening and closing days of the trading week. In addition, Azizan and Saad-

Mohamed (2009) examined the seasonality effect in the Saudi Arabian stock market for the period 2003–2007. Their study suggests the existence of seasonality in stock returns in the Saudi Arabian stock market for both daily and monthly data. The maximum average return (positive) was found on Tuesdays and the lowest (negative) return on Thursdays. Furthermore, the maximum average returns were found in the months of February, June and August and the minimum average returns (negative) in the months of April and October.

It is important to point out that Arab markets have other peculiar anomalies that have yet to be examined since, in addition to following the Western Gregorian calendar, Arab markets also follow the Hijri (Islamic) calendar. A study that merges both calendars to study causal relationships and predictable patterns would be interesting.

The effects of moving Islamic calendar events such as the month of Ramadan have not received as much attention from stock market researchers as the fixed calendar events. In Islamic countries, moving calendar events such as Ramadan have large effects on economic and financial elements. During the month of Ramadan, the financial markets in the Islamic countries experience changes in their trading activities with reduced banking and working hours and greater religious orientation of the market participants (Seyyed et al., 2005).

Most Islamic countries use both the Gregorian and the Islamic lunar calendars. The Islamic calendar predominantly marks religious activities and holidays, whereas the Gregorian calendar is used by businesses and governments. The lunar Islamic year is called the Hijri calendar. The Hijri calendar has twelve months that start with the new moon. However, lunar months have, on average, only 29.53 days. Thus, the Islamic year is shorter than the Gregorian year by eleven days. Ramadan is the ninth month of the Hijri calendar. During the month of Ramadan, everyone above the age of twelve years is expected to fast from dawn to sunset. At sunset each day during Ramadan, Muslim communities break the fast with

bountiful and expensive meals. Food prices soar during the month of Ramadan as a result of increased demand (Abadir and Spierdijk, 2005).

Simultaneously, during the month of Ramadan, the economic activities in Islamic countries slow down and working hours are reduced significantly in most sectors. In spite of the fast, grocery sales rise during Ramadan because people buy more food than usual. Furthermore, electricity consumption rises during Ramadan as a result of increased late night socio-religious activities and shopping. However, trading in stock markets are expected to decline during Ramadan as many Muslims consider speculative trading a form of gambling, which is religiously forbidden by Islam.

However, Alper and Arouba (2001) examined moving calendar effects for the stock market in Turkey. The result shows that conventional methods to de-seasonalize moving events data do not remove all deterministic seasonal components. On the other hand, Husain (1998) examined the effect of Ramadan for the Pakistani stock market, the results indicate no significant change in the mean return during Ramadan; however, return volatility declined significantly.

2.5.5. Profitability of Any Calendar Effects

The original premise of the weak form efficiency is that the time series of stock prices follows a random walk. The strict random walk model presumes that the successive increases of a time series are serially independent and that their probability distribution is identical through time. However, this assumption is not essential to prove that a market is weak form efficient. A weak form efficient market would benefit if historical prices could not help market participants to gain abnormally high returns.

If the abnormally high returns cover the transaction costs, including brokerage costs, and bid-ask spread, then the market is identified as inefficient and market anomalies could be adapted in trading strategies.

Many of the early empirical studies that investigated the weak form of the EMH were based on tests of whether the different trading rules could earn profits, such as filter rules (Fama and Blume, 1966), relative strength rules (Levy, 1967a, 1967b; Jensen and Bennington, 1970; Ackemann and Keller, 1977; Bohan, 1981; Brush and Boles, 1983; Jacobs and Levy, 1988) and moving average rules (Van Horne and Parker, 1967; James, 1968). The evidence from these studies generally indicated that trading strategies based on exploiting apparent trends in historical share price data did not yield returns that were superior to a buy-and-hold strategy, even before transaction costs were taken into account.

Van Horne and Parker (1967) conducted a series of tests where they bought (sold) a security if its current share price was greater than (less than) its average value over the previous 100, 150 and 200 days by a certain percentage. However, none of the thirty variations of the test proved profitable when compared with a buy-and-hold strategy. James (1968) arrived at a similar conclusion when he noted that the use of monthly moving averages did not seem to offer investors any significant benefits.

Brock et al. (1992) analysed data on the Dow Jones Industrial Average (DJIA) for a 90-year period from 1897 to 1986, while Hudson et al. (1996) examined prices for the Financial Times Industrial Ordinary Index over a 59.5-year period from 1935 to 1994. Both studies employed two of the simplest and most popular classes of technical trading rules (*moving average* and *trading range breakout* rules). The general conclusion that emerged from the two studies is that these technical trading rules have predictive ability if sufficiently long series of data are considered. Buy signals offer positive returns, whereas sell signals offer

negative returns; the sell signals emanating from technical trading rules seem to have greater predictive ability than their buy signal counterparts. To illustrate, when fixed length moving average rules were employed, Brock et al. found that the rule earned an average 10-day return of 0.53% on buy strategies as against -0.40% return generated for sell strategies. The average 10-day return based on the trading range breakout rule was slightly higher at 0.63% for buy strategies, while it was -0.24% for sell strategies. Similar conclusions emerged in the UK investigation by Hudson et al. (1996): the average 10-day holding period return on buy strategies based on fixed length moving average rule was 0.99%, while the average return for sell strategies was -0.63%. Their trading range breakout rule generated an average 10-day return of 0.70% for buy strategies and -0.43% for sell strategies.

Brock et al. (1992) did not closely examine whether their trading rules can be used to earn excess returns in a *costly* trading environment. Nevertheless, this practical aspect of trading rule development is subjected to scrutiny in Hudson's et al. (1996) UK study. They hypothesize that the ability of technical trading rules to earn returns in excess of transaction costs depends directly on the profit generated *per round trip transaction*. When transaction costs are integrated into the analysis, the authors found that the technical rules are unlikely to make returns over and above a naive buy-and-hold strategy.

2.6. Volatility and Market Efficiency

There is a debate as to the relationship between volatility and efficiency. Seminal papers like those of Fama (1991), Merton (1985), Kleidon (1988) and Cochrane (1991) suggest there is none, but more recent papers like Errunza et al. (1994), Cuthbertson et al. (1996), Omet et al. (2002) and Islam and Oh (2003) call this into question, especially in countries where relative price volatility is more prevalent.

The tests of the EMH relate to the issues of predictability, anomaly, seasonality, volatility and the existence of bubbles. Studies of all these issues enable an analyst to draw a conclusion about the efficiency of the financial market of a country (Cuthbertson et al., 1996).

A common characteristic of stock return behaviour observed in empirical studies is the clustering of stock price changes. Large price changes tend to be followed by large changes in returns, while small changes in price are followed by small changes in returns. In the presence of this characteristic, known as volatility clustering, any conclusion regarding the efficiency of the market must be interpreted with caution. This is particularly vital in the case of developing markets which are, in general, found to be inefficient in the sense that these markets are predictable. However, the extent of inefficiency may be overestimated as these markets are also more volatile. It is therefore suggested in the literature that efficiency tests should be conducted after controlling these markets for volatility (Errunza et al., 1994).

Whereas financial time series seem to exhibit properties such as leptokurtosis, skewness and time-varying volatilities, most empirical studies fail to account for these features and, as such, the use of GARCH models is suggested when investigating stock market anomalies (Connolly, 1989).

The ARCH model introduced by Engle (1982) allows the variance of the error term to vary over time, in contrast to the classical regression model, which assumes a constant variance; to model a time series using an ARCH process, let ϵ_t denote the error terms (return residuals, with respect to a mean process). These ϵ_t are split into a stochastic piece z_t and a time-dependent standard deviation σ_t characterizing the typical size of the terms so that

$$\epsilon_t = \sigma_t z_t \qquad \textbf{Equation 2.1}$$

where z_t is a random variable drawn from a Gaussian distribution centred at 0 with standard deviation equal to 1

where the series σ_t^2 are modelled by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2$$ **Equation 2.2**

and where $\alpha_0 > 0$ and $\alpha_i \geq 0, \ i > 0$.

An ARCH(q) model can be estimated using ordinary least squares. A methodology to test for the lag length of ARCH errors using the Lagrange multiplier test was proposed by Engle (1982). This procedure is as follows:

First: Estimate the best fitting autoregressive model AR(q):

$$y_t = a_0 + a_1 y_{t-1} + \cdots + a_q y_{t-q} + \epsilon_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i} + \epsilon_t$$ **Equation 2.3**

Second: Obtain the squares of the error $\hat{\epsilon}^2$ and regress them on a constant and q lagged values:

$$\hat{\epsilon}_t^2 = \hat{\alpha}_0 + \sum_{i=1}^{q} \hat{\alpha}_i \hat{\epsilon}_{t-i}^2$$ **Equation 2.4**

where q is the length of ARCH lags.

The null hypothesis is that, in the absence of ARCH components, we have $\alpha_i = 0$ for all $i = 1, \cdots, q$. The alternative hypothesis is that, in the presence of ARCH components, at least one of the estimated α_i coefficients must be significant. In a sample of T residuals under the null hypothesis of no ARCH errors, the test statistic TR^2 follows χ^2 distribution with q

degrees of freedom. If *TR²* is greater than the chi-square table value, we *reject* the null hypothesis and conclude there is an ARCH effect in the ARMA model. If *TR²* is smaller than the chi-square table value, we *do not reject* the null hypothesis.

Whereas, Bollerslev (1986) generalized the ARCH process by allowing for a lag structure for the variance, since stock returns are highly fluctuating, the generalized ARCH models, i.e. the GARCH models, have been found to be valuable in modelling the time series behaviour of stock returns (Akgiray, 1989; French et al., 1987). Bollerslev (1986) allows the conditional variance to be a function of the lag's squared errors as well as of its past conditional variances; the formula (5) below presents GARCH(p, q):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$$

Equation 2.5

Furthermore, in order to identify **t**he lag length *p* of a GARCH(p, q) process is established in three steps:

First step: Estimate the best fitting AR(q) model:

$$y_t = a_0 + a_1 y_{t-1} + \cdots + a_q y_{t-q} + \epsilon_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i} + \epsilon_t$$

Equation 2.6

Second step: Compute and plot the autocorrelations of ε^2 by

$$\rho = \frac{\sum_{t=i+1}^{T} (\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)(\hat{\epsilon}_{t-1}^2 - \hat{\sigma}_{t-1}^2)}{\sum_{t=1}^{T} (\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)^2}$$

Equation 2.7

Third step: The asymptotic, that is for large samples, standard deviation of $\rho(i)$ is $1/\sqrt{T}$. Individual values that are larger than this indicate GARCH errors. To estimate the total

number of lags, use the Ljung-Box test until the values of these are less than, say, 10% significant. The Ljung-Box Q-statistic follows χ^2 distribution with n degrees of freedom if the squared residuals ϵ_t^2 are uncorrelated. It is recommended that T/4 values of n are considered. The null hypothesis states that there are no ARCH or GARCH errors. Rejecting the null thus means that there exist such errors in the conditional variance.

However, Al-Loughani and Chappel (1997) found that the FTSE 100 Index between 1983 and 1989 did not follow a random walk but demonstrated significant heteroscedasticity (variances were serially correlated). Their results provided evidence against the random walk hypothesis. The results did not necessarily provide evidence against the weak form of the EMH, however, since they did not test whether the predictability of volatility provided the opportunity to earn excess profits (Redhead, 2008). Nonetheless, it has been suggested that the serial correlation in variance arises from the inappropriateness of the asset pricing model used rather than from market inefficiency (Schwaiger, 1995).

There are numerous studies explaining the sources of volatility observed in different markets:

- Stoll and Whaley (1990) argue that volatility of daytime returns is related to the release of public information during the day.

- Jones et al. (1994) found that volatility is higher on days when exchanges are open than when exchanges are closed, even if no trades occur during open trading time.

- French and Roll (1986) illustrated that the greater trading period variance is due to more private information being released during this time period, since traders are more likely to obtain this information and act on it during trading hours.

- Barclay et al. (1990) attribute the higher weekend volatility on the Tokyo Stock Exchange to the release of private information.

- Chan et al. (1996) discovered that volatility patterns for Asian and European stocks are consistent with the arrival of public information but not private information.

2.6.1. Evidence from Developed Countries

Black (1976) found evidence that stock returns are negatively correlated with changes in return volatility, i.e. an asymmetry affect; volatility tends to rise in response to 'bad news' (negative excess returns) and fall in response to 'good news' (positive excess returns). French et al. (1987) supported the argument that unexpected stock market returns are negatively correlated to unexpected changes in volatility. Campbell and Hentschel (1992) found that an increase in volatility raises the required rate of return on common shares and hence lowers stock prices. On the other hand, Glosten et al. (1993) and Nelson (1991) found that negative unanticipated returns increase conditional volatility, while positive unanticipated returns reduce it. Generally, all those studies report that returns in stock markets are time varying and conditionally heteroscedastic, supporting the usefulness of employing GARCH models.

Kenourgios and Samitas (2008) investigated the day-of-the-week effect on return and volatility for major Athens Stock Exchange (ASE) indices over the period 1995–2005. They found that the day-of-the-week effect in both the return and volatility equations is present over the period 1995–2000, but not over the sub-period of 2001–2005. The day-of-the-week effect is present in mean returns for the ASE over the period 1995–2000, which is consistent with the evidence provided by Alexakis and Xanthakis (1995), Coutts et al. (2000) and Mills et al. (2000) during the period 1985–1997. Furthermore, they find that there is strong evidence for the day-of-the-week effect in both return and volatility equations during the period 1995–2000, which is in line with the international evidence of Kiymaz and Berument (2003). Therefore, it seems that this stock market anomaly has weakened in both return and

volatility during the period 2001–2005, supporting international evidence with regards to its disappearance or attenuation in developed stock markets since the 1990s.

Similar studies were performed for some developed equity markets. For example, Karolyi (1995) includes the volatility of foreign stock returns to explain the conditional variance of home country stock returns in the case of the United States and Canada. Berument and Kiymaz (2001) use the S&P500 index and report that there are differences in stock market volatility across the days of the week, with the highest volatility observed on Fridays. Kiymaz and Berument (2003) found that the day-of-the-week effect is present in both return and volatility for Canada, Germany, Japan, the United Kingdom and the United States.

Hung-Chun and Hung (2010) investigated the daily volatility forecasting for the Standard & Poor's 100 stock index series from 1997 to 2003. Empirical results indicate that the GJR-GARCH model achieves the most accurate volatility forecasts, closely followed by the EGARCH model. Such evidence strongly demonstrates that modelling asymmetric components is more important than specifying error distribution for improving volatility forecasts of financial returns in the presence of fat-tails, leptokurtosis, skewness and leverage effects. Furthermore, if asymmetries are neglected, the GARCH model with normal distribution is preferable to those models with more sophisticated error distributions.

2.6.2. Evidence from Developing Countries

Ho and Cheung (1994) examined seasonal variation patterns in return volatility. They used data on daily stock price indices of eight Asian markets (Hong Kong, Japan, Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand) from January 1975 to December 1989 to compile daily returns. They found the existence of day-of-the-week variations in volatility in most of the emerging Asian stock markets. However, out of the five markets that had a

significant day-of-the-week effect in variance, three had the lowest volatility on the last trading day.

Choudhry (2000) examined the daily returns and conditional variance (volatility) to test for the day-of-the-week effect on seven emerging stock markets in Asia – India, Indonesia, Malaysia, the Philippines, South Korea, Taiwan and Thailand – from January 1990 to June 1995. The GARCH model was used for the empirical research. The results suggested the presence of significant day-of-the-week effects on both stock returns and volatility, though they are not identical in all seven countries. Similarly, Berument and Kiymaz (2001) examined the volatility for the Istanbul Stock Exchange (ISE) for the period 1986–2001. They used the GARCH model and the results show a high volatility on Mondays (the first trading day of the week).

Subadar (2009) investigated the effects of any seasonality on stock market returns and volatility on the Stock Exchange of Mauritius. A standard GARCH model was used on daily Stock Exchange Index of Mauritius returns from 1998 to 2006. The results obtained indicate significant presence of leptokurtic features of the stock market returns. The mean returns were significant on all days except Mondays. In addition, the stock return volatility was positive on all five trading days, though the magnitude of the day-of-the-week effect on volatility was insignificant.

Kamaly and Tooma (2009) investigated the day-of-the-week effect on returns as well as on volatility for twelve major Arab stock markets in eleven different countries (Bahrain, Egypt, Jordan, Kuwait, Lebanon, Morocco, Oman, Palestine, Qatar, Saudi Arabia and the UAE 'Abu Dhabi and Dubai') from 2002 to 2005. The results reveal that the significant day-of-the-week effect on volatility is higher compared to the case of returns. In fact, eight markets exhibited a significant day-of-the-week effect on volatility. However, similarly to the case of returns, the

beginning and the end of the trading week marked abnormal high volatility compared to the other trading days. As an example, six markets (Egypt, Jordan, Kuwait, Palestine, Qatar and Saudi Arabia) are characterized by excess volatility on the first trading day and three markets (Egypt, Kuwait and Saudi Arabia) are characterized by excess volatility on the last day of trading. This result is consistent with similar studies that reported significant day-of-the-week effects on returns and on volatility (Berument and Kiymaz, 2001). Only Oman is characterized by a negative and significant day-of-the-week effect on volatility on the last day of trading.

Al-Zoubi and Al-Zu'bi (2007) examined the stock return behaviour in the Amman Stock Exchange (ASE) for market efficiency, the time-varying risk-return relationship, the persistence of the stock volatility and the leverage effect for the holding period of 1990 to 2000. The result indicates that the ASE displayed negative skewness, excess kurtosis and deviation from normality. The ASE volatility tends to change over time, and is serially correlated.

2.6.3. Modelling Volatility

This research examines whether small fluctuations in investors' attitudes towards risk, which could result from weather-related and Ramadan-related (Islamic calendar) shifts in their mood states, can have a non-negligible impact on market volatility. This part was motivated by Mehra and Sah (2002), who found that weather influences volatility.

Since poorer social moods can be associated with more disagreement in valuation opinions among investors, bad weather can be expected to lead to less volatility (Baker and Stein, 2004; Lucey and Dowling, 2005). Moreover, studies such as Brown (1999), Gervais and Odean (2001) and Statman et al. (2006) suggest that when investors are in a good mood

(which can be associated with fair weather) they tend to trade more, which in turn increases volatility.

Furthermore, an explanation given by Kaplanski and Levy (2009) that, if *seasonal affective disorder*[10] (SAD) induces seasonality in returns, and returns are negatively correlated with volatility, then SAD can indirectly create seasonality in volatility in the opposite direction. Therefore, this research assumes that other weather conditions and Ramadan might have a similar indirect effect on volatility. Finally, another explanation of a positive association between bad weather and volatility could be based on psychological studies, which link poor mood with an increase in the subjective probability of undesired outcomes (Kliger and Levy, 2003).

2.7. Sentiment and Behavioural Finance Framework (Socio-Economic Theory)

The efficient market hypothesis assumes that investors behave rationally in the sense that they use all relevant information and analyse it in the most effective way with a view of achieving the best possible outcomes. However, many investors appear to behave in irrational ways; irrelevant information, such as rumour, is used and the analysis may be subject to misperceptions, emotions and other psychological biases.

Prechter's socio-economic hypothesis (1999) suggested that human interaction spreads moods and emotions. It is argued that, when moods and emotions become widely shared, the resulting feelings of optimism or pessimism cause uniformity in financial decision-making. This amounts to herding and has impacts on financial markets at the aggregate level.

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[10] Seasonal affective disorder (SAD), also known as winter depression, winter blues, summer depression, summer blues, or seasonal depression, is a mood disorder in which people who have normal mental health throughout most of the year experience depressive symptoms in the winter, summer, spring or autumn year after year. In the Diagnostic and Statistical Manual of Mental Disorders, SAD is not a unique mood disorder, but is *"a specifier of major depression"* (Lurie et al., 2006).

Furthermore, Calvo and Mendoza (1997) examined the effect of herd behaviour on the volatility of the capital market at the beginning of the Mexican crisis; from 1991 to mid-1993 short-term public debt was smaller than gross reserves. A large debt-reserves imbalance developed in 1993–1994, and ended with the collapse of the currency; short-term public debt was nearly three times larger than reserves. Tesobonos alone, including commercial bank holdings, exceeded US$22 billion in December 1994, compared with gross reserves of less than US$13 billion at the beginning of the month. By the end of December 1994, reserves fell to nearly US$6 billion, well below the critical US$l0 billion set by the Bank of Mexico. Calvo and Mendoza's (1997) focus was on the effects of the globalization of financial markets. According to that paper, as the number of markets grows and the share of the country's assets in the investors' portfolios declines, the payoff of gathering information on country-specific information becomes smaller and the incentives for herding behaviour grows stronger.

Kaminsky and Schmukler (1999) studied the origins of the Asian crisis and discuss the harmful effect of rumour, arguing that the existence of herd behaviour significantly deteriorates the economic conditions in periods of market stress. Lu and Zhu (2006) pointed out the destabilizing effect on the stock market of China caused by the herd behaviour of the fund investors. Patterson and Sharma (2007) assumed that, due to short-term pressure caused by investors, moves in market prices of assets from their fundamental values may provide opportunities for the formation of bubbles and crashes.

It has been argued that the stock market is a direct index to social mood; it reflects the combined level of optimism or pessimism in a society at any given time (Prechter, 1985, 1999; Green, 2004). Nofsinger (2005), for example, argues that social mood influences the

judgments made by consumers, investors and corporate managers. He indicates that the level and nature of business activity will follow social mood rather than lead it.

2.7.1. Influence of Emotion and Mood

Studies by psychologists have found that mood appears to affect predictions about the future. People in a good mood are more optimistic about the future than people in a bad mood (Wright and Bower, 1992). The impact of mood on financial decisions has been referred to as the *"misattribution bias"* (Nofsinger, 2005). If a person is in a good mood, they will have a tendency to be optimistic when evaluating an investment. Good moods may cause people to be more likely to take risky investments (for example choosing stocks rather than bonds). Nofsinger (2002) has suggested an optimism bias. Optimism reduces critical analysis during the investment process and causes investors to ignore negative information. Furthermore, mood affects investment behaviour (Baker and Nofsinger, 2002; Nofsinger, 2002). It has been suggested that good moods make people less critical. Good moods can lead to decisions that lack detailed analysis.

People transmit moods to one another when interacting socially. People not only receive information and opinions in the process of social interaction, they also receive moods and emotions. Moods and emotions interact with cognitive processes when people make decisions. There are times when such feelings can be particularly important, such as in periods of uncertainty and when the decision is very complex. The moods and emotions may be unrelated to a decision, but nonetheless affect the decision. Moods and motives produced by spiritual factors will affect individual decisions. The general level of optimism or pessimism in society will influence individuals and their decisions, including their financial decisions.

There is a distinction between emotions and moods. Emotions are often short term and tend to be related to a particular person, object or situation. Moods are free-floating and not attached to something specific. A mood is a general state of mind and can persist for long periods. Mood may have no particular causal stimulus and have no particular target.

A positive mood is accompanied by emotions such as optimism, happiness and hope. These feelings can become extreme and result in euphoria. A negative mood is associated with emotions such as fear, pessimism and antagonism. Nofsinger (2005) suggested that social mood is quickly reflected in the stock market, such that the stock market becomes an indicator of social mood. Prechter (1999), in proposing a socio-economic hypothesis, argued that moods cause financial market trends and contribute to a tendency for investors to act in a concerted manner and to exhibit herding behaviour.

Many psychologists would argue that actions are driven by what people think, which is heavily influenced by how they feel. How people feel is partly determined by their interactions with others. According to the socio-economic hypothesis (Prechter, 1999; Nofsinger, 2005), moods can be transmitted through social contact and a widely shared, or social, mood emerges. Contact between people conveys mood as well as information. Collectively, shared moods influence individual decisions, with the effect that trends emerge. At times, mood can dominate over reason in the decision-making process. It has been found that people in depressed moods are less willing to take risks (Yuen and Lee, 2003) and a negative mood is associated with a desire for asset preservation and safety (Kavanagh et al., 2005). A positive mood renders people more trusting (Dunn and Schweitzer, 2005) and, for many people, trust in the financial services industry is a big issue when considering investments. A positive social mood results in perceptions of trustworthiness, low risk and

high returns whilst negative social mood is associated with low trust, high perceived risk and low anticipated returns (Olson, 2006).

Furthermore, social mood is a collectively shared state of mind (Prechter, 1999; Nofsinger, 2005; Olson, 2006). Investors with no knowledge of analysis are particularly likely to be influenced by social mood when making investment decisions. DeLong et al. (1990) illustrated a class of investors whose expectations were not justified by fundamentals; they referred to them as *"noise traders"*. Unjustified expectations are referred to as *investor sentiment*. When sentiment is shared amongst investors, stock prices can deviate from fundamental values for long periods.

People in a peer group tend to develop the same tastes, interests and opinions (Ellison and Fudenberg, 1993). Social norms emerge in relation to shared beliefs. These social norms include beliefs about investing. The social environment of investors influences investment decisions. This applies not only to individual investors but also to market professionals. Fund managers are a peer group; fundamental analysts are a peer group; technical analysts are a peer group. Indeed, market professionals in aggregate form a peer group. It is likely that there are times when these peer groups develop common beliefs about the direction of the stock market.

2.7.1.1. Influence of Weather and Biorhythmic Variables on Investors' Mood

Weather and length of daylight are factors that can affect mood. The effects of such factors on investment decisions have been researched. Hirshleifer and Shumway (2003) investigated the effects of sunshine on stock market returns. When the sun is shining people feel good. This may increase optimism and affect investment decisions. It may be the case that investors are more likely to buy shares when the sun is shining. The purchases would cause stock

prices to rise. Stock markets in twenty-six cities were examined by the authors. They found that stock market returns (price increases) were higher on sunny days. When comparing the sunniest days with the worst days, it was found that there was an annualized difference of 24.6% on average.

Kamstra et al. (2003) looked at the relationship between hours of daylight and stock market returns. They found that stock markets performed relatively poorly during the autumn as the hours of daylight fell. This was most marked for the more northerly stock markets. Consistent with this theory is the observation that the effect occurred over October to December in the northern hemisphere, and over April to June in the southern hemisphere. This study is consistent with the view that sunlight affects mood and mood affects investment decisions. Sunlight enhances optimism about the future and the prospective future returns from investments.

Empirical evidence from existing studies that have investigated the effects of weather and environmental conditions on volatility is mixed. Chang et al. (2008) show that New York City cloudiness has a significant positive effect on intraday volatility of NYSE firms over the entire trading day. These authors used two volatility proxies, one based on the range of the intraday prices and the other on the basis of the standard deviation of the bid-ask mid-point returns. Both of these proxies are uncommon in the literature and their accuracy is unknown. Dowling and Lucey (2008) studied the empirical effect of seven mood proxies on both the returns and variances of thirty-seven national equity market indices and twenty-one small capitalization indices. They employed GARCH-type processes to approximate and model the variations in the conditional variance of returns. Their results show that wind, precipitation, geomagnetic storms, daylight saving time changes and SAD are all positively related to conditional volatility for most of the indices considered.

Kaplanski and Levy (2009) considered the effect of SAD and temperature on the VIX options implied volatility index that is traded in the Chicago Board Options Exchange (CBOE). They used a measure of so-called 'actual' volatility based on the historical standard deviation of a monthly window of daily returns. The authors found that the number of daylight hours (temperature) is negatively (positively) related only to the 'perceived' volatility proxy by the VIX and not to the 'actual' historical volatility measure. Another study that indirectly shows a positive relationship between volatility and bad weather is that of Kliger and Levy (2003). These authors, based on their usage of S&P500 index options data, found that bad mood as a proxy for total cloud cover and precipitation, makes investors place higher-than-usual probabilities on adverse events.

Mehra and Sah (2002) show that even small fluctuations in investors' attitudes towards risk, which could result from weather-related shifts in their mood states, can have a non-negligible impact on market volatility. Chang et al. (2008) suggested that the empirical implication for the relationship between weather and volatility is that social moods can be associated with more disagreement in valuation opinions among investors; therefore bad weather can be expected to be inversely related to market volatility. On the other hand, studies such as those of Brown (1999), Gervais and Odean (2001) and Statman et al. (2006) suggest that when investors are in a good mood, which can be associated with fair weather, they tend to trade more, which in turn increases volatility. Moreover, another explanation has been given by Kaplanski and Levy (2009) that if SAD induces seasonality in returns and returns are negatively correlated with volatility, then SAD can indirectly create seasonality in volatility in the opposite direction.

2.7.2. Herd Behaviour

Hirshleifer (2001) states that people have a tendency to conform to the judgements and behaviours of others. People may follow others without any apparent reason. Such behaviour results in a form of herding. If there is a uniformity of view concerning the direction of a market, the result is likely to be a movement of the market in that direction.

Herding is an irrational behaviour and low information cost strengthens herding. Banerjee (1992) defines herding as *"everyone doing what everyone else is doing, even when their information suggests doing something different."* Furthermore, Shiller (2000) supposed that the meaning of herd behaviour is that investors tend to do as other investors did. They imitate the behaviour of others and disregard their own information. Kultti and Miettinen (2006) proposed that, if the cost of the information about predecessors' actions is very expensive, then all the agents will act according to their own signals but, if observing is free, one acts in accordance with herding behaviour. Facing financial panic, investors may not have enough time to collect valuable information from many disorderly data. Investors may herd during financial panic. Prechter and Parker (2007) suggest that uncertainty about valuation may cause herding.

Walter and Weber (2006) distinguished between intentional and unintentional herding. Intentional herding is seen as arising from attempts to imitate others, whereas unintentional herding emerges as a result of investors analysing the same information in the same way. Intentional herding could develop as a consequence of poor availability of information. Investors might imitate the behaviour of others in the belief that others have traded on the basis of information. When imitating others in the belief that they are acting on information becomes widespread, there is an informational cascade.

Another possible cause of intentional herding arises as a consequence of career risk. If a fund manager loses money whilst others make money, that fund manager's job may be in threat. If a fund manager loses money whilst others lose money, there is more job security. So it can be in the fund manager's interest to do as others do (this is sometimes referred to as the 'reputational reason' for herding). Since fund managers are often evaluated in relation to benchmarks based on the average performance of fund managers, or based on stock indices, there could be an incentive to imitate others since that would prevent substantial underperformance relative to the benchmark.

Walter and Weber (2006) found that investors bought stocks following price rises and sold following falls. If such momentum trading is common, it could be a cause of unintentional herding. Investors do the same thing because they are following the same strategy. It can be difficult to know whether observed herding is intentional or unintentional.

Hwang and Salmon (2006) investigated herding in the sense that investors, following the performance of the market as a whole, buy or sell simultaneously. Their investigations into the US, UK and South Korea markets show that herding increases with market sentiment. They found that herding occurs to a greater extent when investors' expectations are relatively identical. Herding is strongest when there is confidence about the direction in which the market is herding. Herding appeared to be persistent and slow moving. This is consistent with the observation that some bubbles have taken years to develop.

Kirman (1991) suggests that investors may not necessarily base decisions on their own views about investments, but upon what they see as the majority view. The majority being followed are not necessarily well-informed rational investors. The investors that are followed may be uninformed and subject to psychological biases that render their behaviour irrational (from the perspective of economists). Rational investors may even focus on predicting the

behaviour of irrational investors rather than trying to ascertain fundamental value; this may explain the popularity of technical analysis among market professionals.

Deutsch and Gerard (1955) distinguish between 'normative social influence' and 'informational social influence'. Normative social influence does not involve a change in perceptions or beliefs, merely conformity for the benefit of conformity. An example of normative social influence would be that of professional investment managers who copy each other on the grounds that being wrong when everyone else is wrong does not jeopardize one's career, but being wrong when the majority get it right can result in job loss. This is a form of regret avoidance. If a bad decision were made, a result would be the pain of regret. By following the decisions of others, the risk of regret is reduced. This is safety in numbers. There is less fear of regret when others are making the same decisions.

Informational social influence entails acceptance of a group's beliefs as providing information. For example, a share purchase by others delivers information that they believe that prices will rise in future. This is accepted as useful information about the stock market and leads others to buy also. This is an informational cascade; people see the actions of others as providing information and act on that information. Investors buy because they know that others are buying, and in buying they provide information to other investors, who buy in turn. Informational cascades can cause large, and economically unjustified, swings in stock market levels. Investors cease to make their own judgments based on factual information and use the apparent information conveyed by the actions of others instead. Investment decisions based on relevant information cease, and hence the process whereby stock prices come to reflect relevant information comes to an end. Share price movements come to be disconnected from relevant information.

Welch (2000) investigated herding among investment analysts. Herding was seen as occurring when analysts appeared to mimic the recommendations of other analysts. It was found that there was herding towards the prevailing consensus, and towards recent revisions of the forecasts of other analysts. A conclusion of the research was that in bull markets the rise in share prices would be reinforced by herding.

Furthermore, the media are an integral part of market events because they want to attract viewers and readers. Generally, significant market events occur only if there is similar thinking among large groups of people, and the news media are vehicles for the spreading of ideas. The news media are attracted to financial markets because there is a persistent flow of news in the form of daily price changes and company reports (Redhead, 2008).

The media seek interesting news and can be fundamental propagators of speculative price movements through their efforts to make news interesting (Shiller, 2000). They may try to enhance interest by attaching news stories to stock price movements, thereby focusing greater attention on the movements. The media are also prone to focus attention on particular stories for long periods. Shiller refers to this as an 'attention cascade'. Attention cascades can contribute to stock market bubbles and crashes.

Davis (2006) confirmed the role of the media in the development of extreme market movements. The media were found to exaggerate market responses to news, and to magnify irrational market expectations. At times of market crisis, the media can push trading activity to extremes. The media can trigger and reinforce opinions.

Nevertheless, Brown (1999) examined the effect of noise traders (non-professionals with no special information) on the volatility of the prices of closed-end funds (investment trusts). A shift in sentiment meant these investors moved together and an increase in price volatility

resulted. Walter and Weber (2006) also found herding to be present among managers of mutual funds.

2.7.3. Overconfidence

Psychological research has indicated that there is a self-attribution bias in decision-making. When an investment is successful, the investor believes that it is due to his or her skill. An unsuccessful investment is seen to fail as a result of bad luck or the actions of others. The self-attribution bias leads to overconfidence. Overconfidence is also reinforced by the hindsight bias, which is the false belief held by people who know the outcome of an event that they would have predicted the outcome. Overconfidence may be particularly characteristic of inexperienced investors who find that their initial investments are profitable. Their belief in their own skill leads them to invest more. Thus, a bull market can generate overconfidence, which causes more investing, thereby reinforcing the upward price movement. There are those who interpret their gains in a bull market as arising from their own skills. They see certainty where there is uncertainty. This can lead them to invest beyond a rational level, and painful losses result when the market falls.

Overconfidence can arise from excessive confidence in the quality of one's information and an exaggerated view of one's ability to interpret that information. This leads to an unwarranted degree of certainty about the accuracy of one's forecasts and a corresponding underestimation of risk (Barber and Odean, 1999). As a consequence, overconfident investors are prone to invest to a greater extent than would be the case if they properly understood the quality of their forecasts. Barber and Odean (1999) found that overconfident investors tend to take more risks than less confident investors do.

During the bull market, individual investors increased their levels of trading. Investors allocated higher proportions of their portfolios to shares, invested in riskier stocks (often technology companies), and many investors borrowed money in order to increase their shareholdings (Barber and Odean, 2001). It is likely that, during the bull market, individual investors attributed much of their success to their own expertise and became overconfident as a result.

2.7.4. Illusion of Control

A psychological bias that helps to produce overconfidence is the illusion of control. People often behave as if they have influence over uncontrollable events (Presson and Benassi, 1996). A number of attributes have been identified as fostering the illusion of control. One of these is the outcome sequence. Early positive outcomes give a person more illusion of control than early negative outcomes. This is akin to the tendency for some people to become addicted to gambling if their first few bets are successful. In a rising stock market, people investing for the first time will experience gains. This is likely to engender the illusion of control, overconfidence, and the inclination to invest more. If significant numbers of people invest more, prices will continue to rise, thereby reinforcing these psychological biases.

The illusion of control and overconfidence may explain why a great number of investors choose actively managed funds when index funds outperform them and have lower charges. It might be that overconfidence in their own selection abilities and the illusion of control provided by the ability to choose between funds cause investors to pick actively managed funds even though index funds offer better potential value (Redhead, 2008).

Langer (1975) mentions that people usually find it hard to accept that outcomes may be random. He makes a distinction between chance events and skill events. Skill events involve

a fundamental link between behaviour and the outcome. In the case of chance events, the outcome is supposed to be random; however, people often think of chance events as skill events. When faced with randomness, people normally behave as if the event were controllable or predictable. If people engage in skill behaviour, such as making selections, their belief in the controllability of a random event becomes stronger. Additionally, there is substantial evidence that investment managers are unable to outperform stock markets. Yet, since investment managers engage in skill behaviours of analysis and choice, they are likely to see portfolio performance as controllable. Retail investors and financial advisors also tend to think that the performance of their investment choices is controllable; the act of selection between mutual funds enhances the illusion of control.

Another attribute that fosters the illusion of control is the acquisition of information. Increased information increases the illusion of control and the degree of overconfidence. This has been called the illusion of knowledge (Nofsinger, 2005; Peterson and Pitz, 1988). The information may or may not be relevant to the investments. Particularly, for investors with little knowledge of investment, information does not give them as much understanding as they think because they lack the expertise to interpret it. They may be unable to distinguish relevant and reliable information from irrelevant and unreliable information. However, to the extent that stock market gains lead investors to seek information, the information obtained is likely to increase the illusion of control and the extent of investing. The resulting investment will help to perpetuate the share price rises and thereby the psychological biases.

2.7.5. Narrow Framing

Narrow framing refers to the tendency of investors to focus too narrowly. One aspect is focus on the constituents of a portfolio rather than the portfolio as a whole. Since individual

investment tend to be more volatile than the investor's portfolio as a whole, such narrow framing causes investors to overestimate price volatility. This could cause people to invest too little (Redhead, 2008).

Another dimension of narrow framing is the focus on the short term even when the investment horizon is long term. It is not rational for an investor accumulating assets for retirement in twenty-five years' time to be concerned about the week-to-week performance of the portfolio. Yet long-term investors do focus on short-term volatility. Studies have shown that when, in experimental situations, people have been presented with monthly distributions of returns they are less likely to invest than when they are shown annual distributions (with the annualized volatility being the same in both cases). The implication is that focus on short-term volatility deters investment. It appears that people do not appreciate the effects of time diversification. Time diversification is the tendency for good periods to offset bad periods with the effect that the dispersion of investment returns does not increase proportionately with the period of the investment. Investors who focus increasingly on short-term fluctuations overestimate stock market risk and allocate too little of their money to stock market investment (Redhead, 2008).

2.8. Conclusion

The history of economic thought has shown the tendency for new and old theories to be synthesized.

This thesis takes a similar approach. It will use market efficiency as the main theoretical framework, given its emphasis on statistical analysis. The researcher believes that examining the results from just an efficiency perspective is highly limiting as the observed behaviour of Jordanian investors will be influenced by both Islamic ethical considerations and behavioural

psychological forces. These are likely to be especially important during the holy month of Ramadan. Interpretation of the results will therefore apply the concepts and ideas identified in both the behavioural finance and ethics-based literature.

This chapter has identified the debate in relation to market efficiency. After Fama introduced the EMH, market anomalies, such as the calendar effect, appeared in the financial market and challenged the validity of the EMH. These market anomalies disappeared after they were documented in the literature, especially in developed countries, whereas in developing countries the debate around market efficiency still remained. In fact, the developing markets are more tentative. In these markets, a number of theoretical arguments reject the weak form efficiency because of their thin traded markets (Mobarek and Keasey, 2000), the scarcity and uncertain validity of corporate information (Blavy, 2002), and a number of structural and institutional specificities, including the fragmentation of capital markets and the presence of political and economic uncertainties, which may also account for departure from efficiency (El-Erian and Kumar, 1995).

Therefore, the research undertaken aims at contributing to the debate in relation to the market efficiency of the Amman Stock Exchange (ASE). The study undertaken examines random walk and calendar anomaly effects (with consideration of the Islamic calendar) and applies behavioural finance concepts and ideas as a theoretical basis. In addition, the research goes beyond market efficiency to explore the relationship between risk and return by examining the volatility of the ASE.

3. Chapter Three: Jordan Background

3.1. Introduction

This chapter analyses recent developments in the Jordanian economy and the Amman Financial Market (AFM). Jordan is a small Arab country with insufficient supplies of water, oil and other natural resources. Poverty, unemployment and inflation are fundamental problems; however, since assuming the throne in 1999, King Abdallah has undertaken some broad economic reforms in a long-term effort to improve living standards.

The main challenges facing Jordan are reducing dependence on foreign grants, eliminating the budget deficit, and attracting investment to promote job creation. It was estimated that Jordan's labour force would approximate 1.667 million by 2009; the official rate of unemployment was 13% in 2008 but the unofficial rate was approximately 30%.[11]

For an emerging market economy like Jordan, the AFM is unusually large in terms of market capitalization (almost 300% of GDP by 2005, 136% of GDP by 2009).[12] The ASE plays an important role in channelling and intermediating capital in the Jordanian economy, which currently depends to a significant extent on foreign capital inflows. Furthermore, Jordan strives hard to improve the quality of market information in the stock market as well as the flow of this information.

The ASE has had its own indices since 1980, and introduced new indices based on free-float market capitalization. In 2010, Jordan launched the Dow Jones ASE 100 index, to enhance

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[11]   Central   Intelligence   Agency   World   Factbook.   [online],   available   at https://www.cia.gov/library/publications/the-world-factbook/geos/jo.html [7 December 2010].
[12] In 2009, it was less than 120% in the UK, less than 85% in the US, less than 60% in Japan and less than 10% in   China   (Greenfaucet,   Investors   Information,   Educations,   [online]   available   at http://www.greenfaucet.com/?q=node/14465 [7 December 2010].

the ASE's exposure to international investors. Therefore, it is expected that the level of efficiency has been improved in the last ten years.[13]

The next section presents an overview of Jordan. Section 3.3 identifies the key feature of the Jordanian economy. Section 3.4 examines the AFM and the recent developments in Amman's financial system. This is followed by a conclusion.

3.2. Country Background

The Hashemite Kingdom of Jordan is positioned at the convergence of the three continents of Asia, Africa and Europe. It has a total area of 89,342 km and shares borders with five Middle Eastern countries: Iraq, Syria, Saudi Arabia, Israel, and Palestine.[14]

Graph 3.1: Location of Jordan in the Middle East

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The government ended subsidy levels for oil and gas and other consumer and manufactured goods in 2008 in an effort to control the budget. Jordan is currently exploring nuclear power generation to forestall energy shortfalls. Jordan's conservative banks, financial institutions

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[13] AMEINFO, Country Guide, [online] available at https://www.cia.gov/library/publications/the-world-factbook/geos/jo.html [7 December 2010].
[14] Investment Banking and Capital Markets (2002), *The Jordanian Economy/Country Report*, Jordan.

and financial services sector had been largely protected from the recent worldwide financial crisis (2007) but many businesses, in particular in the tourism, transportation and real estate sectors, predicted a delayed downturn during 2008 and 2009.

However, latest figures published by the Jordanian Department of Statistics in 2010 reveal that real GDP growth rate reached 3.1% in 2010 compared to 2.3% in 2009. This improvement in the rate of economic growth was driven by the recovery in services and exports. Furthermore, the budget deficit decreased by more than 3% compared to 2009 to stand at 5.4% of GDP. In light of the steady rate of population growth, estimated as being 2.2%, the per capita real GDP grew by 0.8%, compared to 0.1% in 2009. The improvement in the aggregate demand helped reduce unemployment from 12.9% in 2009 to 12.5% in 2010.

The consumer price index resumed its rise in 2010. This rise in the CPI was driven by the increase in the price of basic commodities, mainly oil and food items, after experiencing a moderate contraction in 2009. The annual inflation rate, measured by the percentage change in the average CPI, amounted to 5.0% in 2010 compared to 0.7% in 2009.

3.2.1. Population, Religion and Language

The population of Jordan was 4,900,000 in 1999 and is estimated to be approximately 6,269,285 by 2009.[15] The population growth rate was estimated to be about 2.189% in 2009. Jordan has a relatively young population, with 31.3% under the age of 15 years and only 4.2% above 65 years of age.[16]

The majority of the population is of Muslim faith at around 92%, with a Christian minority approximating 8%. Jordan is by law an Islamic country; the king is a descendant of the

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[15] Central Intelligence Agency World Factbook. [online], available at https://www.cia.gov /library/ publications /the-world-factbook/geos/jo.html [7 December 2010].
[16] Department of Statistics Database, [online] available at http://www.dos.gov.jo/dos_home/dos_ home_e /main/index_fig.htm [7 December 2010].

traditional guardians of Mecca. Minority religious groups have autonomy regarding certain questions and Jordan is noted for religious freedoms and tolerance.

Islam dominates the society, but Christianity is a vital force; Christians have a relatively high level of involvement in the fields of education, economy and the state. Since the 1980s, Islam has become a stronger force in society, and conservative ideas have gained ground. Behind this was both a general revival in the Muslim world and the work of the Muslim Brotherhood in Jordan, who operated with the consent of authorities. Modern Jordan has a relatively short Islamic history; there are virtually no mosques before the 1940s.[17]

Arabic is both the official language and the language of communication in day-to-day life, although several languages are spoken in Jordan. English is fairly widely spoken and it is the main foreign language in Jordan, especially in business and commerce, and is widely understood by the upper and middle classes.

3.2.2. Currency

The unit of currency is the Jordanian Dinar (JD), which is divided into 100 fils and is issued by the Central Bank of Jordan. In October 1995, in a move to restore further confidence in local currency, the government pegged the Jordanian Dinar to the US dollar at the rate of 0.708 per dollar, which allows it to fluctuate against other foreign currencies, subject to their exchange rate fluctuations in international markets against the US dollar.[18]

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[17] Looklex Encyclopaedia Database, [online] available at http://looklex.com/e.o/jordan.religions.htm [7 December 2010].

[18] Central Bank of Jordan (2000) *The Thirty Seven Annual Report*. Amman, Jordan: Research Department.

3.2.3. Political Regime

The Hashemite Kingdom of Jordan is a constitutional monarchy, which was ruled by His Majesty King Hussein Bin Talal from 1952 until his death in February 1999. His Majesty King Abdullah Bin Al-Hussein has since ascended to the throne.

The head of the government is a Prime Minister who is appointed by the King. The Prime Minister nominates a Council of Ministers that are responsible for the executive function of the government.[19]

The legislative power is comprised of the King and the Council of the Nation, which consists of the Upper House of Parliament (52 members appointed by the King) and the Lower House of Parliament (104 members directly elected on a one-person-one-vote system and serving a four-year term).

Jordan is considered to be one of the most open political systems in the region. Democracy was affirmed in 1989 after the abolition of the long-applied martial law. The increasingly democratic atmosphere can be felt in discussions of issues in Parliament. Burgeoning population and more open political environment have led to the emergence of a variety of small political parties. Parliamentary elections were recently held in November 2010. The Islamist opposition lost many of the seats it had gained in 2003.

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[19] US. Department of State, Electronic Information and Publications, [online] available at http://www.state.gov/r/pa/ei/bgn/3464.htm.[7 December 2010].

3.2.4. Employment

Jordan's labour force was estimated to be approximately 1.667 million in 2009. The country suffers from a high rate of unemployment, estimated at around 12.9% in 2009. The sector composition of the workforce in 2007 was estimated to be as follows: 2.7% employed in agriculture, 20% in the industrial sector and 77% in other services.[20]

3.3. Jordanian Economy Overview

Jordan is classified a *"lower middle income country"* by the World Bank. The per capita GDP is $4,700. According to Jordan's Department of Statistics, almost 13% of the economically active Jordanian population residing in Jordan was unemployed in 2008, although unofficial estimates cite a 30% unemployment rate.[21]

Education and literacy rates and measures of social well-being are relatively high compared to other countries with similar incomes. Jordan's population growth rate has declined in recent years and is currently 2.189%, as reported by the Jordanian Government.

One of the most important factors in the government's efforts to improve the well-being of its citizens is the macroeconomic stability that has been achieved since the 1990s. Jordan's 2008 and 2009 budgets emphasized increases in the social safety net to help people most impacted by high inflation, but these increases were not included in the 2010 budget because of fiscal austerity plans and the low inflation rates during 2009.

The average rate of inflation in 2009 was -0.1%. The currency has been stable with an exchange rate fixed to the US dollar since 1995 at JD 0.708 to the dollar. In 2008, Jordan

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[20] Central Intelligence Agency World Factbook. [online], available at https://www.cia.gov /library/publications /the-world-factbook/geos/jo.html [7 December 2010].

[21] US. Department of State, Electronic Information and Publications, [online] available at http://www.state.gov /r/pa/ei/bgn/3464.htm.[7 December 2010].

participated in a Paris Club debt buyback to retire more than $2 billion in debt using privatization proceeds that, at the time, reduced the percentage of external debt to GDP from 46% to 32%.[22]

Furthermore, Jordan adapted three economic reform programmes, also known as economic adjustment programmes, for the periods 1989–1993, 1992–1998 and 1999–2001, whose implementation accompanied the two five-year plans for the periods 1993–1997 and 1999–2003.

3.3.1. The 1989–1993 Period

The Jordanian economy faced a difficult situation in late 1988, represented by the decrease of income from the expatriates from Kuwait and the Gulf region, the discontinuation of Arab financial assistance, and the contraction of exports to neighbouring countries, which led to the initiation of the economic adjustment programme for the 1989–1993 period.

The programme aimed to (Marashdeh, 1996):

- Reduce the chronic imbalances in the balance of payments and budget.
- Achieve fiscal and monetary stability.
- Build strong foundations for sustained economic growth with stable prices.

However, the above programme was heavily dependent on the following factors:

- The private sector expanding its role in economic development.
- The government rationalizing its resources to achieve sustained economic growth and provide a stable investment environment.

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[22] US. Department of State, Electronic Information and Publications, [online] available at http://www.state.gov /r/pa/ei/bgn/3464.htm.[7 December 2010].

- The government restructuring the tax system to improve the flexibility and comprehensiveness of the tax system (Marashdeh, 1996).

3.3.2. The 1992–1998 Period

Due to the Gulf War and the discontinuation of Arab financial assistance to Jordan, the adjustment programme for the period 1989–1993 came to a halt. Thereafter, the government adopted a new social adjustment programme during the period 1992–1998 (Shibli, 1999).

Its aims were to:

- Promote financial and monetary stability.
- Remove price and production distortions.
- Increase domestic savings.
- Promote private domestic investment.
- Reduce the budget and balance of payment deficits.

The programme projected a growth rate of the GDP at a constant factor of 3% and the GDP growth at constant market prices of 3% as well.

However, GDP grew at a constant factor of 9.2% and at constant market prices by 11.3%, as shown in Tables 3.1 and 3.2.

Table 3.1: Projected Growth Rate from Second Adjustment Programme (1992–1998)[23]

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Table 3.2: Real GDP and GDP Per Capita of Jordan (1992–1998)[24]

This item has been removed due to third party copyright. The unabridged version of the thesis can be viewed at the Lanchester Library, Coventry University.

During the final three years of the programme, the Jordanian economy started facing challenges such as an increasing unemployment rate, a decrease in the export growth rate, and numerous other economic hardships. In addition, during the period 1994–1996, monetary policy and floating the interest rate were applied. That was then accompanied by a decrease in the inflation rate, which led to the increase of the real interest rate, which negatively affected investment and economic growth, while simultaneously increasing poverty and unemployment.

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[23] Al-Hindawi, H. (2001), *The Transmission Mechanism of the Monetary Effect in the Jordanian Economy*, unpublished Master's thesis, Amman: Jordan University: 36.

[24] Central Bank of Jordan (2000) *The Thirty Seven Annual Report*. Amman, Jordan: Research Department.

[25] GDP in millions of Jordanian Dinars (JD) (the exchange rate is 0.708 JD per dollar).

[26] Per Capita in Jordanian Dinars (JD) (the exchange rate is 0.708 JD per dollar), (it should be notes that population of Jordan raise rapidly from 3.8 million by 1992 to 4.6 million by 1998, and to 6.2 million by 2009, this is largely influence of immigration from Iraq and Gulf Countries. Therefore, GDP per capita data should be interpreted with care).

3.3.3. The 1999–2001 Period

During the period 1999–2001, there was an agreement with the International Monetary Fund on the third adjustment programme. That had the same aims as the second adjustment programme, which included achieving high economic growth rate, decreasing inflation and increasing foreign reserves, by striving to attain stability for the Jordanian Dinar exchange rate and reducing the budget deficit (Maciejewski, 1987).

Jordan's economic performance generally exceeded the programme's (1999–2001) objectives (IMF, 2002). It was characterized by stronger-than-expected growth, low inflation, the maintenance of a comfortable level of official international reserves, and a significant reduction in net public debt in relation to GDP. Real GDP grew by 4.2% in 2001, despite the adverse effects of the September 11 events and the worsening conflict in the West Bank and Gaza. This growth was fairly broad based, and was led by strong increases in domestic exports (25%), construction (11.1%), transport and communications (5.6%), and manufacturing (4.9%). At the same time, consumer price inflation averaged less than 2%.

Official international reserves remained stable during 2001 at about US$2.6 billion, equivalent to seven months of import cover, 30% of JD broad money, and over 100% of reserve money. Government and government-guaranteed net debt declined by 2 percentage points to 94% of GDP – a cumulative reduction of 65 percentage points over the last decade. The Amman Stock Exchange index rose by 30% in 2001, buoyed by the strong performance of the financial sector and the US ratification of the Free Trade Agreement (IMF, 2002).

3.4. Major Developments of the Amman Financial Market (AFM)

The establishment of public shareholding companies in Jordan began in the early 1930s. Ever since, the Jordanian public have purchased and traded shares of public companies. The first corporate bonds were issued in the country in the early 1960s. Originally, capital market transactions were handled in individual brokerage offices without any overall administrative organization.

Because of the increasing economic importance of the stock market, Jordan was required to establish a stock exchange. Establishing a bourse had been an idea in the minds of many Jordanian economists since the early 1960s, and it became a reality in 1976. The market began with the establishment of the Amman Financial Market (AFM) to meet the saving and investment demands of that time.

3.4.1. Amman Financial Market

The Amman Financial Market (AFM) was established in 1976 and on 1 January 1978 it had its first day of business as a legally and financially independent public financial institution under the patronage of the Ministry of Finance. It is a general independent financial institution (Shibli, 1999), which enjoys both supervisory and executive roles.

The AFM is responsible for the promotion and development of both primary and secondary capital markets in Jordan.

The primary market, or the initial public offers market, is where new shares and bonds are issued. There is no specific pattern for the issuance of stocks and bonds at the primary

market. The secondary market is comprised of first and second markets, the bond market, off-the-trading-floor transactions, and the natural funds market.[27]

The AFM aims to:

- Mobilize savings by encouraging investments in securities and channelling savings to serve the interests of the national economy.
- Regulate and control the issuance of securities and dealing thereof to ensure the soundness, ease and speed of transactions, as well as ensure the protection of both the national financial interests and the interests of small savers.
- Gather and publish relevant data (Central Bank of Jordan, 1989, p. 26).

The market started with the stock of 66 listed companies in 1978 and the capitalization of the stock market was JD 286 million, while the trading volume was JD 5.7 million. The listed companies of the market were officially grouped into four sectors: banking and finance; insurance; services; and industrial. By 2009, the listed companies in the ASE had increased to 272. The trading volume capitalization rose from JD 286 million in 1978 to JD 22 billion in 2009.

Table 3.3 illustrates the number of companies, the trading volume and the market capitalization during the period 1978–2009. As shown in the table, the number of listed companies rose during the period from 1978 to 1985, and then decreased during the years of 1988 to 1990. This decline was mainly attributed to merger activity in the market, particularly in the insurance sector (Al-Gharaibeh, 2004). There were 158 companies listed on ASE by the end of 2002, compared with 161 by the end of 2001. During the year 2002, the shares of three companies were listed and the shares of four companies were de-listed. This included

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[27] Investment Banking and Capital Markets (2002), *The Jordanian Economy/Country Report*, Jordan.

two merger transactions between four companies to form two new companies[28]. Since 2003, the number of companies has increased every year and reached 272 by 2009. Figure 3.1 below demonstrates the changes in the number of companies from 1978 to 2009.

Figure 3.1: Number of Companies of Amman Stock Exchange (1978–2009)
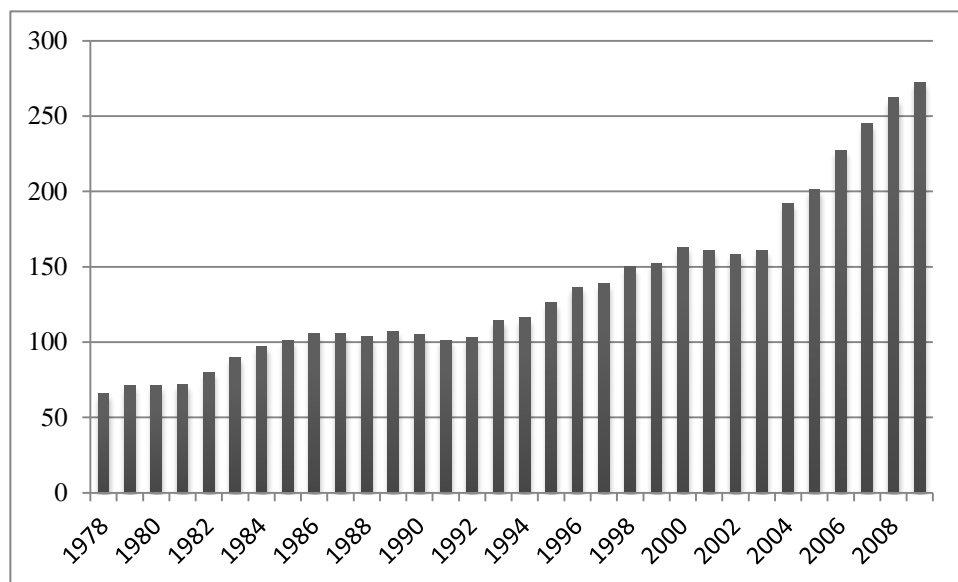
Table 3.3 shows the market capitalization of companies listed on ASE. It was JD 286.1 million in 1978, and in 2009 it reached JD 22 billion (the Jordanian government pegged the Jordanian Dinar to the US dollar at the rate of 0.708 per dollar). However, during this period, it went down to JD 3509.6 million in 2000 compared to JD 4137.7 million at the end of 1999. It is recognized that the Jordanian stock market is a thin market; consequently, there is limited information available for investors. Hence, risk is high, which in turn raises the cost of obtaining external financing. Moreover, in 2005, market capitalization reached the highest level (JD 26 billion) before it dropped in 2006 to JD 21 billion. Then, in 2007, it reached the highest level in AFM history at JD 29 billion; however, the global financial crisis (2007) affected the financial sector in Jordan, resulting in a drop in market capitalization in 2008 and

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[28] Amman Stock Exchange (2002), *Annual Report*, Amman, Jordan: Research and External Relations Department.

2009. Figure 3.2 illustrates the changes in market capitalization in the AFM from 1978 to 2009.

Figure 3.2: Market Capitalization of Amman Stock Exchange (JD) (1978–2009)
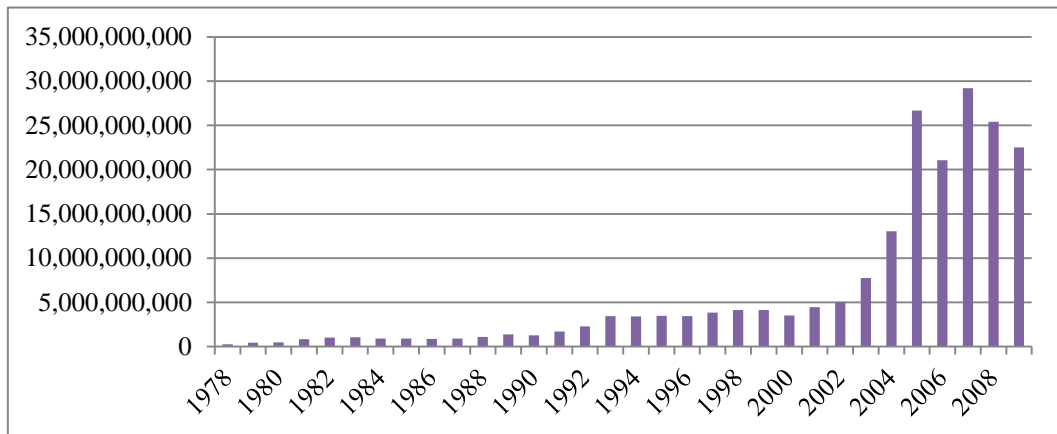
Table 3.3 shows the value traded in the ASE by sectors during the period 1978–2009. In 1978, the trading volume was JD 5 million and in 2009 it was JD 9 billion. Figure 3.3 demonstrates the change in value traded from 1978 to 2009.

Figure 3.3: Value Traded of Amman Stock Exchange (JD) (1978–2009)
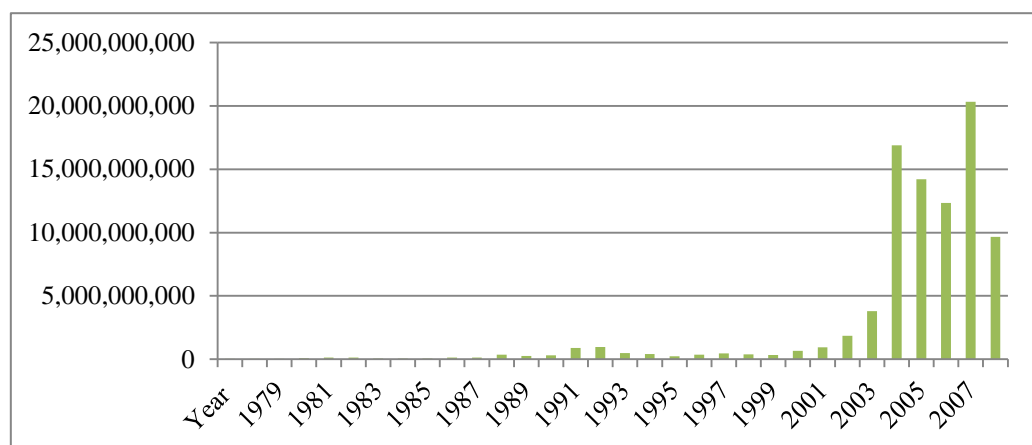
Table 3.3: Number of Listed Companies, Trading Volume and Market Capitalization in the ASE (1978–2009)

Year	Number of Listed Companies	Value Traded (JD)	Market Capitalization (JD)
1978	66	5,615,891	286,118,483
1979	71	15,843,159	452,291,527
1980	71	41,431,076	495,526,486
1981	72	75,417,027	834,614,580
1982	80	128,288,963	1,034,818,001
1983	90	141,427,111	1,053,358,110
1984	97	59,318,623	911,686,265
1985	101	66,730,872	926,905,946
1986	106	69,522,993	891,808,105
1987	106	148,178,293	929,380,379
1988	104	132,625,222	1,104,677,475
1989	107	367,589,840	1,400,406,829
1990	105	268,885,973	1,293,210,890
1991	101	302,836,729	1,707,095,165
1992	103	886,950,983	2,295,649,288
1993	114	968,613,802	3,463,930,183
1994	116	495,076,052	3,409,293,505
1995	126	418,958,544	3,495,438,521
1996	136	248,583,344	3,461,156,739
1997	139	355,244,623	3,861,951,390
1998	150	464,374,268	4,156,558,122
1999	152	389,476,334	4,137,711,690
2000	163	334,724,633	3,509,640,709
2001	161	668,652,674	4,476,364,817
2002	158	950,272,995	5,028,953,990
2003	161	1,855,176,028	7,772,750,866
2004	192	3,793,251,050	13,033,833,515
2005	201	16,871,051,948	26,667,097,118
2006	227	14,209,870,592	21,078,237,222
2007	245	12,348,101,910	29,214,202,327
2008	262	20,318,014,547	25,406,265,528
2009	272	9,665,310,642	22,526,919,427

Table 3.3 shows that the value traded increased from JD 1.8 billion in 2003 to JD 3.7 billion in 2004 and reached 9.6 billion in 2009. In 2006, the service sector had the largest value traded with JD 9.2 billion; 65% of the total value traded. The banking sector followed with a value traded of JD 2.8 billion, 20 % of the total value traded. The industry sector had a value

traded of JD 2.0 billion, 14% of the total value traded. Finally, the insurance sector followed with a trading volume of JD 89 million, 1 % of the total value traded. Table 3.4 displays the value traded from 1978 to 2006[29].

Table 3.4: Value Traded Per Sector in the ASE (1978–2006)

Year	Banking	Insurance	Services	Industrial	Total
1978	1,909,388	211,581	605,792	2,889,130	5,615,891
1979	6,837,164	932,825	1,315,201	6,757,969	15,843,159
1980	17,339,167	931,044	5,944,764	17,216,101	41,431,076
1981	28,903,515	6,619,151	7,828,845	32,065,516	75,417,027
1982	54,198,621	13,553,451	18,552,277	41,984,614	128,288,963
1983	95,726,894	6,534,397	16,634,169	22,531,651	141,427,111
1984	34,387,848	2,642,570	6,243,573	16,044,632	59,318,623
1985	47,429,847	2,574,124	3,766,969	12,959,932	66,730,872
1986	39,719,883	4,212,281	4,610,438	20,980,391	69,522,993
1987	40,735,013	7,404,634	6,297,346	93,741,300	148,178,293
1988	42,273,622	3,098,922	9,459,852	77,792,826	132,625,222
1989	86,698,562	7,841,808	32,713,056	240,336,414	367,589,840
1990	71,177,094	6,422,945	30,840,497	160,445,437	268,885,973
1991	75,523,292	4,794,580	35,435,609	187,083,248	302,836,729
1992	202,807,731	25,309,246	128,018,415	530,815,591	886,950,983
1993	282,551,879	32,946,207	127,939,623	525,176,093	968,613,802
1994	186,791,403	7,845,031	91,257,939	209,181,679	495,076,052
1995	149,619,498	7,364,131	110,160,986	151,813,929	418,958,544
1996	83,095,667	3,105,991	51,029,859	111,351,827	248,583,344
1997	165,445,904	4,528,160	55,220,936	130,049,623	355,244,623
1998	192,664,521	5,931,034	46,979,741	218,798,972	464,374,268
1999	128,121,996	7,618,634	50,800,991	202,934,713	389,476,334
2000	128,555,301	4,143,961	54,073,563	101,023,712	287,796,537
2001	300,276,414	6,220,168	92,935,515	262,934,343	662,366,440
2002	349,776,183	11,418,714	114,074,787	471,434,261	946,703,945
2003	524,838,111	39,141,702	440,921,031	850,275,166	1,855,176,011
2004	1,692,995,377	43,427,020	1,000,692,488	1,056,136,165	3,793,251,050
2005	6,043,405,201	179,878,428	8,003,977,852	2,643,790,467	16,871,051,948
2006	2,870,080,566	89,032,967	9,233,082,106	2,017,674,953	14,209,870,591

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[29] Amman Stock Exchange (2006), *Annual Report*, Amman, Jordan: Research and External Relations Department.

In May 1997, a new securities law divided the AFM's activities and functions into three new bodies:

- Jordan Securities Commission (JSC)

- Amman Stock Exchange (ASE)

- Securities Depository Centre (SDC)

This structure separated the monitoring and executive roles.[30]

3.4.1.1. Jordan Securities Commission (JSC)

The JSC is one of the three entities established in accordance with Securities Law No. 23 of 1997. The JSC is a government agency affiliated with the Office of the Prime Minister, and it can be considered a financially and administratively independent institution.

Its function is to assume responsibility for regulating and monitoring the capital market in Jordan, and to provide an appropriate climate to assure sound transactions and to protect the rights of market participants. The JSC also plans to establish an investment culture in the capital market aimed at encouraging investment and increasing the national capital.

3.4.1.2. Amman Stock Exchange (ASE)

The ASE was established as a private non-profit institution with administrative and financial autonomy. It is the only body licensed as a regular market for securities dealings. The ASE has issued rules and procedures for the electronic trading of securities. The stock market regulates the electronic trading procedures for all companies in the market. These regulations

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[30] Investment Banking and Capital Markets (2002), *The Jordanian Economy/Country Report*, Jordan.

provide positive support for investors and the transparency of their dealings and provide greater confidence in the stock market and support its effort to attract investment.

There are many other characteristics of the ASE, which include:

- It is a thin and small market. Despite the increasing number of listed companies, the market is dominated by the banking sector, which represents 62% of market capitalization as of December 2005, followed by the services (20%), industrial (16%) and insurance (2%) sectors. The banking sector is itself dominated by the Arab Bank, which represents 41% of the total market capitalization (Saadi-Sedik and Martin, 2006).

- For any listed` stock, price variations are not allowed to exceed, in either direction, 10% of its opening price (subsequently amended to 5%) on any trading day.

- The daily trading session of the ASE, on average, lasts two hours. Stock price quotations are transmitted live from the trading floor via Reuters Monitor Network Worldwide.

- The listed stocks are traded on the trading floor of the ASE by auctioning (Civelek and Al-Khouri, 1991).

3.4.1.3. Securities Depository Centre (SDC)

The SDC was established under the temporary Securities Law No. 23 in 1997. It started running in May 1999 as a private non-profit institution, financially and administratively independent. It is responsible for registering securities, clearing and organizing trades, settling payments and accepting share deposits.

The SDC is one of the major institutions in the Jordan Capital Market as it holds the ownership registers of all issued shares. It has been assigned, in cooperation with the Jordan

Securities Commission and the Amman Stock Exchange, the task of developing the Jordan Capital Market.

3.5. Conclusion

It may be expected that the rapid development of the Jordanian economy would be accompanied by increases in the level of market efficiency. However, it should be noted that, at the same time, there has been a strengthening of the observance of Islamic customs. This is likely to have had a significant influence on the ways in which financial markets operate.

According to Tal (2005), several factors gave rise to increased adherence to Islamic practices. The 1979 Islamic Revolution in Iran enhanced the ascent of Islamic fundamentalism in the Middle East. The Shah's ousting, the rise of Khomeini, the anti-Western and anti-royalty atmosphere pervasive in Iran threatened Jordan, in view of the fact that king Hussein was identified as a long-time ally of the West and friend of the Shah, and also because the Islamic movement in Jordan derived inspiration from the triumph of Iran's Islamic Revolution.

At the same time, Jordan's socio-economic plight hastened the Islamic movement's transformation into becoming the regime's main opposition, particularly in the 1980s. The primary cause of the crisis was Jordan's economic dependency on Arab oil in light of major changes in the Arab oil economy. In the 1970s and early 1980s Jordan enjoyed prosperity that paralleled the economic boom in the neighbouring Arab oil-producing states; but with the decline in oil prices in the early 1980s, Jordan's revenues plummeted, its economic growth was stunted, and Jordan suffered from a severe economic crisis throughout the decade. Against the background of the economic slump, the disappointment of pan-Arabism and socialist movements in the Arab world and elsewhere (for example, the Soviet Union and Eastern Europe), and the lack of ideological alternatives, the Islamic movement's popularity

increased rapidly. The Muslim Brotherhood's slogan *"Islam is the solution"* was favoured over any foreign ideology proffered by the infidels.

Since the 1980s, the increased interest in incorporating Islam more fully into daily life has been expressed in a variety of ways in Jordan. Women wearing conservative Islamic dress and headscarves are seen with greater frequency in the streets of urban as well as rural areas; men with beards are also seen more often. Attendance at Friday prayers has risen; as has the number of people observing Ramadan. Ramadan has also begun to be observed in a much stricter fashion; all public eating establishments are closed during Ramadan and no alcohol is sold or served. Accordingly, it is expected that Jordanian investors during the month of Ramadan might respond differently to the market information released, than in the other months of the year.

From a market efficiency perspective, it can be identified that the Jordanian capital market is mature by regional standards and has been in operation for thirty years. A major reform was implemented in 1997 to improve the market's structure and regulation. Three new institutions replaced the Amman Financial Market (AFM), namely: (i) the Jordan Securities Commission (JSC); (ii) the Amman Stock Exchange (the ASE, which started its operations on 11 March 1999); and (iii) the Securities Depository Centre (SDC). 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 recent performance of the ASE has been exceptional, partly reflecting long- standing domestic efforts to promote financial equity markets. The average annual increase of the ASE index during the period 2000–2005 has been 36%, which is impressive compared with the historical average of 13%. Since the establishment of the Jordanian capital market in 1978, its legal foundations have been strengthened and its products and liquidity improved. As a result,

it is more likely that the level of efficiency in the Jordanian stock market improved after 1999. However, it should be noted that, despite the increasing number of listed companies, the market is still dominated by the banking sector, which represented 62% of market capitalization as at December 2005. The banking sector is itself dominated by Arab Bank, which represents 41% of the total market capitalization. How efficient the Jordanian market is in the light of these changes and the increasing impact of Islamic customs on market trading remains to be seen.

4. Chapter Four: Theoretical Framework, Hypotheses and Dataset

4.1. Introduction

The objective of this chapter is to describe and discuss the methods and tools the researcher uses to empirically examine evidence in respect to the level of efficiency of the Amman Stock Exchange (ASE) for the period 1992–2007. This chapter presents the data used for the empirical analysis found in Chapters Five and Six. Section 4.2 illustrates that the main sample (1992–2007) is divided into two sub-samples in order to facilitate the examination of the robustness of the research. Section 4.3 presents the theoretical framework and the hypotheses tested and examined in this research. Section 4.4 presents the statistical definition of *market efficiency* applied in the research conducted; this is examined in the context of the *random walk hypothesis* (the original model of weak form efficiency is that the time series of stock prices follows a random walk). The random walk model presumes that successive prices in the time series are serially independent and that their probability distribution is identical through time. Section 4.5 demonstrates the design of the tests utilized in Chapters Five and Six. The justification of applying these tests is then presented in Section 4.6. A conclusion follows in section 4.7.

4.2. Data

The daily closing prices from the ASE daily reports were collected for the period of 1 January 1992 to 31 December 2007. After holidays were excluded, this provided a total of 3914 daily observations, 819 weekly observations and 192 monthly observations. Returns were

calculated as the first differences in the natural logarithms of the stock market prices[31]. Graph 4.1 illustrates the movements in the ASE price index in the HA[32] part and the DLM[33] part illustrates the movements in ASE returns.

Graph 4.1: ASE Price Index and Daily Returns from 01/01/1992 to 31/12/2007
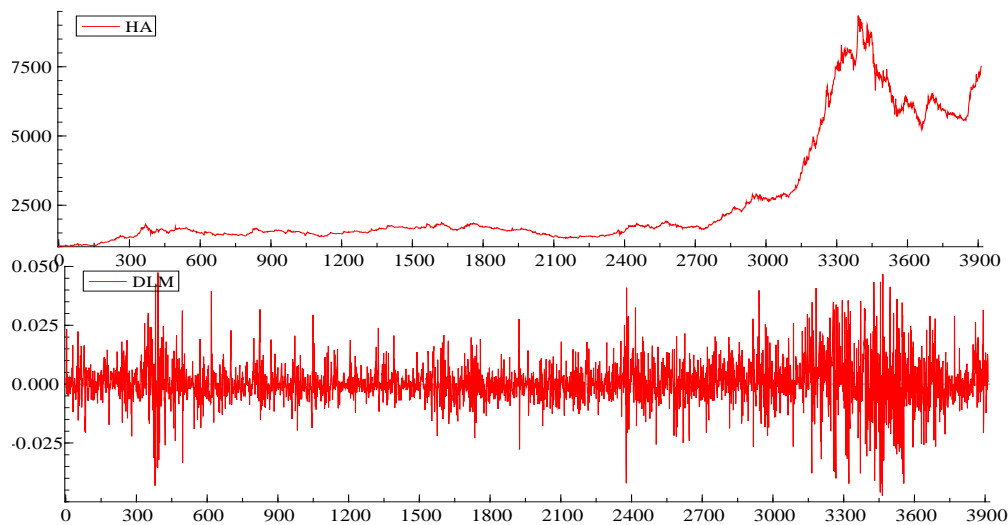
Graph 4.1, in the HA part, shows that after 2004 the price index jumped rapidly. In January 2004 it was 2668.2 and by the end of 2007 it was 7519.2; it increased twice in four years. Moreover, the DLM part of Graph 4.1 illustrates that, after the period of 2004 to 2007, the returns of the ASE were more volatile than normal. Therefore, the whole observation period is divided into two sub-periods to determine whether the result obtained from the main sample period will be confirmed by the two sub-samples.

The first sub-sample ran from 1 January 1992 to 28 February 1999; the second sub-sample ran from 1 March 1999 to 31 December 2007. After holidays were excluded, these

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[31] Number of observations of price index returns is 3912 for the main sample (1992–2007) as first trading day and last trading day are excluded.

[32] HA: ASE price index from 01/01/1992 to 30/12/2007.

[33] DLM: ASE daily returns from 01/01/1992 to 30/12/2007.

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respectively provided 1752 and 2157[34] daily observations. Graphs 4.2 and 4.3 illustrate the

movement of the price index during the different periods.

Graph 4.2: ASE Price Index and Daily Returns from 01/01/1992 to 28/02/1999
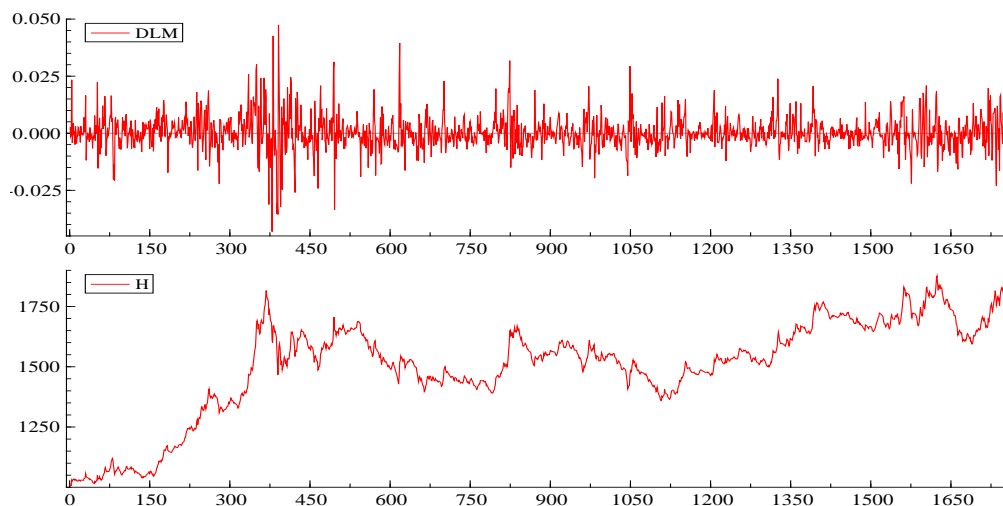
Graph 4.3: ASE Price Index and Daily Returns from 01/03/1999 to 31/12/2007
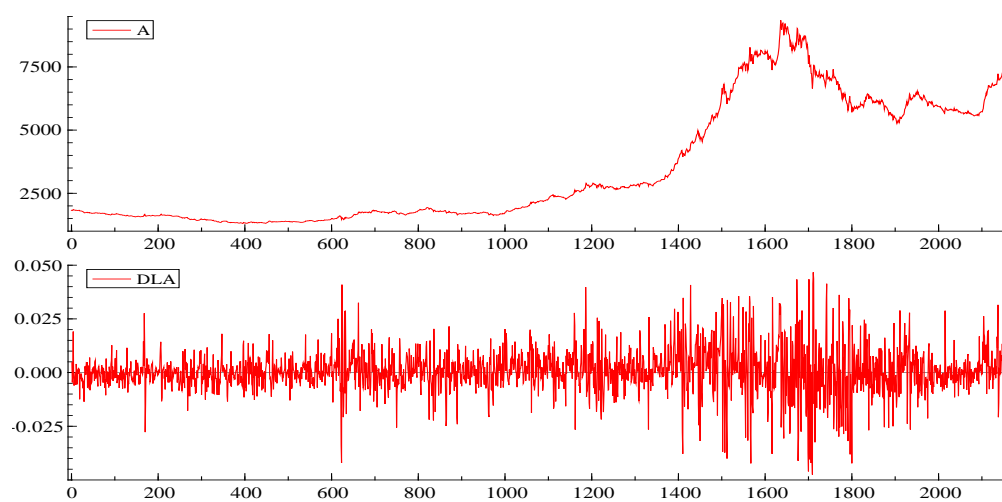
Graph 4.2, for the sample 1992–1999, illustrates that during this period the price index had

positive trends. Similarly, Graph 4.3, for the sample 1999–2007, shows exactly the same

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[34] The sum of the observations of first sample (1992-1999) and the second sample (1999-2007) is 3909, because the first and the last day in the first sample (1992-2007) are excluded as well as the last day in the second sample (1999-2007) to calculate the returns.

movement found in the main sample (1992–2007). Moreover, the graphs show that during the period 2004–2007 the volatility is higher than normal.

Table 4.1 displays the mean, standard deviation, skewness and kurtosis for the three samples. The frequency distribution for the main sample and two sub-samples are not normal. The three samples are positively skewed with values more than zero. Furthermore, the three samples have positive kurtosis with values of more than 3.

Table 4.1: Descriptive Statistics of Daily Returns in the ASE for the Three Samples

Sample Period	Number of Observations	Mean	Std. Deviation	Skewness	Kurtosis
01/01/1992 to 31/12/2007	3912	0.0005139	0.00914534	0.114	4.405
01/01/1992 to 28/02/1999	1752	0.0003394	0.00721871	0.396	5.753
01/03/1999 to 31/12/2007	2157	0.0006567	0.01045421	0.011	3.261

Most empirical financial research assumes that the distribution of security returns does not adversely affect either the one or two sample t-statistics. This assumption has its roots in the asymptotic properties of the t-statistics. Lehmann and Romano (2005) show that, asymptotically, both the one and two sample t-statistics are relatively insensitive to non-normality. Thus, both statistics are valid regardless of the underlying distribution. This does not imply, however, that the t-statistics will necessarily have more power than other statistics because, as Lehmann notes, the t-statistic is optimal only when the underlying sample distribution is normal. As a result, when the underlying sample distribution is non-normal, the performance of the t-statistic becomes an empirical question.

This research does not include dividend payments in the daily return series, as this information is not available. Mills and Coutts (1995) state that lack of information about dividend payments in the daily return series does not invalidate the results; moreover,

Lakonishok and Smidt (1988) assert that their findings of anomalies remain unchanged irrespective of whether the dividend adjusted data was used or not.

4.3. Theoretical Framework and Hypotheses

As mentioned earlier in Chapter Two, this research will apply *market efficiency* as the main theoretical framework, given its emphasis on statistical analysis. However, examining the results from just an efficiency perspective is highly limiting as the observed behaviour of Jordanian investors will be influenced by both Islamic ethical considerations as well as behavioural psychological forces. These are likely to be especially important during the holy month of Ramadan. For this reason, the interpretation of the efficiency results will be made in the context of the concepts and ideas identified in both behavioural finance and ethics-based literature.

4.3.1. Hypotheses

The aim of this research is to contribute to the debate in relation to the market efficiency of one of the emerging markets, namely the Amman Stock Exchange (ASE). The focus of the research is to examine whether or not the Islamic culture of Jordanian society has any specific impact on market efficiency.

In order to achieve the aim of this research, the analysis commences in Chapter Five by testing the random walk hypothesis, employing the standard Western Gregorian calendar as the framework. In Chapter Six, potential calendar effects are then explored to identify whether historical information about the ASE is useful for market participants to gain higher returns; these are examined using both the Gregorian calendar and the Islamic calendar.

After confirming that the ASE does *not* follow a random walk and identifying the existence of a significant calendar effect (for both the Gregorian and Islamic calendars), the research explores the relation between risk and return through an examination of volatility. This is undertaken in the context of the Islamic calendar in Chapter Seven. The justification for this analysis is found in Chapter Six, which identifies that returns in Ramadan are higher than in any other month of the year and also that volatility increases towards the end of the month of Ramadan (which can be interpreted as a religion-based social mood effect). The last substantive chapter of the analysis, Chapter Seven, focuses on social mood effects by examining the influence of, and the interaction between: Ramadan effects, weather mood effects and biorhythm mood effects on ASE returns and volatility.

Within the above theoretical context, the research develops a series of different hypotheses for each chapter of the analysis. In Chapter Five, the hypothesis tested is as follows:

Ho: Amman stock market returns follow a random walk.

H1: Amman stock market returns do not follow a random walk.

In Chapter Six, testing is conducted for the type of calendar anomalies found in the literature using the Gregorian calendar as well as the Islamic calendar. Four different hypotheses are identified in Chapter Six. The first hypothesis tested is in respect to the day-of-the-week effect:

Ho: Amman stock market returns exhibit no day-of-the-week effect.

H1: Amman stock market returns exhibit a day-of-the-week effect.

The second hypothesis tests in respect to the month-of-the-year effect:

Ho: Amman stock market returns exhibit no month-of-the-year effect.

H1: Amman stock market returns exhibit a month-of-the-year effect.

The remaining hypotheses test the impact of the holy month of Ramadan on market efficiency by testing for the following using Islamic calendar data.

In respect to an Islamic month-of-the-year effect:

Ho: Amman stock market returns exhibit no Islamic month-of-the-year effect.

H1: Amman stock market returns exhibit an Islamic month-of-the-year effect.

In respect to the profitability of trading rules based on religious-holiday calendar anomalies:

Ho: Abnormal profits made in the month of Ramadan do not cover the transaction cost.

H1: Abnormal profits made in the month of Ramadan cover the transaction cost.

In Chapter Seven, the research delves beyond the issue of informational efficiency to explore the relationship between risk and return in the context of volatility. Fama (1991) argues that efficiency and volatility are unrelated. However, the author of this thesis argues that, in the context of the holy month of Ramadan, this may not be the case. The focus is specifically on the impact that the holy month of Ramadan has on volatility levels via religion-based social mood effects as well as other social mood factors (weather and biorhythm variables).

As stated in Chapter six, there are considerable changes in volatility levels associated with specific periods within Ramadan. A further contribution that this thesis provides to the literature is the modelling of the associated volatility using a GARCH analysis. Previous research has examined the relationship between mood proxies and returns or variances. However, the author of this thesis has not found any literature relating specifically to the

impact of the Muslim religious holiday on volatility. Thus, four hypotheses are examined in Chapter Seven as follows.

In respect to the month-of-Ramadan effects:

Ho: Volatility levels in stock market returns do not differ during Ramadan.

H1: Volatility levels in stock market returns differ during Ramadan.

In respect to the social mood effects:

Ho: Volatility levels in stock market returns are not affected by mood.

H1: Volatility levels in stock market returns are affected by mood.

As well as examining the ASE for inefficiencies within a statistical framework, the thesis also applies behavioural finance and ethics-related analyses in an attempt to explain why these inefficiencies occur. This element of the thesis lays emphasis on the importance of social mood in influencing investor behaviour.

4.4. Statistical Definition of Efficient Market Hypothesis and Random Walk

Fama (1970) presented a general notation explaining how investors generate price expectations for stocks. Cuthbertson et al. (1996) describe it as:

$$\mathrm{E}\left(p_{j,t+1} \middle| \Phi_t \right) = \left[1 + \mathrm{E}\left(r_{j,t+1} \middle| \Phi_t \right) \right] p_{j,t} \qquad \textbf{Equation 4.1}$$

Where:

E: is the expected value operator.

$p_{j,t+1}$: is the price of security j at time $t+1$.

$r_{j,t+1}$: is the return on security j during period $t+1$.

Φ_t : is the set of information available to investors at time t.

Furthermore,

$E\left(p_{j,t+1}\middle|\Phi_t\right)$: is the expected end-of-period price on stock j, given the information available

at the beginning of the period Φ_t .

$\left[1 + E\left(r_{j,t+1}\middle|\Phi_t\right)\right]$: is the expected return over the forthcoming time period of stocks having the

same amount of risk as stock j.

According to the EMH, stock market traders cannot earn abnormal profits on the available

information set Φ_t other than by chance. Moreover, if the share price overvalued or

undervalued, that means:

$$\chi_{jt+1} = p_{j,t+1} - E\left(p_{j,t+1}\middle|\Phi_t\right)$$ **Equation 4.2**

Where:

χ_{jt+1} : denotes the extent to which the actual price for security j at the end of the period

differs from the price expected by investors based on the information available Φ_t .

As a result, in an efficient market it must be true that:

$$E\left(\chi_{j,t+1}\middle|\Phi_t\right) = 0 \qquad\qquad \textbf{Equation 4.3}$$

This means that the information set Φ_t is always reflected in the stock price. Therefore, the *rational expectations* of the returns for a particular stock according to the EMH can be presented as:

$$p_{t+1} = E\, p_{t+1} + \varepsilon_{t+1} \qquad\qquad \textbf{Equation 4.4}$$

Where:

p_{t+1} : is the stock price.

ε_{t+1} : is the forecast error.

Therefore:

$p_{t+1} - E\, p_{t+1}$ should be zero on average and should be uncorrelated with any information Φ_t.

$E\left(\chi_{j,t+1}\middle|\Phi_t\right) = 0$ when the random variable (good or bad news), the expected value of the forecast error, is zero:

$$E_t \varepsilon_{t+1} = E_t\left(p_{t+1} - E_t\, p_{t+1}\right) = E_t\, p_{t+1} - E_t\, p_{t+1} = 0 \qquad \textbf{Equation 4.5}$$

If the stock market returns indicate *white noise*, *random walk*, *martingale* and *fair game* properties, then this is evidence of market efficiency (Samuelson, 1965). In such

circumstances, returns will not produce any *arbitrage* opportunities and therefore stock market speculators will not be able to gain abnormal profits. According to *fair game theory*, the stock market participants will correct the stock price when an *arbitrage* opportunity arises and as a consequence the price levels will be maintained at the equilibrium prices or *fair price*. This property can be modelled as a random walk:

$$Y_t = Y_{t-1} + \varepsilon_t \qquad\qquad \textbf{Equation 4.6}$$

4.5. Design of Tests

4.5.1. Runs Test

This research utilizes the Wald-Wolfowitz (1940) runs test to test for the randomness of the series. Runs tests are used to examine for serial dependence in share price movements and compare the expected number of runs from a random process with the actual observed number of runs.

According to Poshakwale (1996), the Wald-Wolfowitz runs test is independent of the normality and variance consistency within data. A run is defined as a series of identical signs that are preceded or followed by a different sign. Given a sequence of observations, the runs test examines whether the value of one observation influences the values taken by later observations. If there is no influence (the observations are independent), the sequence is considered random. For example, the sequence "+ + + + - - - - + + + - - + + + + + - - -" consists of six runs, three of which consist of +s and three of −s. The runs test is based on the null hypothesis that the two elements + and - are independently drawn from the same distribution. Under the null hypothesis, the number of runs in a sequence of length N is a random variable whose conditional distribution given the observation of N_+ positive values and N_- negative values ($N = N_+ + N_-$) is approximately normal.

The expected number of runs is calculated as follows:

$$E(R) = \frac{2 * N_1 * N_2}{N} + 1 \qquad \text{Equation 4.7}$$

Where:

N_1: Number of positive changes taken into account length of runs

N_2: Number of negative changes taken into account length of runs

N: Sum of N_1 and N_2

In addition, standard deviation is calculated as follows:

$$\sigma_R = \sqrt{\frac{2 * N_1 * N_2 * (2 * N_1 * N_2 - N)}{N^2 * (N - 1)}} \qquad \text{Equation 4.8}$$

The test statistics Z for the runs test is used as follows:

$$Z_1 = \frac{R_1 - E(R)}{\sigma_R} \qquad \text{Equation 4.9}$$

4.5.2. Serial Correlation Test

Serial correlation tests are used to further examine the ASE for a random walk. The statistical significance of any first order serial correlation is identified using t-tests. Serial correlation tests with a lag of up to 5 were examined. Serial correlation is calculated as:

$$\alpha_k = \frac{\sum_{t=k+1}^{n} \left(Y_t - \bar{Y} \right) \cdot \left(Y_{t-k} - \bar{Y} \right)}{\sum_{t=1}^{n} \left(Y_t - \bar{Y} \right)^2}$$

Equation 4.10

Where:

Y_t : is the current rate of return.

$\bar{Y}$: is the mean rate of return,

K: is the number of lags.

T-tests are estimated by:

$$t_I = \frac{\alpha_k \cdot \sqrt{n-2}}{\sqrt{1-\alpha_k^2}}$$

Equation 4.11

The serial correlation (or autocorrelation) test is a widely employed procedure that tests the relationship between returns in the current period and those in the previous period. If no significant correlation is found, the series is assumed to follow a random walk. If the serial correlation is significantly positive, it means that a trend exists in the series, whereas a negative serial correlation indicates the existence of a reversal in price movements.

Fama (1965) recommends that the most direct and intuitive test for a random walk in a time series is to check for serial correlation. A serial correlation coefficient is estimated from two observations of the same time series at different dates. In a random walk the increments are uncorrelated at all leads and lags.

4.5.3. Variance Ratio Test

The variance ratio test (VR) is employed to examine the predictability of equity returns. This method has the advantage of exhibiting good finite-sample properties (Lo and MacKinlay, 1989) and is sensitive to serial correlation. According to Lo and MacKinlay (1989), the main theme of VR is:

> *"that if a stock's return is purely random, the variance of k-period return is k times the variance of one-period return. Hence, the VR, defined as the ratio of 1/k times the variance of the k-period return to the variance of the one-period return, should be equal to one for all values of k."*

The VR test is based on the idea that if the logarithm of a stock price follows a random walk then the variance of the return over k period must be equal to ($k.\sigma^2$). The variance ratio of q-differenced series is given by:

$$VR(q) = \frac{\sum \sigma^2 c(q)}{\sum \sigma^2 a(q)}$$

Equation 4.12

Where:

- The numerator is an unbiased estimator of 1/q of the variance of the qth differenced series.
- The denominator is an unbiased estimator of the first-differenced series.

The standard test statistic is:

$$Z(q) = \frac{VR(q) - 1}{\left[\theta\theta(q) \right]^{1/2}}$$

Equation 4.13

With

$$\theta(q) = \frac{[2(2q-1)(q-1)]}{[3q(nq)]}$$

Equation 4.14

A refined test statistic, Z*(q) which adjusts for heteroscedasticity proposed by Lo and McKinley (1989), is:

$$Z*(q) = \frac{VR(q) - 1}{\left[\varphi*(q) \right]^{1/2}}$$

Equation 4.15

Where:

$$\varphi*(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q} \right] \delta(j)$$

Equation 4.16

And:

$$\delta(j) = \frac{\sum_{t=j+2}^{nq+1} \left(p_t - p_{t-1} - \mu \right)^2 \left(p_{t-j} - p_{t-j-1} - \mu \right)^2}{\left[\sum_{t=2}^{nq+1} \left(p_t - p_{t-1} - \mu \right)^2 \right]^2}$$

Equation 4.17

Both Z(q) and Z*(q) are asymptotically distributed with mean zero and unit standard deviation.

4.5.4. Length-of-Runs Test (Chi-Square Test)

A chi-square test is used to test if a sample of data is derived from a population with a specific distribution. A chi-square test is used to examine whether a series follows this type of random walk by using the following equation:

$$\chi^2 = \sum (Q_i - E_i)^2 / E_i \qquad \textbf{Equation 4.18}$$

Where:

χ^2 : is the chi-square test

Q_i : is the observed frequency count for the *ith* lagged of returns.

E_i : is the expected frequency count for the *ith* lagged of returns.

And:

$$E_i = n \times p_i \qquad \textbf{Equation 4.19}$$

Where:

p_i : is a proportion of population with value *i*.

n: is the number of observations in the sample.

4.6. Justification for the Empirical Tests Employed

A comprehensive review of the literature illustrates that, even when one sort of test (the serial correlation coefficient test, the runs test, the variance ratio test, etc.) fails to reject the random walk hypothesis, the others may actually reject it. When the monthly prices follow a random walk, the weekly prices or daily prices may not. When the returns on indices for a very long period are independent, the returns on indices for a sub-period may be dependent. Therefore, applying a variety of tests to different types of data and comparing the results on the basis of similar types of data will improve the accuracy of the study.

For example, Squalli (2006) examined market efficiency in the represented sectors of the Dubai Financial Market (DFM) and the Abu Dhabi Securities Market (ADSM). Using daily sector indices from the period 2000–2005, variance ratio tests reject the random walk hypothesis in all sectors of the UAE financial markets except in the banking sector of the DFM. Returns in the two financial markets were negatively serially correlated. Runs tests found the insurance sector in the ADSM to be the only weak form efficient sector.

Worthington and Higgs (2006) examined the weak form market efficiency of the Australian stock market. Daily returns from 6 January 1958 to 12 April 2006 and also monthly returns from February 1875 to December 2005 were examined for random walks using: serial correlation coefficient and runs tests, augmented Dickey-Fuller (ADF), Phillips-Perron, and Kwiatkowski, Phillips, Schmidt and Shin unit root tests, and multiple variance ratio tests. The serial correlation tests indicated inefficiency in daily returns and borderline efficiency in monthly returns, while the runs tests concluded that both series are weak form inefficient. The unit root tests suggested weak form inefficiency in both return series. The results of the more stringent and least restrictive variance ratio tests indicated that the monthly returns

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series is characterized by a homoscedastic random walk, but the daily series violated weak form efficiency.

However, Koop (2009) warns about unit root testing since the ADF test exhibits what statisticians refer to as *low power*. Intuitively, a trend stationary series can look a lot like a unit root series and it can be quite difficult to tell them apart. Furthermore, other kinds of time series models can also appear to exhibit a unit root, when in actuality they do not have unit roots. A prime example is the time series model characterized by abrupt changes or breaks, such as stock prices during the crashes.

The main method in this research is a quantitative approach, represented by the econometric analysis of documentary secondary data. The data collected from ASE daily reports for the period 1992–2007.

Additionally, this chapter used parametric and non-parametric tests to analyse ASE returns. The first test used is the Wald-Wolfowitz (1940) runs test for the randomness of the series. This test does not require the data to follow the normal distribution to be employed, therefore, the runs test is a robust test for randomness in investigating serial dependence in stock price movements. It compares the expected number of runs from a random process with the observed number of runs (Poshakwale, 1996).

The second test is the length-of-run test; it provides additional information that the Wald-Wolfowitz (1940) runs test does not provide. Specifically, it examines the length of the runs. It may be, for example, that a strong trending market will show significant numbers of relatively long runs (Bradley, 1968). The chi-square test is a statistical test used to compare observed length-of-run expected values according to the RWH. This test is a robust test, since

it considers the relative size for each length of run (Levine et al., 2001). The null hypothesis states that there is no significant difference between the expected and observed results.

Nevertheless, the ASE is one of the emerging markets and generally these markets can be characterized by thin trading. A problem arises if thin trading causes several or no changes in stock market prices (Mobarek and Keasey, 2000). Thin trading will invalidate the result obtained from the Wald-Wolfowitz runs test. For that reason, the third test is used: a parametric serial correlation test of independence, examining the relationship between returns in the current period with those in the previous period to identify any correlation in successive stock market price changes (Fama, 1970).

The serial correlation test has been a standard method in applied econometric analysis where, in the case of the residuals being serially correlated, the least squares estimator method will be inefficient. Therefore, it can be inconsistent if the regressions contain lagged dependent variables. Furthermore, strong serial correlation is often an indication of the omission of important explanatory variables.

The fourth test applied is the Lo and MacKinlay (1988) variance ratio (VR) test. This test is robust to many forms of heteroscedasticity and non-normality data and is also sensitive to serial correlation.

VR expands on the fact that the variance of a random walk is linear in the sampling interval; therefore, if stock prices are generated by a random walk (possibly with drift), then, for example, monthly sampled variance of stock market returns should be four times larger than weekly sampled variance, relatively. In addition, comparing the variance estimates per unit time (such as variance obtained from weekly and monthly prices) can indicate the credibility of the random walk theory.

Moreover, the robustness of the results is assessed in various ways. First, similar tests are conducted for various sub-samples of the original sample and by trimming outlying observations. Second, applying different testing procedures helps to reach a conclusion of consistency in the findings (e.g. Urrutia (1994) got different findings from run tests and variance ratio tests).

4.7. Conclusion

This chapter has focused on the theoretical framework used to meet the aim of this research. The research hypotheses tested were within the context of the level of *efficiency* in the ASE. In addition, this chapter discussed the statistical definition of market efficiency in the context of the random walk hypothesis.

The statistical tests described and discussed in this chapter (runs test, length-of-runs test, serial correlation test and variance ratio tests) are applied in Chapters Five and Six. These are followed by Chapter Seven, which employs additional statistical techniques relevant to that chapter.

5. Chapter Five: An Examination of Amman Stock Market Returns from the Perspectives of the Random Walk Hypothesis and Behavioural Finance

5.1. Introduction

The primary objective of this chapter is to identify whether there are any variations in the levels of efficiency in the market capitalization weighted price index of the Amman Stock Exchange for the period 1992–2007.

In common with many emerging markets, the ASE has been growing rapidly in terms of the number of listed companies and trading volumes. As mentioned earlier in Chapter Three, listed companies increased from 66 in 1978 to 245 by the end of 2007, and trading volume increased from JD 5.6 million in 1978 to JD 12,348.1 million in 2007. Despite this growth, the ASE is still dominated by the banking sector, which represented 62.3% of market capitalization at the end of 2005. The banking sector is itself dominated by Arab Bank, which represents 41% of the total market capitalization. Consequently, it is unlikely that the ASE will follow a random walk.

This research examines the degree of efficiency of the market within the context of the random walk model. It then discusses any inefficiency found in the context of behavioural finance theory. Behavioural finance is the study of psychological factors that affect the decisions of financial practitioners and the subsequent effect on the financial markets. Behavioural finance is important for market participants, as it explains why and how markets might be inefficient. Self-deception, including errors in the processing of information, is one of the psychological factors that affect investor decisions, and therefore will affect the level of efficiency of a stock market (Redhead, 2008).

This chapter examines the first hypothesis of whether the ASE stock prices follow a random walk by using the following tests:

- Wald-Wolfowitz runs test.

- Length-of-runs test.

- Serial correlation test.

- Variance ratio (VR) test.

This chapter is structured as follows: Section 5.2 discusses and presents the results obtained from the tests; Section 5.3 applies behavioural finance theory to explain the results found; and Section 5.4 presents the conclusions for this chapter.

5.2. Results and Discussion

5.2.1. Runs Test

This part employs the Wald-Wolfowitz runs test for the randomness of the series. This test is based on whether or not differences between the actual and expected runs are statistically significant, where the expected values are the numbers expected to be found if the data follows a random walk.

Table 5.1 compares the actual runs with the expected runs for three samples. The results show that, for the three samples, the total number of runs (actual number of runs) varies from the expected number of runs. The results of these differences are statistically significant, as presented in Figure 5.1; the x-axis shows the sample period, the y-axis shows the z statistics, and the red straight line shows the critical value of the z statistics (2.575).

Table 5.1: Comparing Actual Runs with Expected Runs of Daily Returns for the Three Samples

	1992–1999	1999–2007	1992–2007
Total runs[35]	1044	1346	2393
N1 (positive returns)[36]	891	1066	1959
N2 (negative returns)[37]	862	1090	1955
N (total returns)[38]	1753	2156	3914
E (R)	877	1078	1957

Figure 5.1: Statistical Significance of Z-Test of Daily Returns for the Three Samples
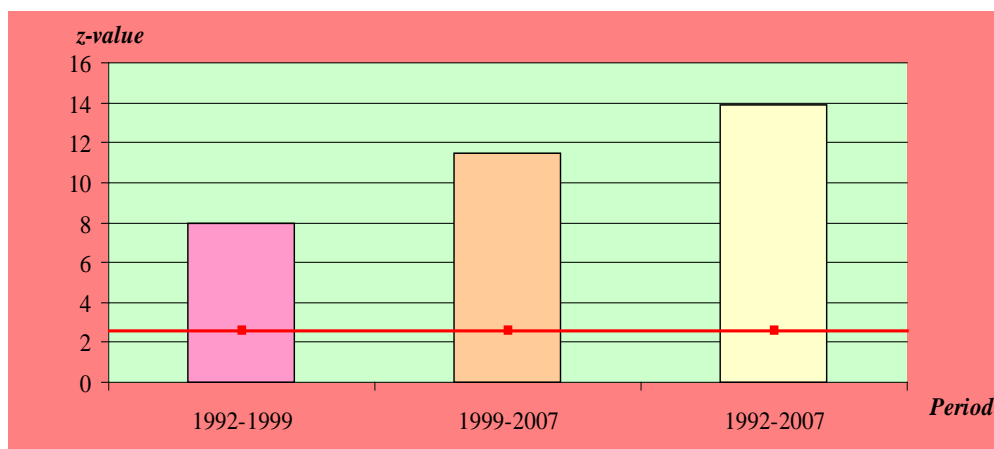
The three samples reject the null hypothesis that the differences between the actual runs and the expected runs have no statistical difference, with 99% confidence. The z statistic for the first sample (1992–1999) is 7.96, for the second sample (1999-2007) is 11.51 and for the full period (1992–2007) is 13.90. The results confirm that as the sample size increased the z value increased and it rejected the null hypothesis. This indicates that the ASE does not follow a random walk.

The second test is the length-of-runs test; it provides additional information that the Wald-Wolfowitz (1940) runs test does not offer. Specifically, it examines the length of the runs.

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[35] Total runs are the sum of positive and negative runs without taking into account the runs length.
[36] N1 (positive returns) is the sum of positive runs taking into account the runs length.
[37] N2 (negative returns) is the sum of negative runs taking into account the runs length.
[38] N (total returns) is the sum of N1 and N2.

5.2.2. Length-of-Runs Test

The runs test is based on whether or not differences between the actual and expected runs are statistically significant, where the expected values are the numbers expected to be found if the data follows a random walk. The length-of-runs test is based on differences between the number of observed and expected observations of runs of a given length.

Table 5.2 below compares the observed runs with expected runs for each length of the three samples. In first sample (1992–1999), the fifth run length is not calculated because the number of observations is less than 5.[39]

Table 5.2: Length-of-Runs Test of Daily Returns for the Three Samples

Length-of-Runs Test						
	1992–1999		1999–2007		1992–2007	
Run Length	Expected	Observed	Expected	Observed	Expected	Observed
1	731.33	570	900.08	757	1631.33	1329
2	321.51	289	395.76	425	717.51	714
3	92.49	148	113.86	121	206.49	270
4	24.24	37	24.81	32	45.01	58
5	-	-	5.12	11	9.29	22

The result shows that, for the three samples, the expected number of runs is different from the observed number of runs for all the lengths. Furthermore, for the three samples, for the 1st and 2nd length, the expected number of observations is greater than the observed number. For the 3rd, 4th and 5th lengths, the observed number is greater than the expected number for the three samples.

The results of these differences are statistically significant and are presented in Figure 5.2; the x-axis shows the sample periods, the y-axis shows the chi-square statistics, the critical

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[39] The minimum expected value in the length-of-runs test should be 5.

value of chi-square are difference between the first sample (degree of freedom is 3) and the other two samples (degree of freedom is 4).

Figure 5.2: Statistical Significance of Chi-Square Test of Daily Returns for the Three Samples
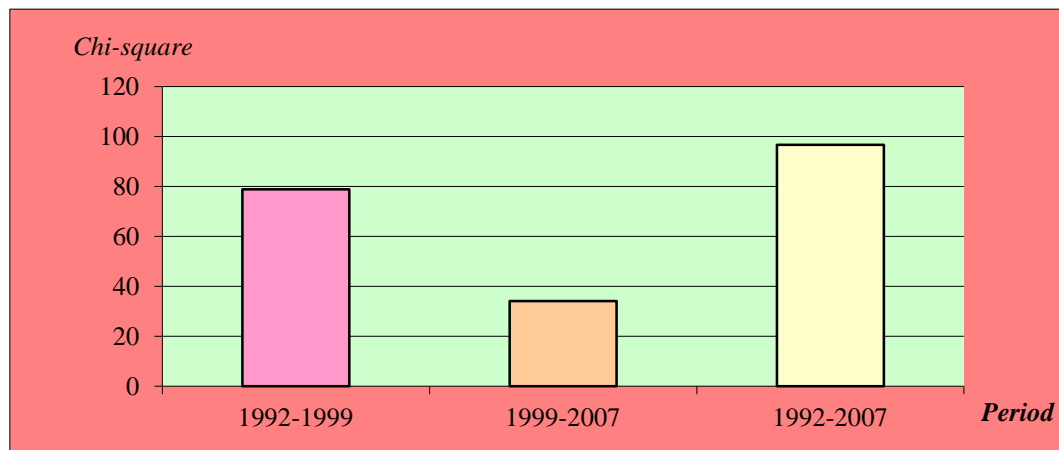
The three samples reject the null hypothesis that the differences between the actual length-of-runs and the expected length-of-runs have no statistical significance, with 95% confidence. Furthermore, the chi-square statistic for the first sample (1992–1999) is 78.9 with a critical value of 7.81, for the second sample (1999–2007) it is 34.18 with a critical value of 9.49, and for the full period (1992–2007) it is 96.71, with a critical value of 9.49. The results confirm the finding obtained from the runs test.

Based on the non-parametric tests (runs test and length-of-runs test), the ASE returns appear to behave inconsistently with the RWH; the results from sub-samples confirm this. Both tests show that the returns are not independent in the main sample (1992–2007) with 95% confidence, as well as in the two sub-samples.

This is consistent with evidence from other studies of emerging markets such as Omran and Farrar's (2006). They investigated the validity of the RWH in five major Middle Eastern

emerging markets (Egypt, Morocco, Turkey, Jordan and Israel) from January 1996 to April 2000.

They applied a range of statistical and econometric techniques. Their results from runs tests show that for Egypt and Morocco the RWH is rejected with 95% and 99% significance, respectively. For Jordan and Turkey, there is evidence for rejecting the RWH with 90% significance only. However, for the Israel index, neither test is significant at any level, suggesting that the series is random (Omran and Farrar, 2006).

5.2.3. Variance Ratio Test

Lo and MacKinlay (1988) presented the variance ratio (VR) test to investigate the random walk hypothesis. The VR test has been used as an alternative to examine the predictability of stock market returns by many studies, such as Grieb and Reyes (1999), Darrat and Zhong (2000), Abrosimova et al. (2005), Hoque et al. (2007), DePenya et al. (2007) and Al-Khazali et al. (2007).

Table 5.3 below shows the VR based on weekly returns of the ASE. In addition, it shows the corresponding z statistics for the null hypothesis that the ratio has a value of 1. For each period sampled, if the value supports the random walk hypothesis, the VR (q) has a value close to 1 for values of q assigned.

Table 5.3: Variance Ratio and Z Statistics of Weekly Returns for the Three Samples

VR(q)	1992–1999		1999–2007		1992–2007	
	Value	Z-Test	Value	Z-Test	Value	Z-Test
2	1.45064	3.25039	0.52795	-4.0851	0.82793	-0.5317
4	1.66678	2.5707	0.63637	-1.682	0.513	-0.8044
8	1.84995	2.0725	0.77897	-0.6466	0.65706	-0.3583
16	0.0479	-1.5601	0.00729	-1.9517	0.03087	-0.6804

The result shows that, for the three samples, the VR (q)s have values not close to 1, leading to the rejection of the null hypothesis for the three samples. The z statistics confirm the result obtained from the variance ratio tests. Overall, the results obtained from variance ratio tests confirm that the ASE does not follow a random walk for VR (2), VR (4), VR (8) and VR (16) at 95% confidence.

To summarize, on the basis of the non-parametric tests (runs test, length-of-runs test and variance ratio test), the returns of the ASE during the period 1992–2007 moved contrary to the RWH, with 95% confidence. Realizing that test results can be highly time-dependent, the full period was divided into sub-periods. The results from the two sub-samples confirm that the ASE does not follow a random walk.

This finding is consistent with other studies of emerging markets such as that of Abraham et al. (2002), which examined the random walk of three major Gulf stock markets (Kuwait, Saudi Arabia and Bahrain) using the VR and runs tests for the period 1992–1998. They rejected the random walk hypothesis for the three markets. They asserted that infrequent trading is widespread in most emerging markets and this could cause rejection of the RWH. However, even after they corrected the data for thin trading in the three markets, the Kuwaiti market still did not follow a random walk, although the Saudi and Bahraini markets did.

Finally, the next test is the parametric test of serial correlation; it is employed to examine the hypothesis of no serial correlation in ASE returns as an alternative test to examine the RWH.

5.2.4. Serial Correlation Test

Serial correlation is a parametric test used in previous research to examine stock market returns, such as the studies by Fama (1965), Solnik (1973), Cooper (1982), Parkinson (1984),

Mookerjee and Yu (1999), Abrosimova et al. (2005), Shiguang (2004) and Starcevic and Rodgers (2007).

The serial correlation test was used to examine randomness in the ASE under the random walk. The statistical significance of any first order serial correlation identified was calculated using *t*-statistics for 2-tails with 99% confidence. A serial correlation test of first lag is reported.

Table 5.4 below presents the serial correlation for the first lag and the statistical significance of any first order serial correlation.

Table 5.4: Serial Correlation Test of Daily Returns for the Three Samples

Serial Correlation Test			
	1992–1999	1999–2007	1992–2007
Serial Correlation of 1st lag	0.286772596	0.17059247	0.203301411
t test	14.21935085	8.697616407	14.24235307
Critical Value	+/- 2.62	+/- 2.62	+/- 2.62

The results show that, for the three samples, the serial correlation of the 1st lag is different from zero. The three samples rejected the null hypothesis of no correlation between the return in time *t* and the return in time *t*-1 with 99% confidence. The three samples show positive serial correlation, which indicates that a trend exists in the series.

This finding is consistent with other studies of emerging markets such as that of Poshakwale (1996); he examined the random walk hypothesis in the context of the India Stock Market, using the serial correlation and runs tests for the period 1987–1994. He found that the India Stock Market does not follow the RWH.

Omran and Farrar (2006) investigated the validity of the RWH in five major Middle Eastern emerging markets (Egypt, Morocco, Turkey, Jordan and Israel) from January 1996 to April

2000; they tested for serial correlation over time between returns based on 6, 12 and 24 lags using a Box-Pierce test. They found highly significant autocorrelation with 99% confidence at all lags for Egypt and Morocco, implying that the series is not completely random. However, for Turkey, Jordan and Israel they could not reject the null hypothesis that the series is random with 90% confidence.

Their findings in Jordan are not consistent with the finding in this research; this could possibly have occurred because they did not examine the first lag, as the first lag produced the strongest evidence of correlation. Furthermore, El-Erian and Kumar (1995) examined the random walk for Jordan and Turkey. Their results show highly significant first-order serial correlations for both Jordan and Turkey.

However, in Jordan, it is possible that autocorrelations in stock returns may result, for example, from infrequent trading (Poterba and Summers, 1988). Hence, rejection of the RWH does not necessarily imply that these markets are not weak form efficient.

On the basis of the parametric test of serial correlation it can be concluded that the returns of the ASE during the period 1992–2007 indicate that the market does not follow a random walk. This is a confirmation of the results from the non-parametric tests (runs test, length-of-runs test and VR test). In addition, after the main sample was divided into two sub-samples, the results from the parametric test show it is consistent with the results from the non-parametric ones, confirming the rejection of the random walk hypothesis for the ASE.

The next part of this chapter will apply behavioural finance theory to the findings in this section. Evidence against the RWH would have important implications for ASE participants and it would invalidate the EMH for the ASE; therefore, behavioural finance is important for market participants, as it will explain why and how markets might be inefficient.

5.3. An Interpretation of the Results from a Behavioural Finance Perspective

Behavioural finance is the study of psychological factors that affect the decisions of financial practitioners and the subsequent effect on the financial markets. Psychological studies in the stock market show there is evidence of systematic biases in the way that investors think, such as overconfidence, illusion of control, hindsight bias, confirmation bias, cognitive dissonance, representativeness, retrievability, narrow framing, mental accounting, conservatism, status quo bias, anchoring, ambiguity-aversion, loss-aversion, regret, emotion, group-think and herding. All the evidence not support the assumption of EMH of rational investors (Redhead 2008).

In a practical sense, the EMH has been built under the assumption that rational investors dominate the stock market; even if it does not require all investors to be rational, it does require that the rational investors outbalance the irrational ones.

As stated in the previous section in this chapter, the results of parametric and non-parametric tests have shown that the ASE does not follow a random walk. This finding highlights that the rational investors in the ASE evidence does not support the irrational ones, especially when the 1st lag serial correlation was found. The irrational investors manipulate the stock market prices to obtain abnormal returns. This is particularly so for the results obtained from the variance ratio, which confirm that the ASE does not following the random walk for VR (2), VR (4), VR (8) and VR (16) at 95% confidence, indicating that there are trading patterns using previous trading prices in the ASE. This may allow market traders who know this information and have experience of Jordanian firms to set stock prices above or below their fundamental value, resulting in an inefficient market.

According to behavioural finance, the style of trades is divided into three types: liquidity trades, portfolio trades and irrational trades. Liquidity trades are when investors have more cash to invest, or need to sell their investments to increase the amount of cash. Pepper and Oliver (2006) indicated that liquidity trades shift the share prices away from their fair value at the efficient level, which will result in the stock market becoming less efficient and the share prices will not reflect all available information.

Portfolio trades that increase portfolio returns and reduce portfolio risk may switch between asset classes such as between cash and shares or between bonds and shares. Furthermore, this category is divided into information trades and price trades. Information trades are responses to news that has implications for share prices. Price trades are responses to price movements that are not justified by new information. Portfolio trades tend to ensure that share prices are efficient in the sense of accurately reflecting all relevant information (Pepper and Oliver, 2006).

Noise trading is trading based on irrationality, including trading based on irrelevant information or psychological biases (Shleifer, 2000). Moreover, noise trades connect to irrational trades on an individual basis. Individual traders could be affected by psychological biases (for example, self-deception). Therefore, noise trading moves the share price away from the efficient prices (above or below the efficient prices, depending upon the net buys or net sells of noise traders). On the other hand, if volume trading is big enough it might keep the level of noise at a low level. Therefore, price trading could be sufficient to avoid large deviations from efficient prices. At times, irrational trading is not at an individual level; it may be that investors operate as a crowd which results in herding. When this group of irrational investors place tremendous pressure on buying specific shares or selling specific shares, it will lead to markets becoming under-pressure. Hence, price trades may be

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insufficient to compensate for the effects of herding in the market. This will potentially lead the market into a crash in share prices or a bubble (Redhead, 2008). Figure 5.3 illustrates the three types of trades.

Figure 5.3: Types of Trades in Financial Markets
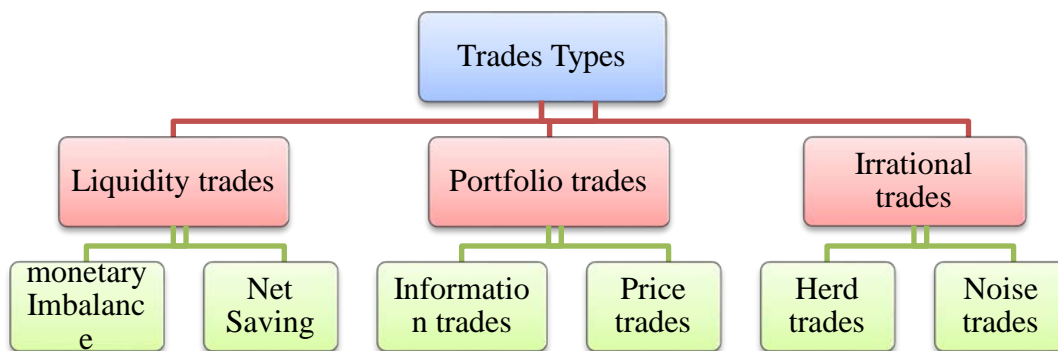
In the ASE, liquidity trades and irrational trades have put tremendous pressure on the market, which has led to an inefficient market, especially when portfolio trades are insufficient to compensate for the effects of liquidity trades and irrational trades. Furthermore, volume trading in the ASE is not substantial enough to reduce the effect of noise traders. Table 5.5 below illustrates yearly trading value in the ASE during the study period. For the period 1990–2001, the average daily trading is valued at less than JD 2.8 million approximately, which indicates that the market suffered from a low level of liquidity during this period. Although during the period 2002–2007 the level of liquidity improved and reached JD 50 million by 2007; however, the highest level of liquidity was in 2005 with a value of JD 69.1 million. Consequently, the ASE trading volume is insufficient to avoid deviations from efficient levels.

Table 5.5: Yearly Trading Value at ASE (1990–2007)

Year	No. of Shares Traded	% Change	Value Traded (JD)	% Change	No. of Transactions	% Change
1990	136,054,317	-30.4	268,885,973	-26.9	157,129	-25.3
1991	161,777,149	18.9	302,836,729	12.6	183,426	16.7
1992	350,650,042	116.7	886,950,983	192.9	339,755	85.2
1993	270,439,340	-22.9	968,613,802	9.2	335,553	-1.2
1994	175,475,801	-35.1	495,076,052	-48.9	253,654	-24.4
1995	175,204,564	-0.2	418,958,544	-15.4	210,879	-16.9
1996	162,489,105	-7.3	248,583,344	-40.7	163,310	-22.6
1997	191,064,386	17.6	355,244,623	42.9	137,957	-15.5
1998	247,856,716	29.7	464,374,268	30.7	137,714	-0.2
1999	271,109,284	9.4	389,476,334	-16.1	154,603	12.3
2000	228,365,333	-15.8	334,724,633	-14.1	133,306	-13.8
2001	340,550,460	49.1	668,652,674	99.8	295,495	121.7
2002	461,815,018	35.6	950,272,995	42.1	448,555	51.8
2003	1,008,564,620	118.4	1,855,176,028	95.2	786,208	75.3
2004	1,338,703,981	32.7	3,793,251,050	104.5	1,178,163	49.9
2005	2,581,744,423	92.9	16,871,051,948	344.8	2,392,509	103.1
2006	4,104,285,135	59	14,209,870,592	-15.8	3,442,558	43.9
2007	4,479,369,609	9.1	12,348,101,910	-13.1	3,457,915	0.4

The rational investor's mechanism is to collect the new information, examine this information and reflect it in the shares prices immediately; the portfolio trader trades according to the information released. If some investors were able to make fair assessments more rapidly than others, they would be able to gain profits from the information received. Even if this assumption does not hold in its absolute form, a high degree of market efficiency would be achieved if a substantial number of rational investors analyse the information, and trade on it, within one day of the information becoming available (Gilson and Kraakman, 2003).

The trading mechanism in the ASE suffers from one major weakness: lack of immediacy. If, for example, there is an imbalance between buy and sell orders during a trading day, successive buy (sell) orders may well be noted on the trading board without counter sell (buy)

orders arriving at the market. In addition, any imbalance between buy and sell orders would cause the price of a stock to suddenly (and by a large percentage) change from one transaction to the next. This is due to the absence of someone (a dealer) standing ready and willing to buy a stock at the bid and sell a stock at the ask (Omet, 2001).

Stock market information cannot be collect and analyse by an individual trader, it requires well-qualified firms who have the ability to exert considerable effort in doing so. If these firms do not exist or are not qualified enough in any market, this may well lead to inefficiency in the market.

In Jordan, the portfolio trades firms are generally not well known and the ones that investors are aware of are not viewed as having a strong reputation amongst investors. Trading in the ASE is considered thin; it lacks trading mechanisms and instruments, such as short selling, lacks the availability of derivatives, and has limitations imposed on margin trading. Hence, these factors combined make it difficult to implement efficient diversification procedures and hinder its liquidity and efficiency (Al-Khouri and Ajlouni, 2007).

Social and psychological factors of behavioural finance, as Shiller (2000) points out, result in investors having a tendency to follow the judgment and behaviour of others. Investors may follow each other without any obvious reason. Such behaviour results in a form of herding, which may help to explain the inefficiency of the ASE. Investors tend to do as other investors do; they imitate the behaviour of others and disregard their own information.

Furthermore, Walter and Weber (2006) distinguished between intentional and unintentional herding. Unintentional herding occurs as a consequence of investors analysing the same information in the same way. Intentional herding could develop as a result of poor availability of information. Investors may imitate the behaviour of others in the belief that

they have traded on the basis of information. In the ASE, lack of information, lack of institutional investors and lack of financial analysts (Al-Khouri and Ajlouni, 2007), lead individual investors to imitate other investors that they believe have traded on the basis of profitable information, resulting in an inefficient market.

As mentioned earlier in chapter Two, according to social influence theory, investors in a peer group tend to develop the same tastes, interests and opinions (Ellison and Fudenberg, 1993). Social standards appear in relation to shared beliefs. These social standards include beliefs about investing. The social environment of investors influences investment decisions. This applies not only to individual investors but also to market professionals. Fund managers are a peer group; fundamental analysts are a peer group and technical analysts are a peer group. Indeed, market professionals in aggregate form a peer group. It is likely that there are times when these peer groups develop common beliefs about the direction of the stock market. Common beliefs tend to cause an inefficient stock market (Christie and Huang, 1995; Welch, 2000).

The decisions of Jordanian investors may not reflect their own views about the investments, but may be based upon what they view as the majority investor's view. The majority investors are being mimicked by other investors, even if they are not a well-informed rational investors. The investors that are followed may be uninformed and subject to psychological biases that make their behaviour irrational. This results in a new group of investors, who try predicting the behaviour of irrational investors rather than trying to determine the fundamental value of share prices. Therefore, the investors will be overreacting to this type of

information and placing more pressure on the market to depart from the efficient level. For example, Jordanian investors have a strong tradition of retail investment in shares.[40]

5.4. Conclusion

This chapter aimed to investigate stock market efficiency in the ASE. Using both parametric and non-parametric tests, the returns of the ASE during the period 1992–2007 moved contrary to the RWH with 95% confidence. Realizing that test results can be highly time-dependent, the full period was divided into sub-periods. The results from the two sub-samples confirm that the ASE does not follow the RWH. Table 5.6 below presents a summary of the results obtained from the tests conducted in this chapter.

Table 5.6: Summary of the Results from All Tests used in Chapter Five to Examine the Random walk of the ASE for the Three Samples

PANEL A	Runs Test, Serial Correlation Test and Length-of-Runs Test					
	Runs Test		Length-of-Runs Test		Serial Correlation Test	
	Random	Non-Random	Random	Non-Random	Random	Non-Random
1992–1999		X		X		X
1999–2007		X		X		X
1992–2007		X		X		X
PANEL B	Variance Ratio Test (Lo and MacKinlay, 1988)					
VR(q)	1992–1999		1999–2007		1992–2007	
	Value	Z-Test	Value	Z-Test	Value	Z-Test
2	1.45064	3.25039	0.52795	-4.0851	0.82793	-0.5317
4	1.66678	2.5707	0.63637	-1.682	0.513	-0.8044
8	1.84995	2.0725	0.77897	-0.6466	0.65706	-0.3583
16	0.0479	-1.5601	0.00729	-1.9517	0.03087	-0.6804

The EMH has been built under the assumption that rational investors are dominating the stock market; even if it does not require all investors to be rational, it requires that the rational

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[40] Jordan Securities Market (2001) 'A Guide for Foreign Investors', [online] available at http://209.85.229.132/search?q=cache:S1Jm6Gsumv4J:www.jsc.gov.jo/inv.pdf+The+decisions+of+Jordanian+investors+may+not+reflect+their+own+views+about+the+investments&cd=2&hl=en&ct=clnk&gl=uk#7) [7 December 2010].

investors outbalance the irrational ones. In the ASE, liquidity trades and irrational trades have placed tremendous pressure on the market, which has led to an inefficient market. This is particularly so when portfolio trades are insufficient to compensate for the effects of liquidity trades and irrational trades.

Investors may imitate one another without any obvious reason. Such behaviour results in a form of herding, which may help to explain the inefficiency of the ASE. Investors tend to do as other investors do; they imitate the behaviour of others and disregard their own information. Furthermore, in the ASE, the lack of information, lack of institutional investors and lack of financial analysts has led individual investors to mimic other investors that they believe have traded on the basis of profitable information, resulting in an inefficient market.

The original model of the weak form efficiency is that the time series of stock prices follows a random walk. The strict random walk model presumes that the successive increases of a time series are serially independent and that their probability distribution is identical through time. However, this assumption is not essential to prove that a market is weak form efficient. A weak form efficient market would benefit if past price information could not influence market participants into gaining abnormally high returns. Therefore, the next chapter examines the calendar effects to clarify whether historical information about the ASE is useful for market participants to gain higher returns.

6. Chapter Six: An Examination of Islamic and Gregorian Calendar Effects, Interpreted from a Behavioural Finance perspective

6.1. Introduction

In the previous chapter, the results of both parametric and non-parametric tests indicate that the returns of the ASE move contrary to the RWH. This chapter examines the second and third hypotheses outlined in Chapter Four. These examine whether or not stock market returns exhibit calendar anomaly effects on a daily, weekly and monthly basis in the market capitalization weighted price index of the Amman Stock Exchange for the period 1992–2007. In addition, the fourth and fifth hypotheses are examined in this chapter. These assess whether or not the stock market returns exhibit any Islamic calendar effects and whether or not these effects are profitable for investors.

Daily closing prices were used from 1 January 1992 to 31 December 2007. After holidays have been excluded, this provides a total of 3,915 daily observations, 819 weekly observations, and 192 monthly observations. Returns were calculated as the first differences in the natural logarithms of the stock market prices. Realizing that test results can be highly time-dependent, the full period was divided into two sub-periods. Therefore, the robustness of the results is assessed in various ways. Firstly, similar tests are conducted for various sub-samples of the original sample and by trimming outlying observations. Secondly, using different testing procedures helps to reach a conclusion of consistency in the findings.

The weak form efficient market hypothesis emphasizes that the current stock prices completely *reflect all historical information*, including historical stock prices. Any knowledge of historical information has already been incorporated into current market prices, and is already known by market participants. Therefore, market participants of the stock

market cannot predict future price changes by analysing historical prices. Any effort to develop a trading strategy based on historical prices will be fruitless in terms of gaining higher returns.

In Islamic countries like Jordan, moving calendar events such as Ramadan have large effects on economic and financial markets. During the month of Ramadan, the financial markets in Islamic countries change their trading activities, working hours are reduced and Muslims become more religiously orientated during this month. What is more, the act of fasting during Ramadan is said to redirect the heart away from worldly activities, its purpose being to cleanse the inner soul and free it from harm. Properly observing the fast is supposed to induce a comfortable feeling of peace and calm. It also allows Muslims to practice self-discipline, self-control, sacrifice and sympathy for those who are less fortunate. It is also intended to make Muslims more generous and charitable. Furthermore, as identified earlier (in Chapter Two) *zakat* become increasingly important during the month of Ramadan. As an example, more emphasis is placed on *Zakat al Fater* (where every Muslim should donate a particular amount of money to poor people before the end of Ramadan). In fact, the Islamic system aims to eliminate poverty from society, rather than merely 'managing' the poor.

Consequently, Ramadan may influence Jordanian investors' behaviour, particularly their moods and emotions. According to Redhead (2008), moods and emotions may be unrelated to an investment decision yet can affect the decision. The general level of optimism or pessimism in society will influence individuals and their decisions, including their financial decisions.

Furthermore, Baker and Nofsinger (2002) and Nofsinger (2002) suggested that mood affects investment behaviour, as good moods make people less critical. Therefore, good moods can produce decisions that lack detailed analysis. According to Hirshleifer and Shumway (2003)

and Kamstra et al. (2003), determinants of mood include weather and the number of hours of daylight. They indicated that these factors affect investment behaviour. Good weather and long hours of sunlight appears to encourage net buying and market growth. Nofsinger (2002) also suggested an optimism bias. Optimism reduces critical analysis during the investment process, and it causes investors to ignore bad news.

This chapter is structured as follows: Section 6.2 examines the calendar anomalies, which are day-of-the-week, month-of-the-year, turn-of-the-month and moving Islamic calendar effects; Section 6.3 presents an interpretation of the results from a behavioural finance perspective; and Section 6.4 presents the conclusions.

6.2. Examination of Calendar Effects

Calendar effects are anomalies in stock prices that relate to the calendar. If stock prices follow weak form market efficiency, then market participants should not be able to gain profits by utilizing the calendar date. At the same time, there is significant empirical evidence supporting the fact that profit opportunities from such anomalies do exist. If that is the case in the ASE, then the market is identified as an inefficient market. This section examines the calendar effects of:

- Day-of-the-week effects

- Month-of-the-year effects

- Turn-of-the-month effects

- Moving Islamic calendar effects

The methodology is used to examine whether or not the mean returns made on one specific day of the week (or month) are significantly different from the returns made on the other days of the week (or month) . This chapter undertakes the following tests:

- Wald-Wolfowitz runs test

- Length-of-runs test

- Serial correlation test

- Testing the difference of two proportions

- Comparing the mean return at the turn of the month

The same data used in the previous chapter are used in this chapter to examine day-of-the-week, month-of-the-year and turn-of-the-month effects. In order to examine moving Islamic calendar effects, the data are adjusted to match the Islamic calendar.

The Islamic calendar is a lunar calendar with twelve lunar months in a year, approximating 354 days. Daily closing prices are used for the Islamic calendar from the period of 26/06/1412 to 22/12/1428, offering 197 monthly observations for the same period. Ramadan is the ninth month of the Islamic calendar. This lunar year is about eleven days shorter than the solar year and Islamic holy days usually shift eleven days earlier with each successive solar year, such as a year of the Gregorian calendar.

This section uses the Wald-Wolfowitz runs test, the length-of-runs test and the serial correlation test, which have been used in the previous chapter. Furthermore, to add credence to the results obtained from the serial correlation test, a fourth test examines the differences of two proportions (Levine et al., 2001). The z-test is used to determine the difference between the samples' means based on the difference between daily means. The last test examines the mean return at the turn of the month. The t-test is used to test the hypothesis that the mean return over the turn of the month is significantly different from the mean return over all other days. Furthermore, the t-test is a robust test; it does not lose much power if the shape of the population from which the samples are drawn departs a bit from a normal distribution (Levine et al., 2001).

Finally, the robustness of the results is assessed in various ways. Firstly, similar tests are conducted for various sub-samples of the original sample and by trimming outlying observations. Secondly, using different testing procedures helps to reach a conclusion of consistency in the findings (e.g. Urrutia (1994) got different findings from the runs test and the variance ratio test).

6.2.1. Day-of-the-Week Effects

The day-of-the-week effect (also called the weekend effect or the Monday effect) states that the average daily return of the market is not the same for all the days of the week, as expected on the basis of the efficient market hypothesis. Empirical studies, such as Cross (1973), French (1980), Gibbons and Hess (1981), Keim and Stambaugh (1986), Lakonishok and Levi (1982), Rogalski (1984), Liano and Gup (1989), Lakonishok and Maberly (1990), Sias and Starks (1995), Kamara (1995), Wang et al. (1997), Draper and Paudyal (2002), and Chen and Singal (2003), have documented the day–of-the-week effect. The first test used to examine the day-of-the-week is a runs test.

6.2.1.1. Runs Test

The Wald-Wolfowitz Runs Test is used to examine the randomness of days of the week. This test is based on whether or not differences between the actual and expected runs are statistically significant for each day of the week, where the expected values are the numbers expected to be found if the data follow a random walk. The null hypothesis is:

Ho: Stock market returns for all days of the week follow a random walk.
H1: Stock market returns for all days of the week do not follow a random walk.

Table 6.1 compares the actual runs with the expected runs for the three samples. The results show that, for the three samples, the total number of runs (actual number of runs) is different from the expected number of runs. For each sample, the number of runs is greater than the expected number of runs under the weak form market efficiency (WFME) hypothesis. The results of these differences are statistically significant, as presented in Figure 6.1; the x-axis shows the day of the week for each sample period, the y-axis shows the z statistics, the red columns show the critical value of the z statistics (2.575), and the blue column shows the calculated value.

Table 6.1: Comparing Actual Runs and Expected Runs of Days of the Week for the Three Samples

	Total Runs	N1 (Positive Returns)	N2 (Negative Returns)	N (Number of Runs)	E (R) (Expected Runs)
1992–1999					
Saturday	231	188	164	352	176.18
Sunday	251	178	172	350	175.94
Monday	235	161	181	342	171.41
Tuesday	227	170	179	349	175.38
Wednesday	240	180	169	349	175.32
1999–2007					
Sunday	218	166	186	352	176.43
Monday	235	176	177	353	177.49
Tuesday	234	186	167	353	176.98
Wednesday	241	180	173	353	177.43
Thursday	242	180	173	353	177.43
1992–2007					
Saturday	231	188	164	352	176.18
Sunday	251	178	172	350	175.94
Monday	241	166	187	353	176.87
Tuesday	227	170	182	352	176.79
Wednesday	242	182	170	352	176.79
Thursday	242	180	173	353	177.43

Figure 6.1: Statistical Significance of Z-Test of Days of the Week for the Three Samples
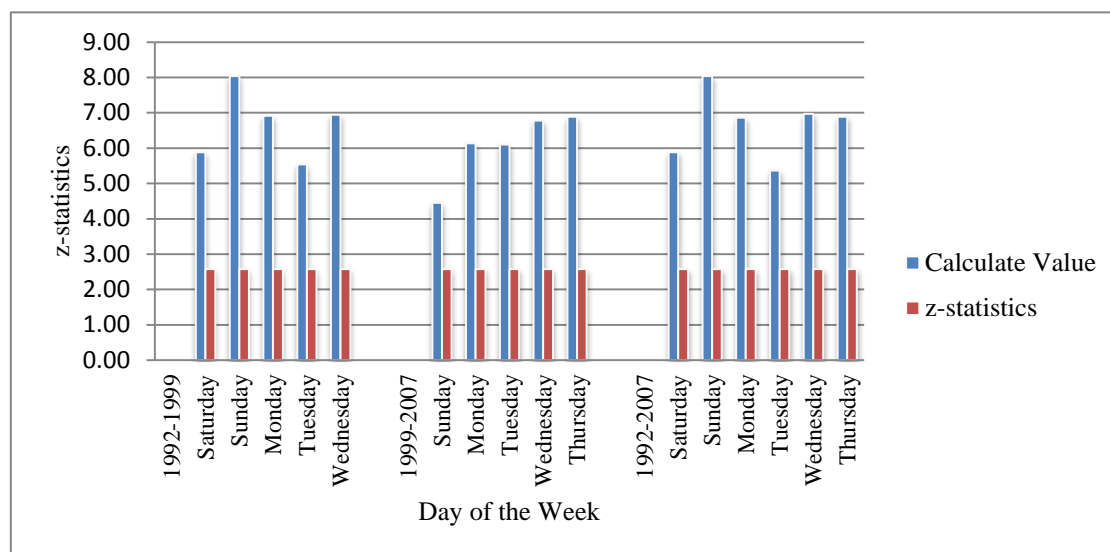
The three samples reject the null hypothesis; for example, using the runs test, the differences between the actual runs and the expected runs are statistically significant, with 99% confidence. The first trading day in the week for the first sample (1992–1999) is Saturday; the z statistic for Saturday in the first sample is 5.88.The first trading day in the week for the second sample (1999–2007) is Sunday. The z statistic for Sunday is 4.45.

The last trading day of the week for the first sample is Wednesday; the z statistic for Wednesday is 6.94. While, in the second sample Thursday is the last trading day of the week and the z statistic for Thursday is 6.88.

The results of the runs test show that day-of-the-week effects exist in the ASE during both the first sample and the second sample. Furthermore, this is confirmed by the main sample. In the US market, French (1980) noted that the average returns were significantly negative over weekends from 1953 to 1977.

The empirical evidence shows that day-of-the-week effects are not limited to the US equity markets. The work of Jaffe and Westerfield (1985), Solnik and Bousquet (1990) and Barone

(1990) found similar day-of-the-week effects in other international equity markets. Although Schwert (2003) reported that day-of-the-week effects (particularly the weekend effect) have disappeared since they were first discovered in the 1980s. Dubois and Louvet (1996), Wang et al. (1997) and Chang et al. (1998) found the day-of-the-week effect still existed in both the US markets and other international markets during the 1990s. The current research's findings confirm that the day-of-the-week effect remains after two decades of research.

The second test is the length-of-runs test; this provides additional information that the Wald-Wolfowitz (1940) runs test does not offer. It specifically examines the length of the runs.

6.2.1.2. Length-of-Runs Test

The length-of-runs test is based on differences between the numbers of observed and expected observations of runs of a given length for each day of the week. Table 6.2 below compares the observed runs with the expected runs for each length of the three samples. In first sample (1992–1999), the fourth and fifth run length is not calculated since the number of observations is less than 5. In the second sample (1999–2007), the fourth length is calculated only for Monday. In the main sample (1992–2007), the fourth length is not calculated for Saturday or Thursday.

Table 6.2: Length-of-Runs Test of Days of the Week for the Three Samples

Run Length	1		2		3		4	
	Expected	Observed	Expected	Observed	Expected	Observed	Expected	Observed
1992–1999								
Saturday	147.16	139	64.48	65	22.52	27		
Sunday	147.16	169	64.48	69	22.52	13		
Monday	145.08	144	63.56	76	22.19	15		
Tuesday	145.91	132	63.93	71	22.32	24		
Wednesday	145.91	154	63.93	67	22.32	19		
1999–2007								
Sunday	178.41	122	78.23	67	28.33	29		
Monday	183.41	143	80.43	72	23.09	15	5.90	5
Tuesday	180.08	151	78.96	55	28.59	28		
Wednesday	181.33	156	79.51	65	28.66	20		
Thursday	176.33	155	77.31	66	27.02	21		
1992–2007								
Saturday	147.16	139	64.48	65	22.52	27		
Sunday	325.5	169	142.95	69	41.08	9	8.94	4
Monday	328.41	147	144.23	77	41.45	16	9.02	1
Tuesday	325.91	131	143.13	71	41.14	21	8.95	4
Wednesday	327.16	156	143.68	67	41.3	14	8.99	5
Thursday	176.33	155	77.31	66	27.02	21		

The results show that, for the three samples, the expected number of runs is different from the observed number of runs for all the lengths. Furthermore, in the three samples, the first length expected number of observations is greater than the observed number (excluding Wednesday in the first sample). The second length expected number of observations is greater than the observed number, for both the second and main samples (excluding Saturday in the main sample (1992–2007)). Conversely, in the first sample, the second length of observed numbers of observations is greater than the expected number.

The result shows these differences are statistically significant, as presented in Figure 6.2 and Figure 6.3; the x-axis shows the sample period, the y-axis shows the chi-square statistics, and the red line shows the critical value of chi-square.

Figure 6.2: Statistical Significance of Chi-Square Test of Days of the Week for the Samples 1992–1999 and 1999–2007
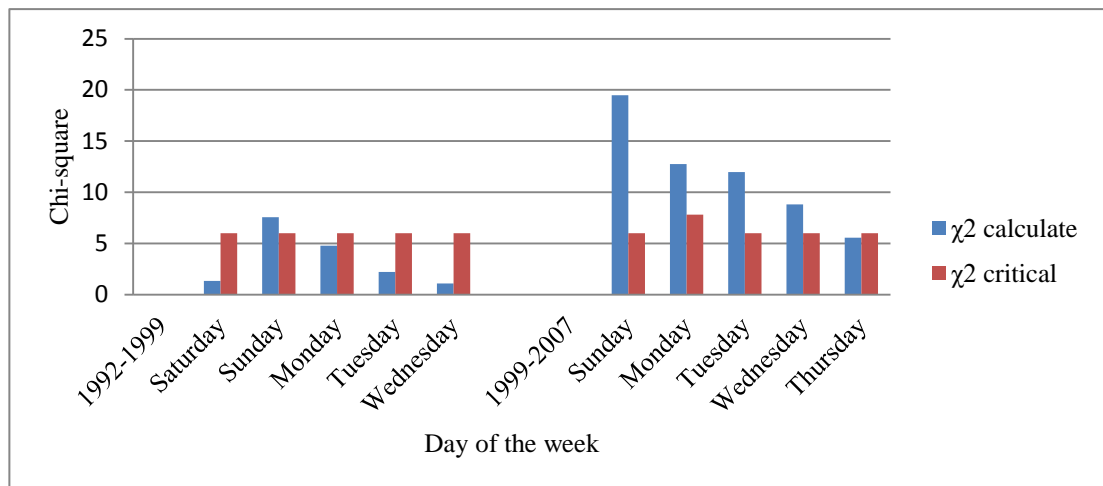
Figure 6.3: Statistical Significance of Chi-Square Test of Days of the Week for the Sample 1992–2007
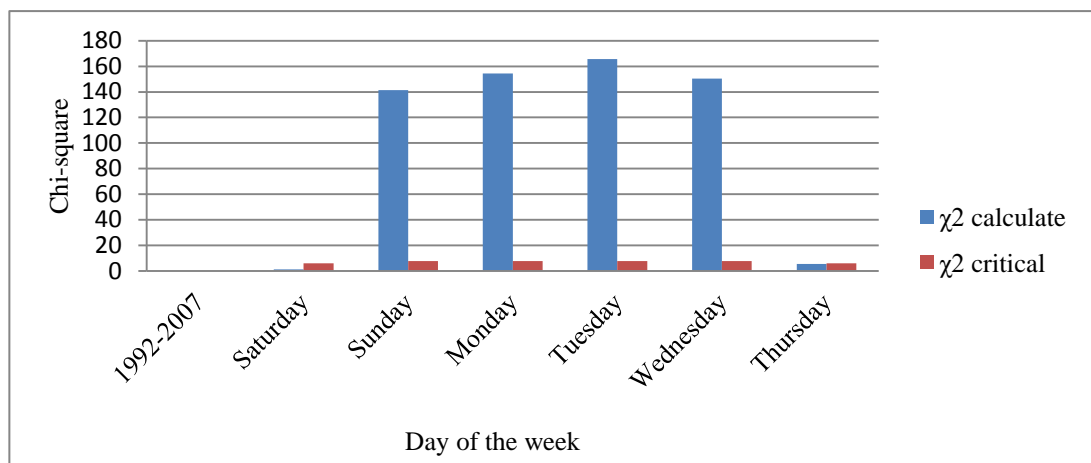
The first sample (1992–2007) has not rejected the null hypothesis of the differences between the actual length-of-runs and expected length-of-runs; there is no statistical difference, with 95% confidence. However, there is an exception for Sunday, where the chi-square statistic is 7.58 and the critical value is 5.99. The second sample (1999–2007) has rejected the null hypothesis, with the exception of Thursday. The chi-square statistic for Thursday is 5.57 and the critical value is 5.99. Furthermore, for the main sample (1992–2007), the test has rejected

the null hypothesis, with the exceptions of Saturday and Thursday; the chi-square statistic for Saturday is 1.3 and for Thursday is 5.57, and the critical value is 5.99 for both days. The results indicate that when the numbers of observations are increased the ASE rejects the null hypothesis.[41]

Based on the non-parametric tests (runs test and length-of-runs test), the ASE returns appear to behave inconsistently with the WFME hypothesis; the results from sub-samples confirm that. Both tests reveal that day-of-the-week effect exists in the ASE, particularly for Sunday, in the main sample and in the two sub-samples. For the main sample, the mean return of Sunday is 0.11%, for the first sub-sample (1992–1999) it is 0.02% and for the second sub-sample (1999–2007) it is 0.19%. On the other hand, Tuesday is the only day of the week for the three samples that had a negative return (see Table 6.3 below).

The results from the length-of-runs tests show that the last day of the week follows the WFME hypothesis for the three samples. For both the main sample (1992–2007) and the second sub-sample (1999–2007), the last day of the week is Thursday. For the first sub-sample (1992–1999), the last day of the week is Wednesday.

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[41] The number of observations in the main sample (1992–2007) for Saturday is 353, for Sunday is 782, for Monday is 788, for Tuesday is 782, for Wednesday is 785 and for Thursday is 423.

Table 6.3: Mean Return of Days of the Week for the Three Samples

Mean Return for Each Day of the Week			
	1992–1999	1999–2007	1992–2007
Saturday	0.000786386	-	0.00078639
Sunday	0.000208133	0.001962293	0.00116944
Monday	0.000305091	0.001142505	0.00077268
Tuesday	-1.6123E-05	-0.00231539	-0.00128631
Wednesday	0.000423718	0.00217618	0.00139483
Thursday	-	0.000195609	0.00019561

However, since the ASE has different working days to the international market,[42] it is possible that investors in the ASE respond immediately to information released on the last day of the week. This is as long as the next day is not a trading day in Jordan, but is a working day in international markets. Therefore, in the ASE the last working day of the week always follows the WFME hypothesis. Nevertheless, ASE traders have the advantage of reflecting on all the information released on Friday and Saturday during Sunday trading; is the first working day of the week in Jordan.

Moreover, ASE traders have the ability to analyse the information released during the weekend and anticipate how the international market will react to this information before the international markets open on Monday, and reflect that in Sunday trading. Therefore, Sunday will not follow the WFME hypothesis.

The existence of day-of-the week effects in stock market returns has been widely documented in the literature, such as in studies by Gibbons and Hess (1981), Lakonishok and Levi (1982), Keim and Stambaugh (1984), Barone (1990), Chiaku (2006) and Apolinario et al. (2006). 'Day-of-the-week effects' refers to differences in stock market returns according to the day of

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[42] For the first sub-sample (1992–1999), working days are Saturday, Sunday to Wednesday. For the second sample (1999–2007) working days are Sunday, Monday to Thursday. The main sample (1992–2007) counts Saturday and Sunday to Thursday.

the week, particularly on Monday. This pattern is commonly known as the weekend effect, or the 'Blue Monday' effect; it refers to significantly lower returns over the period between the Friday close (last day of the week) and the Monday close (first day of the week) of the market. The findings in the ASE differ slightly; Wednesday is the highest return and Tuesday is the only day that has a negative return, as the ASE has different working days to the international market.

The following test is a parametric test of serial correlation; it is employed to examine the hypothesis of no serial correlation in the ASE day-of-the-week return, as an alternative test to examine day-of-the-week effects.

6.2.1.3. Serial Correlation Test

Table 6.4 below presents the serial correlation for the first lag as well as the statistical significance of any first order serial correlation. The result shows that, for the three samples, the serial correlation of the first lag is different from zero. For the first sample, the strongest first lag serial correlation was found on Monday with a value of -2.34%, whereas the weakest correlation was found on Saturday (as a first day of the week for this sample) with a value of -0.02%. In the second sample (1999–2007), the strongest first lag serial correlation was found on Thursday, with a value of -20.18%, while the weakest correlation was found on Tuesday with a value of 1.76%. Moreover, for the main sample (1992–2007), the strongest first lag serial correlation was found on Monday with a value of -20.92%, and the weakest correlation was found on Saturday with a value of 0.02%.

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Table 6.4: Serial Correlation Tests of Days of the Week for the Three Samples

Serial Correlation Test			
	Serial Correlation of 1st lag	t-test	Critical Value
1992–1999			
Saturday	-0.000255263	-0.004781734	+/- 2.62
Sunday	0.015014597	0.283434262	+/- 2.62
Monday	-0.223442867	-3.757618604	+/- 2.62
Tuesday	-0.126031027	-2.215602872	+/- 2.62
Wednesday	0.030213604	0.572340022	+/- 2.62
1999–2007			
Sunday	0.14327047	3.194770152	+/- 2.62
Monday	0.176936087	4.081658762	+/- 2.62
Tuesday	0.017661961	0.369524022	+/- 2.62
Wednesday	0.05971032	1.281334467	+/- 2.62
Thursday	-0.20189677	-3.778651459	+/- 2.62
1992–2007			
Saturday	-0.000255263	-0.004781734	+/- 2.62
Sunday	0.014429184	0.40566411	+/- 2.62
Monday	-0.209274093	-5.335367845	+/- 2.62
Tuesday	-0.124306692	-3.274156341	+/- 2.62
Wednesday	0.027342878	0.775791854	+/- 2.62
Thursday	-0.20189677	-3.778651459	+/- 2.62

It is only for Monday that the three samples rejected the null hypothesis of no correlation between the return in time *t* and the return in time *t*-1, with 99% confidence. However, for the second sample and the main sample, Thursday rejected the null hypothesis of no correlation as well. The finding of Monday effects in the ASE indicates that the ASE is integrated with Western markets and confirms the validity of day-of-the-week effects.

The findings from the serial correlation test are slightly different to non-parametric results in this research. For the three tests, Monday does not follow the WFME (with the exception of the first sample when the length-of-runs test is employed, which shows that Sunday does not follow the WFME hypothesis). Moreover, non-parametric tests show that Sunday does not follow the WFME hypothesis strongly, yet the serial correlation test shows that Sunday does follow the WFME for the three samples (except for the the second sample).

To summarize, the ASE has different working days to the international market. Friday is not a working day in Jordan, yet in the international markets it is, which leads ASE traders to act on the information released on Thursday to avoid any unexpected announcements during Friday or Saturday. Employing parametric tests and non-parametric tests, the ASE returns indicate that day-of-the-week effects are still valid. The same result was confirmed by the sub-samples and the main sample, particularly for Sunday and Monday.

The next test will examine the mean difference between the days of the week, in order to evaluate the credibility of the day-of-the-week effect found by both the parametric and non-parametric tests.

6.2.1.4. Testing the Difference of Two Proportions

This test examines the mean returns obtained from the two different days, which are significantly different. If the t value obtained from this test is greater than the t distribution value for a given confidence level, the observed mean returns are significantly different, using a confidence level of 90%. The assumption under this test is that each day of the week represents a random mean return, which shows that each day of the week has a mean return that is independent from other days of the week.

For the first sample (1992–1999), the Sunday mean return is examined to determine if it is greater (or lower) than other days of the week. For the second sample (1999–2007) and the main sample (1992–2007) Sunday, Monday and Thursday are examined. Table 6.5 below presents the results for the first sample (1992–1999), Table 6.6 presents the results for the second sample (1999–2007) and Table 6.7 below presents the results for the main sample (1992–2007).

Table 6.5: Testing the Differences between Sunday and other Days of the Week for the First Sample (1992–1999)[43]

	1992–1999	
	Sunday	
	t-value	Are means significantly different at 90% confidence level?
Saturday	0.488	No
Monday	0.102	No
Tuesday	0.105	No
Wednesday	0.333	No

Table 6.6: Testing the Differences between Sunday, Monday and Thursday and other Days of the Week for the Second Sample (1999–2007)[44]

	1999–2007							
	Sunday			**Monday**			**Thursday**	
	t-value	Sig.		t-value	Sig.		t-value	Sig.
Monday	1.442	No	Sunday	1.442	No	Sunday	2.98	Yes
Tuesday	2.538	Yes	Tuesday	1.046	No	Monday	1.501	No
Wednesday	1.158	No	Wednesday	0.214	No	Tuesday	0.391	No
Thursday	2.98	Yes	Thursday	1.501	No	Wednesday	1.774	Yes

Table 6.7: Testing the Differences between Sunday, Monday and Thursday and other Days of the Week for the Main Sample (1992–2007)[45]

	1992–2007							
	Sunday			**Monday**			**Thursday**	
	t-value	Sig.		t-value	Sig.		t-value	Sig.
Saturday	1.157	No	Saturday	0.419	No	Saturday	0.355	No
Monday	0.889	No	Sunday	0.889	No	Sunday	1.749	Yes
Tuesday	1.748	Yes	Tuesday	0.813	No	Monday	0.965	No
Wednesday	0.587	No	Wednesday	0.251	No	Tuesday	0.241	No
Thursday	1.749	Yes	Thursday	0.965	No	Wednesday	1.217	No

The results show that, for the first sample, there are no significant differences between Sunday and other days of the week. In the second sample, Sunday rejects the null hypothesis with no significant differences with other days of the week (excluding Wednesday and

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[43] Critical value of t is 1.96 with 95% level of confidence and 1.64 with 90% level of confidence.
[44] Critical value of t is 1.96 with 95% level of confidence and 1.64 with 90% level of confidence.
[45] Critical value of t is 1.96 with 95% level of confidence and 1.64 with 90% level of confidence.

Monday). Thursday also rejects the null hypothesis for the same sample (excluding Monday and Tuesday), whereas Monday, there are no significant differences between Monday and other days of the week. However, in the main sample, Sunday rejects the null hypothesis with Tuesday and Thursday but not for Saturday, Monday and Wednesday. For the same sample, Monday shows no significant differences from other days of the week.

According to this test, the results confirm that there is indeed a day-of-the-week effect, particularly during the weekend. This can be explained by the fact that Jordan has different working days to international markets; in Jordan the first working day of the week is Sunday (since March 1999),[46] whereas in the international markets it is Monday. Hence, this can explain why Sunday is different to other days of the week.

However, this factor is unlikely to drive profits from day-of-the-week effects as the daily returns are significantly lower than the transaction costs (1.05%). Furthermore, the findings of day-of-the week effect seem convincing in thinly traded emerging markets, such as Jordan, where a number of specific factors delay the flow of information. First, illiquidity affects the market's capacity to accommodate orders (Chordia et al., 2005). Second, a low degree of competition results in the presence of dominant players who can cause stock prices to move away from their intrinsic value (Mobarek and Keasey, 2000). Finally, a lack of a 'culture of equity' has a tendency to slow the reaction of market participants to information, limiting efficiency (Aloui, 2005).

The next part of this section considers tests of the month-of-the-year and turn-of-the-month effects. In addition, Islamic calendar effects will be tested in relation to the month of Ramadan. These tests are undertaken using parametric and non-parametric tests.

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[46] Before March 1999, the first working day of the week was Saturday.

6.2.2. Month-of-the-Year Effect

The *month-of-the-year effect* refers to the phenomenon of there being higher returns in certain months. Previous studies of calendar effects have widely documented the month-of-the-year effect in developed and developing markets, such as studies by Roll (1983), Keim (1983) and Rozeff and Kinney (1976). Since January is the month with higher returns, the month-of-the-year effect is also commonly known as the January effect. At the same time, Ariel (1987) and Ogden (1990) provide evidence of the *turn-of-the-month anomaly*, which refers to returns that are greater on the turn-of-the-month trading days than other days of the month.

This section tests the month-of-the-year and turn-of-the-month effects, in addition to testing the month-of-the-year effect using the Islamic Calendar year. These tests are undertaken using the following methods:

- Wald-Wolfowitz runs test

- Length-of-runs test

- Serial correlation test

- Comparing the mean return at the turn of the month

6.2.2.1. Runs Test

The Wald-Wolfowitz Runs Test is used to examine the randomness of the month-of-the-year effect. This test is based on whether or not differences between the actual and expected runs are statistically significant for each month of the year; specifically, where the expected values are the numbers expected to be found if the data follow WFME. The null hypothesis is:

Ho: Stock market returns for all months of the year follow a random walk.

H1: Stock market returns for all months of the year do not follow a random walk.

Table 6.8 compares the actual runs with the expected runs for the three samples. The results show that, for the three samples, the total number of runs (actual number of runs) is different from the expected number of runs. For each sample, the number of runs is greater than the expected number of runs under the WFME hypothesis. The results of whether these differences are statistically significant are presented in Figure 6.4; the x-axis shows the month of the year for each sample period, the y-axis shows the z statistics, the red columns show the critical values of the z statistics (2.575), and the blue columns show the calculated values.

Table 6.8: Comparing Actual Runs with Expected Runs of Months of the Year for the Three Samples

	Total Runs	*N1* (Positive Returns)	*N2* (Negative Returns)	*N* (Number of Runs)	*E (R)* (Expected Runs)
1992–1999					
January	100	85	77	162	81.80
February	88	71	75	146	73.94
March	95	71	74	145	73.46
April	85	68	66	134	67.98
May	79	69	60	129	65.181
June	73	71	67	138	69.94
July	85	77	70	147	74.33
August	81	71	76	147	74.41
September	95	68	80	148	74.51
October	91	75	76	151	76.49
November	85	76	66	142	71.64
December	86	77	69	146	73.78
1999–2007					
January	96	80	74	154	77.88
February	90	62	83	145	71.97
March	103	93	88	181	91.43
April	117	94	91	185	93.47
May	118	91	93	184	92.98
June	118	91	93	184	92.98
July	122	93	103	196	98.74
August	125	101	96	197	99.43
September	126	97	90	187	94.36
October	124	94	98	192	96.95
November	108	87	85	172	86.98
December	99	78	87	165	83.25
1992–2007					
January	196	166	151	317	159.14
February	179	133	159	292	145.84
March	199	163	163	326	164.00
April	203	162	158	320	160.97
May	209	161	159	320	160.99
June	192	162	162	324	163.00
July	208	173	173	346	174.00
August	205	172	172	344	173.00
September	221	165	171	336	168.94
October	215	169	175	344	172.94
November	194	163	152	315	158.30
December	184	156	156	312	157.00

Figure 6.4: Statistical Significance of Z-Test of Months of the Year for the Three Samples
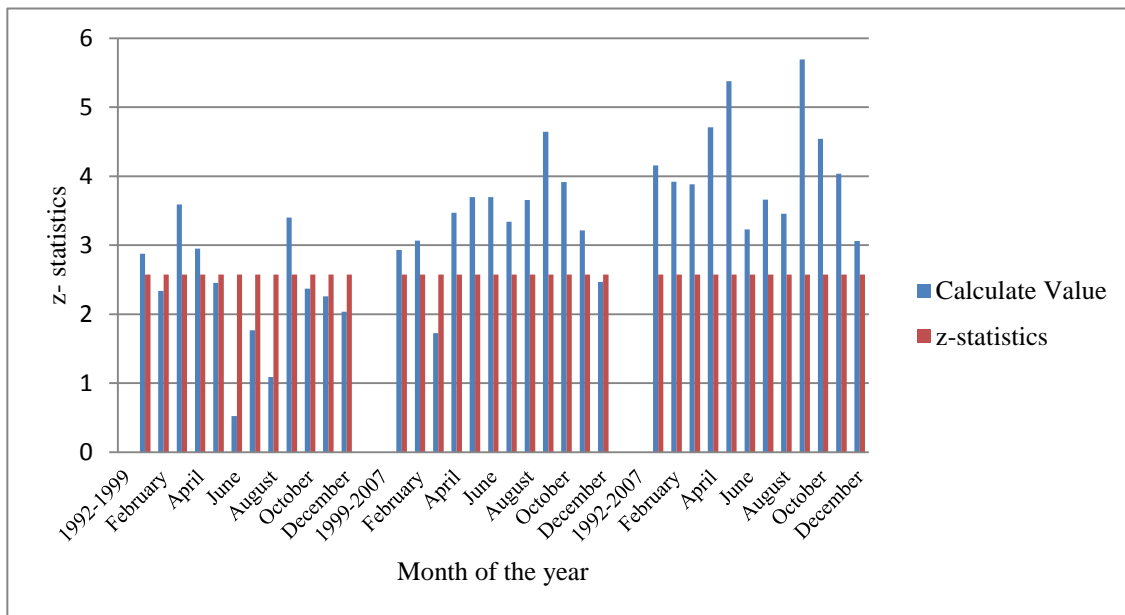
For the first sample (1992–1999), the results for January, March, April and September reject the null hypothesis (the differences between the actual runs and the expected runs have no statistical difference, with 99% confidence). These four months do not follow the WFME hypothesis; the z statistics are 2.87, 3.59, 2.95 and 3.40 respectively. However, for the second sample (1999–2007), only March and December follow the WFME hypothesis; the z statistics are 1.72 and 2.46 respectively. For the full sample (1992–2007), there is statistical difference between actual runs and expected runs, so again the WFME hypothesis is rejected for all months.

Examining the month-of-the-year effect using the runs test shows that month-of-the-year effects exist in the ASE during the first and second sample periods. Furthermore, this result is confirmed by the main sample. The second test used is the length-of-runs test, which provides additional information that the Wald-Wolfowitz (1940) runs test does not offer. Specifically, it examines the length of the runs.

6.2.2.2. Length-of-Runs Test

The length-of-runs test is based on differences between the number of observed and expected observations of runs of a given length for each month of the year. Table 6.9 below compares the observed runs with the expected runs for each length of the three samples. For the three samples, the fourth and fifth run length is not calculated because the number of observations is less than 5.

The results show that, for the three samples, the expected number of runs is different from the observed number of runs for all the lengths. Furthermore, in the three samples, the first length expected number of observations is greater than the observed number (excluding September in the second sample). The results of these differences are statistically significant, as illustrated in Figure 6.5; the x-axis shows the sample period, the y-axis shows the chi-square statistics, and the red line shows the critical value of chi-square.

Table 6.9: Length-of-Runs Test of Months of the Year for the Three Samples

Length-of-Runs Test						
Runs Length	1		2		3	
	Expected	Observed	Expected	Observed	Expected	Observed
1992–1999						
January	68.00	57.00	29.65	25.00	10.31	18.00
February	61.33	48.00	26.72	25.00	9.28	15.00
March	61.33	61.00	26.72	20.00	9.28	14.00
April	56.33	49.00	24.52	25.00	8.51	11.00
May	54.67	46.00	23.78	20.00	8.51	13.00
June	58.42	30.00	25.43	28.00	9.10	15.00
July	62.58	43.00	27.27	25.00	9.47	17.00
August	62.17	40.00	27.08	24.00	9.74	17.00
September	62.17	59.00	27.08	23.00	9.74	13.00
October	63.42	49.00	27.63	29.00	9.90	13.00
November	59.67	46.00	25.98	25.00	9.30	14.00
December	61.33	48.00	26.72	21.00	9.57	17.00
1999–2007						
January	64.67	55.00	28.18	27.00	10.10	14.00
February	60.92	53.00	26.53	25.00	9.50	12.00
March	75.50	46.00	32.95	43.00	11.82	14.00
April	77.58	70.00	33.87	36.00	12.21	11.00
May	77.17	71.00	33.68	31.00	12.09	16.00
June	77.17	71.00	33.68	31.00	11.72	16.00
July	82.17	70.00	35.88	37.00	12.94	15.00
August	82.17	66.00	35.88	46.00	12.94	13.00
September	78.42	80.00	34.23	34.00	12.34	12.00
October	80.50	70.00	35.15	42.00	12.62	12.00
November	72.58	65.00	31.67	30.00	11.36	13.00
December	69.67	51.00	30.38	34.00	10.56	14.00
1992–2007						
January	132.58	111.00	58.07	53.00	20.91	32.00
February	122.17	102.00	53.48	50.00	19.25	27.00
March	136.75	109.00	59.90	62.00	21.57	28.00
April	133.83	120.00	58.62	61.00	21.20	22.00
May	133.83	130.00	58.62	57.00	21.11	22.00
June	135.50	101.00	59.35	60.00	21.37	31.00
July	144.67	113.00	63.38	62.00	22.94	33.00
August	144.25	105.00	63.20	69.00	22.87	31.00
September	140.50	138.00	61.55	58.00	22.27	25.00
October	143.83	118.00	63.02	72.00	22.70	25.00
November	132.17	112.00	57.88	55.00	20.84	27.00
December	130.92	98.00	57.33	54.00	20.64	32.00

Figure 6.5: Statistical Significance of Chi-Square Test of Months of the Year for the Three Samples
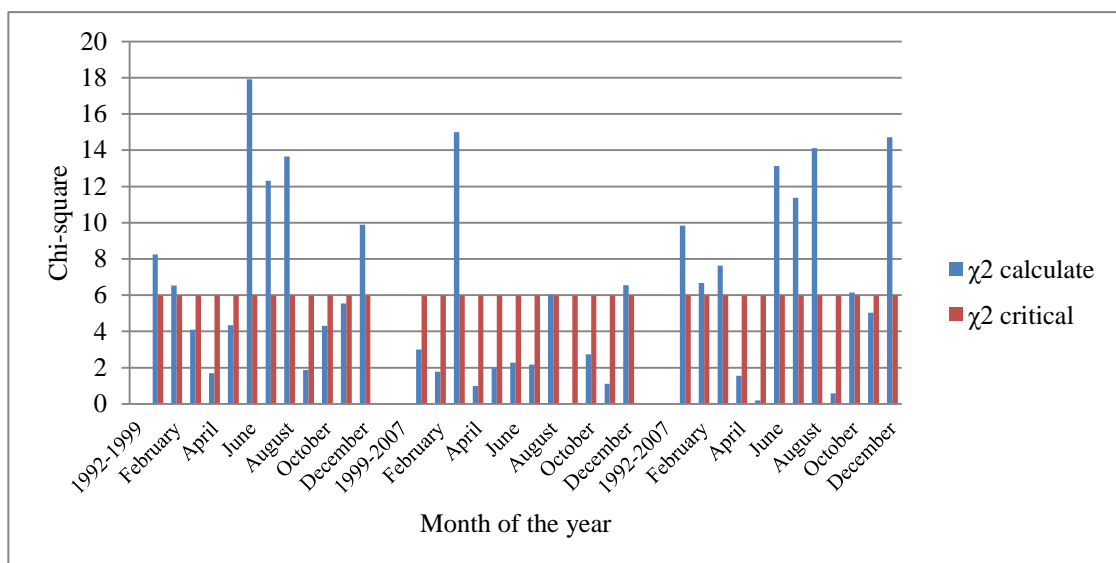
The first sample (1992–1999) rejects the null hypothesis that the differences between the actual length-of-runs and the expected length-of-runs have no statistical difference with 95% confidence for: January, February, June, July, August and December; the chi-square statistics are 8.25, 6.53, 17.90, 12.30, 13.65 and 9.89 respectively, and the critical value is 5.99. The second sample (1999–2007) also rejects the null hypothesis for: March, August and December; the chi-square statistics are 14.99, 6.03 and 6.54 respectively, and the critical value is 5.99. Furthermore, for the full sample (1992–2007), the null hypothesis is rejected for January, February, March, June, July, August, October and December. The chi-square statistic is more than 5.99 for these months (critical value is 5.99). The results indicate that, for the three samples, August and December do not follow the WFME hypothesis.

On the basis of the non-parametric tests (runs test and length-of-runs test), the ASE returns appear to behave inconsistently with the WFME hypothesis; the results from sub-samples confirm that. Both tests revealed that the month-of-the-year effect exists in the ASE. For the main sample (1992–2007), the highest mean returns are found in January and November

(0.16% and 0.12% respectively), whereas the lowest mean returns are found in February and March (-0.01% and -0.03 respectively). Furthermore, the second sample (1999–2007) confirms that January has a higher return (0.20%) and February has the lowest return (-0.07%). However, the first sample (1992–1999) has a slightly different result; December has the highest return (0.10%) and June has the lowest return (-0.01%), as shown in Table 6.10 below.

Table 6.10: Mean Return of Months of the Year for the Three Samples

	Mean Return for Each Month of the Year		
	1992–1999	1999–2007	1992–2007
January	0.00077	0.00266	0.00169
February	0.00032	-0.00072	-0.00020
March	-0.00080	0.00005	-0.00033
April	0.00128	0.00001	0.00055
May	0.00159	0.00030	0.00083
June	-0.00012	0.00055	0.00026
July	-0.00032	0.00050	0.00015
August	-0.00019	0.00037	0.00013
September	0.00137	0.00005	0.00063
October	-0.00080	0.00183	0.00067
November	0.00013	0.00214	0.00123
December	0.00106	0.00010	0.00055

The finding from the runs test and length-of-runs test is that the ASE has month-of-the-year effects. Clearly, December does not follow the WFME hypothesis and January has the highest returns. This finding is consistent with research in the literature, such as the studies of Roll (1983), Keim (1983), Ho (1999) and Fountas and Segredakis (2002), who found that stock markets exhibit month-of-the-year effects. Furthermore, they found that January has significantly higher daily returns compared with other months.

One explanation for this effect may be found in the tax-loss selling hypothesis (Branch, 1977; Dyl, 1977). According to this hypothesis, investors wait until the tax year-end to sell their

common stock 'losers', to realize capital losses to be set against capital gains in order to reduce tax liability. Second, it may be that abnormal returns in January are due to new information provided by the firms at the end of the fiscal year (Rozeff and Kinney, 1976). In reality, many firms' announcements of the previous year's financial performance are made in January.

The following test is a parametric test of serial correlation; it is employed to examine the hypothesis of no serial correlation in ASE month-of-the-year returns as an alternative test to examine month-of-the-year effects.

6.2.2.3. Serial Correlation Test

Table 6.11 below presents the serial correlation test for the first lag and the statistical significance of any first order serial correlation. The results show that, for the three samples, the serial correlation of the first lag is different from zero.

For the first sample, the strongest first lag serial correlation was found in June with 44.9%, followed by May with a value of 34.74% and November with a value of 34.06%. Conversely, the weakest correlation was found in March with a value of 6.54%. In the second sample (1999–2007), the strongest first lag serial correlations were found in November with a value of 27.75% and January with the value of 27.59%. The weakest correlation was found in September with a value of 4.69%. Moreover, for the main sample (1992–2007), the strongest first lag serial correlation was found in May with a value of 48.26%, followed by November with a value of 29.97%; whereas the weakest correlation was found in February with a value of 11.01%.

For all three samples, April, October and November reject the null hypothesis of no correlation between the return in time t and the return in time t-1 with 99% confidence. At the

same time, February is the only month that does not reject the null hypothesis, with 99% confidence.

Furthermore, in the second sample (1999–2007) and the main sample (1992–2007), January, March, April, October and November reject the null hypothesis of no correlation between the return in time t and the return in time t-1 with 99% confidence. Nevertheless, for both samples, February and December do not reject the null hypothesis of no correlation between the return in time t and the return in time t-1 with 99% confidence.

Table 6.11: Serial Correlation Tests of Months of the Year for the Three Samples

	Serial Correlation of 1st lag	*t*-test	Critical Value
Serial Correlation Test			
1992–1999			
January	0.097	1.294	+/- 2.62
February	0.139	1.804	+/- 2.62
March	0.065	0.815	+/- 2.62
April	0.337	4.766	+/- 2.62
May	0.347	4.885	+/- 2.62
June	0.449	7.098	+/- 2.62
July	0.213	2.923	+/- 2.62
August	0.291	4.188	+/- 2.62
September	0.303	4.405	+/- 2.62
October	0.291	4.227	+/- 2.62
November	0.341	4.982	+/- 2.62
December	0.238	3.290	+/- 2.62
1999–2007			
January	0.276	4.012	+/- 2.62
February	0.104	1.316	+/- 2.62
March	0.194	2.884	+/- 2.62
April	0.243	3.794	+/- 2.62
May	0.047	0.651	+/- 2.62
June	0.047	0.651	+/- 2.62
July	0.113	1.682	+/- 2.62
August	0.048	0.695	+/- 2.62
September	0.047	0.656	+/- 2.62
October	0.196	3.020	+/- 2.62
November	0.278	4.283	+/- 2.62
December	0.104	1.409	+/- 2.62
1992–2007			
January	0.226	4.557	+/- 2.62
February	0.110	1.992	+/- 2.62
March	0.180	3.579	+/- 2.62
April	0.266	5.557	+/- 2.62
May	-0.483	-7.079	+/- 2.62
June	0.177	3.503	+/- 2.62
July	0.148	2.988	+/- 2.62
August	0.176	3.597	+/- 2.62
September	0.133	2.621	+/- 2.62
October	0.234	4.957	+/- 2.62
November	0.298	6.310	+/- 2.62
December	0.136	2.591	+/- 2.62

Therefore, the finding of month-of-the-year effect in the ASE leads the author to conclude that the WFME hypothesis is not valid in the ASE. Moreover, the ASE shows that January effects or turn-of-the-year effects are still present in the main sample (1992–2007); this

finding was also confirmed in the second sample (1999–2007) and the first sample (1992–1999).

The result from the serial correlation was almost the same as the (non-parametric) tests in this research. For the three tests, January does not follow the WFME hypothesis (excluding the second sample when the length-of-runs test was employed and for the first sample when the serial correlation test was employed). Moreover, the runs test shows that January does not follow the WFME hypothesis; while the length-of-runs test shows that December does not follow the WFME hypothesis. As for the serial correlation test, the finding is that November does not follow WFME hypothesis strongly.

As mentioned earlier in Section 6.2.2.2., the explanation for this effect might be given by the tax-loss selling hypothesis (Branch, 1977; Dyl, 1977), which is more convincing than hypothesis that it is due to new information being provided by firms at the end of the fiscal year (Rozeff and Kinney, 1976) as it seems Jordanian investors wait until November to start selling their common stock 'losers', to realize capital losses to be set against capital gains in order to reduce tax liability.

Not surprisingly, January follows the WFME hypothesis for the first sample (1992–1999) using the serial correlation test, and for the second sample (1999–2007) using the length-of-runs test, but not for the full sample. It could be that January follows the WFME hypothesis in these two sub-samples by chance rather than for any economic reasons. As indicated earlier in Section 2.5.4.2., a comprehensive review of the literature illustrates that even when one sort of test (serial correlation coefficient test, runs test, variance test, GARCH test, etc.) fails to reject the random walk hypothesis, the others may actually reject it. When the main sample data follow the random walk hypothesis the sub-samples may not follow the random walk hypothesis. Therefore, for this research, applying a variety of tests to different types of

data and comparing the results on the bases of similar sorts of data and tests implemented will improve the accuracy of the study.

The next test examines the turn-of-the-month effect. McConnell and Xu (2008) examined the turn of the month for thirty-five countries and found that turn-of-the-month effect exists in thirty-one countries out of the thirty-five; however; they did not include Jordan in their sample.

6.2.2.4. Turn-of-the-Month Effect

Empirical evidence shows that stock market returns are unusually high around the turn of the month and this phenomenon is persistent over time, for example studies by Ariel (1987), Lakonishok and Smidt (1988), Ogden (1990) and McConnell and Xu (2008).

This section follows the methodology of previous studies by Lakonishok and Smidt (1988) and McConnell and Xu (2008) to examine the turn-of-the-month effect in the Amman Stock Exchange. Daily returns are divided into two subsets, the first half and the last half of the month. The first half of the month includes eight trading days, beginning with the first trading day of the month and then counting forward seven trading days into the current month. The last half of the month includes eight trading days, beginning with the last trading day of the previous month and then counting backwards seven trading days.[47]

According to McConnell and Xu (2008), the 'turn of the month' is considered as encompassing Day -1 through to Day +3, regardless of when the month is determined to begin. Therefore, this part considers the turn of the month as beginning on the last trading day of the month and ending on the third trading day of the following month.

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[47] To avoid duplication in trading days as the number of trading days is less than twenty days in several months.

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Figure 6.6 shows the average stock market returns for the 1992–2007 period. Day -1 is the last trading day of the previous month, Day +1 is the first trading day of the month, Day +2 is the second trading day of the month, and so on.

Figure 6.6: Mean Daily Returns around Turn of the Month for the Main Sample (1992–2007)
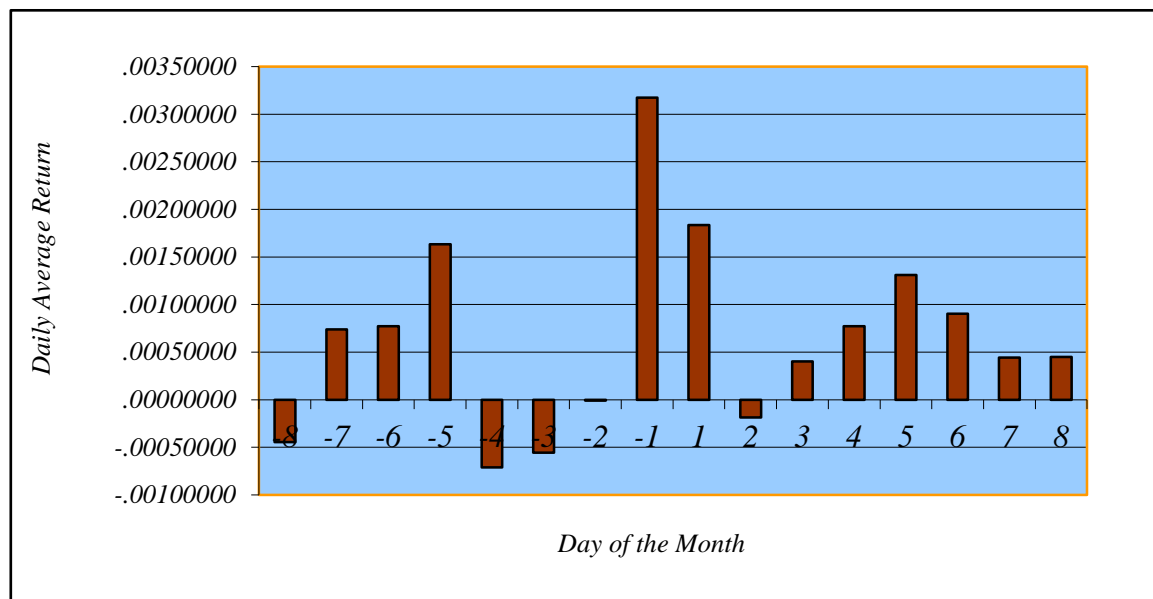
Figure 6.6 shows that Day -1 has high returns (0.31 %) compared to the other days. Furthermore, the first trading day of the month has relatively (0.18%) high returns; however, the second trading day of the month has negative returns (-0.18%). Nevertheless, returns are not equally distributed throughout the month during the study period (1992–2007).

Table 6.12 provides the statistical values for the turn-of-the-month effects for the study period 1992–2007. The first four columns report the mean daily return for Days - 1, +1, +2 and +3. Column 5 provides the mean daily return for the four-day turn-of-the-month interval (Day -1 to Day +3). Column 6 provides the mean daily return for all other days of the month. The final column provides the difference between the mean daily return for the turn-of-the-month interval and the mean daily return for all other days.

Table 6.12: Turn of the Month for the Main Sample (1992–2007)

	Day-1	Day+1	Day+2	Day+3	Day(-1,+3)	Other Days	Difference
Mean Daily Return	0.00317	0.00183	-0.00019	0.00040	0.00196	0.00033	0.00163
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Table 6.12 shows that the mean daily return over the turn-of-the-month interval (-1,+3) is 0.19%, for the other trading days of the month the mean daily return is (0.03%), and the difference between the mean daily return for the turn-of-the-month interval and the mean daily return for all other days is 0.163%. On the other hand, in all cases the p-value is significant (supporting the null hypothesis, for each day around the turn of the month there is a difference between mean returns of a specific day (such as first day of the month) and other days).

Therefore, the finding of turn-of-the-month effects in the ASE confirms that WFME is not persistent in the ASE. Moreover, the ASE shows that returns over the turn of the month period are higher than the other days of the month (0.16%). Thus, the ASE exhibits profit opportunities during the turn of the month.

Furthermore, the finding here is similar to those of previous studies such as Lakonishok and Smidt's (1988); they examined the turn-of-the-month effect in equity returns in US markets and found that the four days at the turn of the month accounted for all the positive returns to the DJIA in the US for 90-years. Furthermore, Ogden (1990) examined stock returns data for the CRSP value-weighted and equally weighted indices for the period 1969–1986. He found that returns are higher than normal on turn-of-the-month days. Recently, McConnell and Xu (2008) found that the turn-of-the-month effect occurred in the US market as well as in thirty-one out of the thirty-five countries they examined.

The next part examines the Islamic calendar as one of the moving calendars specific to month-of-the-year effects. The effects of moving calendar events such as those in the Islamic calendar (more specifically, the month-of-Ramadan effect) have not received as much attention from stock market researchers as the fixed calendar events.

6.2.3. Moving Islamic Calendar Effects

In Islamic countries, moving calendar events such as Ramadan have large effects on economic and financial markets. During the month of Ramadan, the financial markets in the Islamic countries change their trading activities and operate with reduced working hours as Muslims become more religiously oriented (Seyyed et al., 2005).

This section tests the month-of-the-year effect and the turn-of-the-month effects using the Islamic calendar year. These tests are undertaken using the following series of methods:

- Wald-Wolfowitz runs test

- Length-of-runs test

- Serial correlation test

- Comparing the mean returns at the turn of the month

6.2.3.1. Runs Test

The Wald-Wolfowitz runs test is used to examine the randomness of the *month-of-the-year* effect using the Islamic calendar year. This test is based on whether or not differences between the actual and expected runs are statistically significant for each month of the year, where the expected values are the numbers expected to be found if the data follow a random walk. The null hypothesis is:

Ho: Stock market returns for all months of the year follow a random walk.

H1: Stock market returns for all months of the year do not follow a random walk.

Table 6.13 compares the actual runs with the expected runs for the three samples. The results show that the total number of runs (actual number of runs) is different to the expected number of runs. The number of runs is greater than the expected number of runs under the WFME hypothesis. The results showing whether these differences are statistically significant are presented in Figure 6.7; the x-axis shows the month of the year for the sample period, the y-axis shows the z statistics, the red columns show the critical values of z statistics (2.575), and the blue columns show the calculated values.

Table 6.13: Comparing Actual Runs with Expected Runs of Months of the Year for Islamic Calendar Year

	Total Runs	N1 (Positive Returns)	N2 (Negative Returns)	N (Number of Runs)	E (R) (Expected Runs)
1992–2007					
1	194	156	161	317	159.46
2	189	153	165	318	159.77
3	196	166	161	327	164.46
4	192	168	152	320	160.60
5	219	167	172	339	170.46
6	200	157	169	326	163.77
7	218	181	165	346	173.63
8	225	183	158	341	170.58
9 (Ramadan)	220	175	169	344	172.94
10	175	148	146	294	147.99
11	210	169	175	344	172.94
12	167	136	143	279	140.41

Figure 6.7: Statistical Significance of Z-Test of Months of the Year for Islamic Calendar Year
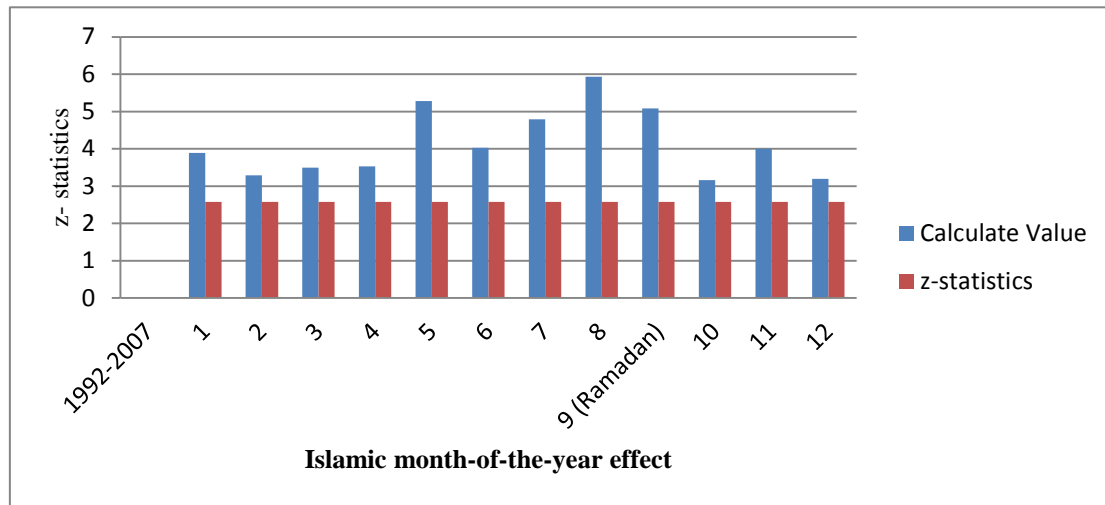
The results show that all the Islamic calendar months reject the WFME hypothesis with 99% confidence; the highest z statistics are found for the 8th month, 5th month and 9th month (Ramadan), at 5.93, 5.28 and 5.08 respectively.

Examining Islamic months of the year using the runs test shows that the month-of-the-year effect exists in the ASE. The second test is the length-of-runs test.

6.2.3.2. Length-of-Runs Test

Table 6.14 below compares the observed runs with the expected runs for each length of the sample period. The fourth and fifth run length is not calculated because the number of observations is less than 5.

Table 6.14: Length-of-Runs Test of Months of the Year for Islamic Calendar Year

Length-of-Runs Test						
Run Length	1		2		3	
	Expected	Observed	Expected	Observed	Expected	Observed
1992–2007						
1	132.58	105.00	58.06	68.00	20.91	21.00
2	133.00	104.00	58.25	53.00	21.07	32.00
3	136.75	108.00	59.90	58.00	21.67	30.00
4	134.25	97.00	58.80	70.00	21.17	25.00
5	141.75	136.00	62.10	55.00	22.37	28.00
6	136.33	114.00	59.72	53.00	21.51	33.00
7	144.67	128.00	63.38	61.00	22.83	29.00
8	142.58	141.00	62.47	58.00	21.81	26.00
9(Ramadan)	145.08	129.00	63.57	61.00	22.20	30.00
10	123.00	91.00	53.85	52.00	18.79	32.00
11	143.83	117.00	63.02	59.00	22.01	34.00
12	117.17	82.00	51.28	63.00	18.45	22.00

The results show that the expected number of runs is different to the observed number of runs for all lengths. Furthermore, the first length expected number of observations is greater than the observed number; however, for the third length, the observed number is greater than the expected number of observations. The results showing whether these differences are statistically significant are presented in Figure 6.8; the x-axis shows the sample period, the y-axis shows the chi-square statistics, and the red line shows the critical values of the chi-square statistics.

Figure 6.8: Statistical Significance of Chi-Square Test of Months of the Year for Islamic Calendar Year
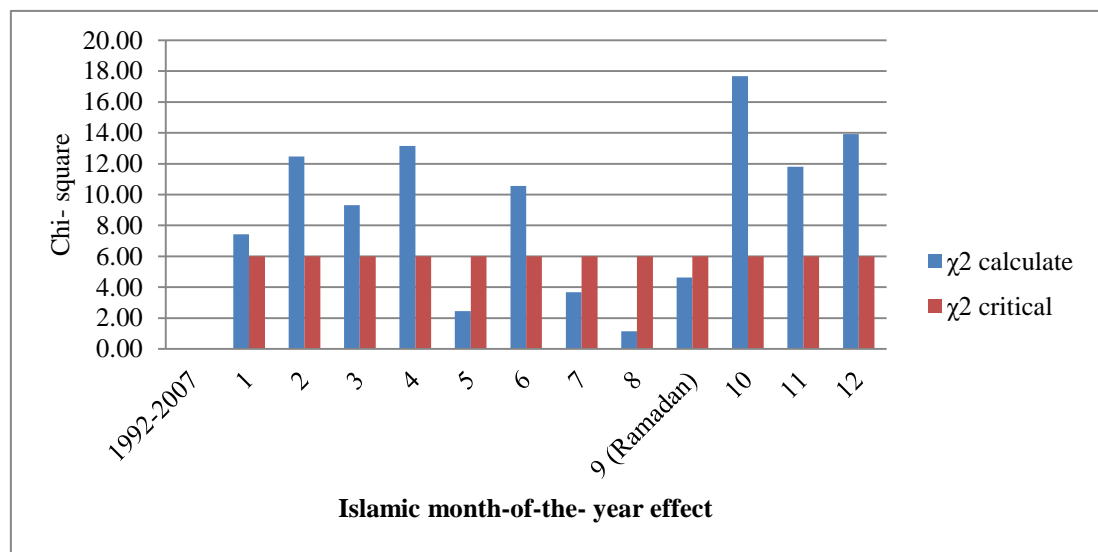
The results show that it rejects the WFME hypothesis for all months with the exception of the 5th, 7th, 8th and 9th (Ramadan) months; the chi-square statistics for these months are 2.46, 3.68, 1.14 and 4.63 respectively, and the critical value is 5.99. However, the month after Ramadan (the 10th) strongly rejects the null hypothesis with a critical value of 17.67.

Based on non-parametric tests (runs test and length-of-runs tests), the ASE returns appear to be inconsistent with the WFME hypothesis. Both tests reveal that the Islamic month-of-the-year effect exists in the ASE. However, the runs test shows the Ramadan effect whereas the length-of-runs test rejects that. Simultaneously, both tests reject the WFME hypothesis for the month after Ramadan.

The highest mean returns were found in the third month and in the month of Ramadan (0.137% and 0.134% respectively); whereas the lowest mean returns were found in the 5th month (-0.0006%), as illustrated in Table 6.15 below.

Table 6.15: Mean Return of Months of the Year for Islamic Calendar Year

Mean Return of Islamic Month of the Year 1992–2007	
Month of the Year	**Mean Return**
1	3.49E-05
2	-0.000329051
3	0.001374211
4	0.000956776
5	-6.87E-05
6	-0.000326033
7	0.000883306
8	0.000281628
9 (Ramadan)	0.001343798
10	0.001211286
11	0.000150189
12	0.00065918

The next test is the non-parametric test of serial correlation; it is employed to examine the hypothesis that there is no serial correlation in the Islamic month-of-the-year returns as an alternative test to examine the month-of-the-year effect.

6.2.3.3. Serial Correlation Test

Table 6.16 below presents the results of tests undertaken for the statistical significance of any first order serial correlation found. The results show that the serial correlation of the first lag is different from zero.

Table 6.16: Serial Correlation Test of Months of the Year for Islamic Calendar Year

Serial Correlation Test			
	Serial Correlation of 1st lag	*t* test	Critical Value
1992–1999			
1	0.20	4.22	+/- 2.62
2	0.26	5.52	+/- 2.62
3	0.28	6.01	+/- 2.62
4	0.19	3.98	+/- 2.62
5	-0.49	-7.42	+/- 2.62
6	0.16	3.21	+/- 2.62
7	0.03	0.47	+/- 2.62
8	0.08	1.56	+/- 2.62
9(Ramadan)	0.13	2.65	+/- 2.62
10	0.26	5.51	+/- 2.62
11	0.27	5.85	+/- 2.62
12	0.27	5.90	+/- 2.62

The strongest first lag serial correlation was found in the 5th month with a value of 48.67%, followed by the 3rd month with a value of 28% and the 12th month with a value of 27.11%. The weakest correlation was found in the 7th and 8th months with values of 2.5% and 8.05% respectively. Furthermore, only the 7th and 8th month do not reject the null hypothesis of no correlation between the return in time *t* and the return in time *t*-1, with 99% confidence. The month of Ramadan rejects the null hypothesis of no correlation between returns with 99% confidence.

The finding of month-of-the-year effects in the ASE, especially the Ramadan effect, leads to the conclusion that the WFME hypothesis is not valid in the ASE using Islamic calendar data. The result from serial correlation test was similar to the pervious (non-parametric) tests in this research. The three tests show that the 10th month does not follow the WFME hypothesis. Moreover, the runs test and serial correlation test show that the month of Ramadan strongly does not follow the WFME hypothesis. In addition, the length-of-runs test shows that the 10th month strongly does not follow the WFME hypothesis.

The next test examines the turn-of-the-month effect using the Islamic calendar. Using the Gregorian calendar in Section 6.2.2.4, the results show that a turn-of-the-month effect exists. The next test considers whether that is also the case when the Islamic calendar is used.

6.2.3.4. Islamic Turn-of-the-Month Effect (Islamic Calendar)

Empirical evidence in this research shows that stock market returns are unusually high around the turn of the month when the Gregorian calendar is employed; this part of the thesis will examine that for the Islamic calendar.

Figure 6.9 shows average stock market returns for the 1992–2007 period. Day -1 is the last trading day of the previous month, Day +1 is the first trading day of the month, Day +2 is the second trading day of the month, and so on.

Figure 6.9: Daily Average Returns of Months of the Year for Islamic Calendar Year
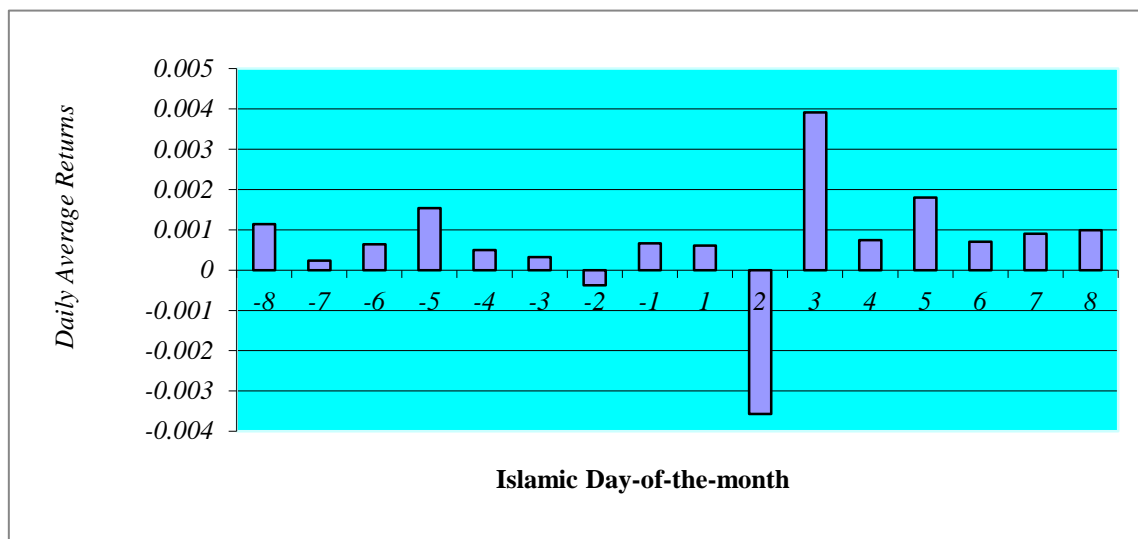
Figure 6.9 shows that Day +3 has high returns (0.39 %) compared to the other days. Furthermore, Day -1 and Day +1 have positive returns; however, Day +2 has the lowest

returns (-0.35%) compared to the other days. Nevertheless, returns are not equally distributed throughout the month in the Islamic calendar.

Table 6.17 gives the statistical values for the turn-of-the-month effects for the Islamic calendar. The first four columns report the mean daily return for Days - 1, +1, +2, and +3. Column 5 provides the mean daily return for the four-day turn-of-the-month interval (Day -1 to Day +3). Column 6 provides the mean daily return for all other days of the month. The final column provides the difference between the mean daily return for the turn-of-the-month interval and the mean daily return for all other days.

Table 6.17: Turn of the Month for Islamic Calendar Year

	Day-1	Day+1	Day+2	Day+3	Day(-1,+3)	Other Days	Difference
Mean Daily Return	0.00066	0.00062	-0.00359	0.00382	0.00085	0.00054	0.00031
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Table 6.17 shows that the mean daily return over the turn-of-the-month interval (-1,+3) is 0.08%. Over the other trading days of the month, the mean daily return is 0.05% and the difference between the mean daily return for the turn-of-the-month interval and the mean daily return for all other days is 0.03%. In all cases the p-value is significant.

The finding here is similar to that for the Gregorian calendar in this research. In both types of data, the return over the turn-of-the-month period is higher than the other days of the month. Furthermore, the finding for the turn of the month in the ASE is consistent with results from previous research such as the study by McConnell and Xu (2008); they found that the turn-of-the-month effect occurs in the US market as well as in thirty-one out of the thirty-five countries examined.

6.3. Interpretation of the Results from a Behavioural Finance Perspective

As identified earlier in Chapter Two, many psychologists would argue that actions and performances of people are driven by what they think, which is heavily influenced by how they feel. How people feel is partly dependent on their interactions with others. If an investor is in a good mood, there will be a tendency for them to be optimistic when evaluating an investment. Good moods may cause investors to be more likely to make risky investments (Redhead, 2008). Weather and the length of daylight are also factors that can affect mood (Hirshleifer and Shumway, 2003; Kamstra et al., 2003).

If Muslim investors in the ASE behave differently during the month of Ramadan, this would indicate that religious belief is another factor that influences investors' moods. At the same time, it supports the behavioural finance theory that the actions and performances of investors are influenced by how they feel. How investors feel is partly dependent on their beliefs.

This part is divided into two sections; the first section interprets the results according to mood effects in relation to weather factors and the second section examines the importance of religious beliefs.

6.4. Interpretation of the Results According to Mood Effects by Looking at Weather Factors

People often attribute their feelings to the wrong source, leading to incorrect judgments. As an example of this problem of *misattribution*, people feel happier during good weather (such as on sunny days) than during bad weather (such as on cloudy days). Psychologists have been documenting the correlation between weather and behaviour for decades. Factors such as sunshine have been linked to tipping (Rind, 1996) and lack of sunshine to depression (Eagles,

1994) and suicide (Tietjen and Kripke, 1994). The majority of evidence suggests that people feel better when they are exposed to more sunshine.

If investors are more optimistic in good weather, they may be more inclined to buy stocks. Specifically, they may incorrectly attribute their good mood to positive economic prospects rather than good weather. This suggests that weather is positively correlated with stock returns. Furthermore, depression has been linked with seasonal affective disorder, a condition that affects many investors during the season of relatively fewer hours of daylight such as during cloudy and rainy days (or months). In contrast, if investors are rational maximizer, there is little reason to speculate that weather is correlated with stock returns.

In Jordan, the general features of the weather are related to its location, east of the Mediterranean Sea. It forms part of the subtropical zone, where the year is divided into two main seasons: a hot dry summer and a cool wet winter. Table 6.18 below presents the climate average in Jordan from 1990 to 2005.

Table 6.18: Climate Average Data of Jordan (1990–2005)[48]

Table 6.18 above shows that, the coldest months in Jordan are December, January, February and March. During these months, the average mean maximum temperature is less than 18°C and the average mean minimum temperature is less than 7°C. Furthermore, the average total monthly rainfall during these months is more than 50 mm with the exception of March when it is 37.2 mm. The average mean relative humidity is more than 66%. The best weather in Jordan is generally in April and November. During these two months, the average mean maximum temperature is nearly 20°C, and the average mean minimum temperature is nearly 10°C.

March is the last month of the winter season in Jordan and October is last month of the summer season. It may therefore be expected that investors' moods may change and they are more likely to be depressed in March and October. Any depression may more heavily

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[48] Jordan Meteorological Department, [online] available at http://met.jometeo.gov.jo/portal/page?_pageid_= 113,1,113_56214:113_82177&_dad=portal&_schema=PORTAL&E_STN=SYNP0013&E_ELEM=534   [15 July 2010].

influence the stock market returns for these two months compared to other months of the year.

The previous section in this chapter, using parametric and non-parametric tests, found that ASE price movements contradicted the WFME hypothesis. The results from sub-samples confirmed that. The results revealed that the month-of-the-year effect exists in the ASE. Table 6.19 below summarizes the average mean return and standard deviation for each of the three samples.

Table 6.19: Mean Return and Standard Deviation of Months of the Year for the Three Samples

	1992-1999		1999-2007		1992-2007	
	Mean Return	Std. Deviation	Mean Return	Std. Deviation	Mean Return	Std. Deviation
January	0.07%	0.79%	0.26%	1.18%	0.16%	1.00%
February	0.03%	0.50%	-0.07%	1.24%	-0.01%	0.94%
March	-0.08%	0. 48%	0.00%	1.16%	-0.03%	0.92%
April	0.12%	0.66%	0.00%	1.06%	0.05%	0.91%
May	0.15%	0.87%	0.03%	7.55%	0.08%	5.83%
June	-0.01%	0.74%	0.05%	0.91%	0.02%	0.84%
July	-0.03%	0.99%	0.04%	1.19%	0.01%	1.11%
August	-0.01%	0.93%	0.03%	0.76%	0.01%	0.83%
September	0.13%	0.74%	0.00%	0.97%	0.06%	0.87%
October	-0.08%	0.44%	0.18%	0.92%	0.06%	0.76%
November	0.01%	0.59%	0.21%	1.12%	0.12%	0.92%
December	0.10%	0.59%	0.00%	1.05%	0.05%	0.86%

Table 6.19 presents summary statistics of the monthly mean returns for each month of the year in the three samples. In the first sample (1992–1999), the mean return for the best weather for April is 0.12% and for November is 0.01%; the mean return for both months is 0.06%. It seems that April returns are better than November returns with respect to the weather. Conversely, for the bad weather, the mean return for March is -0.08% and for October is -0.08. Both months have a negative return, which is expected as bad weather will have negatively influenced the mood during these months.

Furthermore, the spread of the monthly return around the mean is slightly higher during all the months (standard deviation in each month is more than five times the monthly returns), which indicates that the returns are highly volatile during this period for all months. However, April has the lowest spread compared with the rest of the months; this month presents a high return and a low risk that may be presented as a profitable opportunity for ASE investors.

In order to identify whether temperature influences the stock market returns in Jordan, *t*-tests[49] are used to examine whether or not average monthly returns differ by statistically significant amounts compared to the months of the best weather (April and November). Tables 6.20, 6.21 and 6.22 below present the results.

Table 6.20: One-Sample T-Test of Monthly Returns for the First Sample (1992–1999)

					95% Confidence Interval of the Difference	
Test Value = 0.06% (average mean return in April and November during 1992–1999)						
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Jan	0.134	162	0.893	0.00%	-0.15%	0.17%
Feb	-0.877	146	0.382	-0.03%	-0.14%	0.07%
Mar	-3.704	146	0.00	-0.14%	-0.25%	-0.04%
Apr	1.037	134	0.302	0.05%	-0.09%	0.20%
May	1.177	130	0.241	0.09%	-0.11%	0.29%
Jun	-1.285	139	0.201	-0.08%	-0.24%	0.08%
Jul	-1.239	149	0.217	-0.10%	-0.31%	0.11%
Aug	-1.157	148	0.249	-0.08%	-0.28%	0.11%
Sep	1.121	148	0.264	0.06%	-0.09%	0.22%
Oct	-4.109	151	0.00	-0.14%	-0.24%	-0.05%
Nov	-1.122	142	0.264	-0.05%	-0.18%	0.07%
Dec	0.755	146	0.451	0.03%	-0.09%	0.16%

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[49] Critical value of *t* is 1.96 with 95% level of confidence and 1.64 with 90% level of confidence.

Table 6.21:One-Sample T-Test of Monthly Returns for the Second Sample (1999–2007)

					95% Confidence Interval of the Difference	
Test Value = 0.10% (average mean return in April and November during 1999–2007)						
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Jan	1.7	154	0.091	0.16%	-0.09%	0.41%
Feb	-1.716	145	0.088	-0.18%	-0.44%	0.09%
Mar	-1.144	180	0.254	-0.10%	-0.32%	0.13%
Apr	-1.314	185	0.19	-0.10%	-0.31%	0.10%
May	-0.135	189	0.893	-0.07%	-1.50%	1.35%
Jun	-0.723	184	0.471	-0.05%	-0.22%	0.13%
Jul	-0.636	196	0.525	-0.05%	-0.28%	0.17%
Aug	-1.222	196	0.223	-0.07%	-0.21%	0.08%
Sep	-1.399	187	0.164	-0.10%	-0.28%	0.09%
Oct	1.179	192	0.24	0.08%	-0.10%	0.25%
Nov	1.285	173	0.201	0.11%	-0.11%	0.33%
Dec	-1.159	166	0.248	-0.09%	-0.31%	0.12%

Table 6.22: One-Sample T-Test of Monthly Returns for the Main Sample (1992–2007)

					95% Confidence Interval of the Difference	
Test Value = 0.08% (average mean return in April and November during 1992–2007)						
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Jan	1.424	317	0.155	0.08%	-0.07%	0.23%
Feb	-1.963	292	0.051	-0.11%	-0.25%	0.03%
Mar	-2.388	327	0.017	-0.12%	-0.25%	0.01%
Apr	-0.662	320	0.509	-0.03%	-0.17%	0.10%
May	-0.018	320	0.985	-0.01%	-0.85%	0.84%
Jun	-1.33	324	0.184	-0.06%	-0.18%	0.06%
Jul	-1.242	346	0.215	-0.07%	-0.23%	0.08%
Aug	-1.678	345	0.094	-0.08%	-0.19%	0.04%
Sep	-0.527	336	0.599	-0.03%	-0.15%	0.10%
Oct	-0.528	344	0.598	-0.02%	-0.13%	0.09%
Nov	0.658	316	0.511	0.03%	-0.10%	0.17%
Dec	-0.696	313	0.487	-0.03%	-0.16%	0.09%

Table 6.20 shows that for the first sample 1992–1999 the average mean returns for March and October are significantly different to those of April and November. It appears that the weather does affect investors' moods, revealing that bad weather affects ASE investors

negatively. However, Table 6.21 shows that for the second sample (1999–2007) the mean difference returns of March are negative compared with the period of the best weather returns; the difference is, however, not significant. This period shows a high level of volatility, especially between 2004 and 2007; it shows cluster volatility, which may reduce the influence of the weather effects. Nevertheless, when the test examines the main sample period (1992–2007), the results show that the average mean return of March is significantly different to that of the other months.

This indicates that March is more important than October in Jordan. March is the last month of the winter season with an average temperature of less than 7°C, average rainfall of more than 37 mm, and high humidity (66%). The weather in Jordan may influence Jordanian investors' behaviours and, by the end of the winter season in March, investors may feel more depressed. Any depression will cause investors to be in a bad mood. If the investors are in a bad mood in March, their expectations about future prices will be pessimistic; therefore, investors may be more willing to sell their shares during this month to avoid future risks, according to their pessimistic outlook about future prices. An increase in the selling of shares during March will provide an indicator to other investors about the pessimistic future outlook and then this may drive more investors to sell their shares. Consequently, this may result in shares becoming underpriced and the returns during this month to be negative.

6.5. Interpretation of the Results According to Mood Effects by Looking at the Ramadan Factor

In Jordan, Ramadan is an Islamic religious observance that takes place during the ninth month of the Islamic calendar; the month in which the *Qur'an*, according to tradition, was revealed to the Prophet Muhammad. It is the Islamic month of fasting, in which participating Muslims do not eat or drink from dawn until sunset. Fasting is meant to teach the person

patience, sacrifice and humility. Ramadan is a time to fast for the sake of Allah, and to offer more prayer than usual. Muslims also believe that, through good deeds during Ramadan, they are doubly rewarded compared to other months. During the holy month, Muslims ask for forgiveness for past sins, pray for guidance and help in refraining from everyday evils, and try to purify themselves through self-restraint and good deeds.

After the ASE data was adjusted to match the Islamic calendar year, using non-parametric tests (runs test and length-of-runs test), the ASE returns appeared to behave inconsistently with the WFME hypothesis. Both tests reveal that the Islamic month-of-the-year effect appears in the ASE. However, the runs test shows the Ramadan effect, whereas the length-of-runs test rejects that. Simultaneously, both tests reject the WFME hypothesis for the month after Ramadan. The finding of month-of-the-year effects in the ASE, especially the Ramadan effect, leads to the conclusion that the WFME hypothesis is not valid in the ASE in relation to the Islamic calendar. The results from the serial correlation test were quite similar to the previous (non-parametric) tests. For all three tests, the 10th month does not follow the WFME hypothesis. Moreover, the runs test and serial correlation test show that the month of Ramadan strongly does not follow the WFME hypothesis, while the length-of-runs test shows that the 10th month strongly does not follow the WFME hypothesis.

Therefore, although during Ramadan Muslims in Jordan spent the daytime feeling hungry, which is expected to have a bad influence on investor mood, this is more than offset by the positive impact of the religious holiday, which leads investors to trade more. If investors are more optimistic during Ramadan, they may be more inclined to buy stocks during this month. One of the months of the highest returns in the Islamic calendar is the month of Ramadan (0,13%). Table 6.23 below summarizes the mean return of the Islamic calendar.

Table 6.23: Mean Return of Months of the Year for Islamic Calendar Year

Mean Return Month-of-the-Year of Islamic Calendar Year	
1	3.49E-05
2	-0.00033
3	0.001374
4	0.000957
5	-6.87E-05
6	-0.00033
7	0.000883
8	0.000282
9 (Ramadan)	0.001344
10	0.001211
11	0.00015
12	0.000659

T-tests are used to examine whether the average mean return during the month of Ramadan is different from the average mean returns of all other months (excluding Ramadan). For example, Ramadan is compared against the mean returns of the other eleven months in the sample. Table 6.24 presents the mean returns of eleven months of the Islamic calendar year, excluding one month each time. Table 6.25 presents the results from the t-test for the month of Ramadan.

Table 6.24: Descriptive Statistics of the Mean Returns of Eleven Months of Islamic Calendar Year Excluding One Month Every Time

	N	Mean	Std. Deviation
Exc1st	3594	0.0005534	0.0194306
Exc2ed	3593	0.0005858	0.0193757
Exc3ed	3584	0.0004322	0.0194871
Exc4th	3590	0.0004712	0.0195316
Exc5th	3572	0.0005664	0.0092112
Exc6th	3585	0.0005876	0.0194635
Exc7th	3565	0.000475	0.0195483
Exc8th	3570	0.0005332	0.0196058
ExcRamadan	3564	0.0004299	0.019619
Exc10th	3617	0.0004541	0.019399
Exc11th	3567	0.0005461	0.0195418
Exc12	3631	0.0004998	0.0193585
Valid N (listwise)	3564		

Table 6.25: One-Sample T-Test Examining the Mean Returns of Other Islamic Months against the Month of Ramadan

	Test Value = .000429905					
	t-value	df	Sig. (2-tailed)	Mean Difference	99% Confidence Interval of the Difference	
					Lower	Upper
Ramadan	2.383	347	0.018	0.00091	-0.00007	0.00190

Table 6.25 shows that Ramadan has significantly different mean returns compared with other months of the year. Religious beliefs in Jordan may influence investor behaviour; investors may feel happier when they follow religious activities (fasting and *zakat*) during Ramadan. This happier state may cause investors to be in a good mood. If the investors are in a good mood in Ramadan, their expectations about future prices will be optimistic. Therefore, investors are more willing to buy shares during this month to gain more profit according to their optimistic outlook about future prices. The increase in share buying during Ramadan

will provide indicators to other investors about the optimistic future expectations and then this may drive other investors to buy shares. As a result, shares may become overpriced and the returns during that month will be positive.

According to behavioural finance, another bias based on optimism is *outcome bias*. This can potentially explain why Ramadan has high returns. Outcome bias causes people to expect that they will get what they want. Decisions are made in the expectation that what they want to happen will happen; in other words, wishful thinking (Redhead, 2008).

In Jordan, during Ramadan, investors may expect a high return on an investment because a high return is what is wanted. Jordanian Muslim investors believe that during the month of Ramadan, through good deeds, they are rewarded doubly compared to normal. Therefore, they may expect to gain a high return during Ramadan as Islamic religious festivities encourage trading rather than saving, and this may lead investors to become more overconfident and to underestimate risk.

6.6. Interaction between Weather Mood Effects and Ramadan Mood Effects

In Jordan, investors' moods decline during the month of March and this may lead to depression. This depression may influence the stock market returns in March and could result in negative returns compared with other months of the year. Conversely, April and November are the best months in terms of weather in Jordan. April returns have the lowest spread compared with those of the rest of the months; this month presents a high return and a low risk that may be presented as a profitable opportunity for ASE investors. This reveals that a weather effect does indeed exist in the ASE.

Ramadan has significantly different mean returns compared with other months of the year. Hence, religious beliefs in Jordan may influence investor behaviour; Muslim investors may

feel happier when they follow their religious practices, particularly during Ramadan. This happier period may cause investors to be in a good mood. If investors are in a good mood during Ramadan, their expectations about future prices will be optimistic. Therefore, the Ramadan effect does exist in the ASE.

The Islamic calendar is a lunar calendar, and months begin when the first crescent of a new moon is sighted. Since the Islamic lunar calendar year is 11—12 days shorter than the solar year and contains no intercalation, Ramadan migrates throughout the seasons. During the period of study, 1992–2007, Ramadan started on 22 February in 1992 and moved back eleven days every year subsequently. In 2007, Ramadan started on 13 September. Therefore, Ramadan did not fall during good or bad weather periods during the data period (it did fall in November and October, but not in March or April). This study cannot find sufficient data to determine whether or not Ramadan has an impact on the weather effects (the Jordanian stock market started calculating the weighted price index in 1992).

6.7. Profitability of Trading on Weather and Ramadan Mood Effects

The empirical results of tests for mood effects seem to be inconsistent with theories of market efficiency. The profitability of this anomaly is the main concern for the market participants. In fact, market investors try to exploit any anomalies in their trading strategies to obtain high returns.

This section examines whether or not the weather effects and Ramadan effects found produce profit opportunities for ASE investors. The section compares the returns from a buy-and-hold strategy against one of trading randomly. Transaction costs are deducted from profits.

ASE investors incur two main types of transaction costs: commission fees and a marketability (liquidity) cost. The commission fees that are paid to brokers can be either fixed or

negotiable. In either case, this cost is unavoidable because all investors can trade only through the agency of a stockbroker.

The more important aspect of the trading costs is the marketability cost. Demsetz (1968) argued that the market-maker provides the service of 'predictive immediacy'. This is why the spread between the market-maker's bid and ask prices is used as an operational measure of marketability.

Table 6.26 presents the commission fees in the ASE. The cost of each trading position is calculated according to the market value. The total commission fee is 0.74%. However, because the highest bid prices and the lowest ask prices are not published in the ASE, an estimate is used for this from Omet (2001). Based on his empirical findings, the mean transacting cost in the Jordanian capital market is estimated at 1.05 %. The bid-ask spread is 0.31 approximately. This mean transacting cost in Jordan (1.05%) is relatively high, compared to the mean transacting costs in the NYSE (0.26%) (Venkataraman, 2001).

Table 6.26: Commission Fees in the ASE

Institution	Value
Jordan Securities Commission	0.05%
Amman Stock Exchange	0.05%
Securities Depository Centre	0.04%
Brokers	0.6%

The profitability of the weather effects in the ASE, using a buy-and-hold strategy to buy on the last trading day of March and sell on the last trading day of April, is 0.47%. This is quite high but when it is compared to the transaction cost (1.05%) it is not profitable. This indicates that, even though the weather may influence investor mood and therefore market efficiency, it is not enough to adopt as a trading rule to obtain higher returns than normal.

For Ramadan effects, ASE investors could gain 0.58% average returns if they employed a buy-and-hold strategy of buying on the last trading day of month before Ramadan and selling on the last trading day of Ramadan. This is greater than the profit obtained from the weather effects yet when transaction costs are considered it is not profitable. This indicates that, even though Ramadan influences investor mood and therefore affects market efficiency, it is not enough to produce a trading rule to obtain higher returns than normal.

6.8. Conclusion

This chapter aimed to test the weak form market efficiency of the Amman Stock Exchange and did so by examining the calendar effects in the ASE. In Islamic countries, like Jordan, moving calendar events such as Ramadan have large effects on economic and financial markets. The chapter has examined the moving calendar effects in the ASE. Evidence on return seasonality would have important implications for ASE participants and it would invalidate the efficient market hypothesis for the ASE. If these calendar anomalies are not profitable then the market can be considered efficient, according to Redhead (2008).

Using both parametric and non-parametric tests, the returns of the ASE during the period 1992–2007 moved contrary to the WFME hypothesis. Realizing that test results can be highly time-dependent, the full period was divided into sub-periods. The result from the two sub-samples confirmed that the ASE does not follow the WFME hypothesis. The data was then adjusted to match the Islamic calendar. The results from the runs tests and serial correlation tests reveal that the month of Ramadan and the following month do not follow the WFME hypothesis. Table 6.27 below summarizes the results obtained from the tests used in this chapter.

Furthermore, the result from the difference of two proportions tests for Sunday indicates that mean returns are different between Sunday and the rest of the days of the week (excluding Monday and Wednesday) for the second sample (1999–2007). This finding increases the credibility of day-of-the-week effects. The results obtained from the difference between the TOM (Day -1 to Day +3) and other days of the month, using the Gregorian calendar and Islamic calendar, are positive in both cases; in both cases the p-value also confirm that TOM days (Day -1 to Day 3) are statistically significant. This finding indicates that the ASE shows trading patterns over the turn-of-the-month period.

Furthermore, weather effects and the Ramadan effect are also factors that can affect mood. The effects of such factors on investors' decisions have been researched in this chapter. The results indicate that good weather has a positive influence on Jordanian investors, such as in April and in November. This can be compared to the negative influence during periods of bad weather, such as in March. For example, April has significant positive returns compared with March.

However, May and September have higher returns in the first sample (1992–1999) but not in the second sample (1999–2007) or the main sample (1992–2007). Cao and Wei (2005) defined a 'comfortable' temperature as being 18.33°C. In May the average temperature in these two months is 27.9°C and in September it is 30.6°C., which might explain why these two months did not have high returns in the second sub-sample (1999–2007) and the main sample (1992–2007).

In addition, Ramadan has significant positive returns relative to other months. This reveals that, although during Ramadan Muslim in Jordan spend the daytime feeling hungry, investors in general feel positive during this religious holiday. If investors are more optimistic during

Ramadan, they may be more inclined to buy stocks during this month. Thus, Ramadan has higher returns compared to other months.

The cost of transactions is the main barrier to investors exploiting any market anomalies. If the transaction cost is higher than the profit that can be gained from such anomalies, then the investors will not adopt them in their trading strategies. In countries like Jordan, the transaction cost (1.05%) outweighs the benefit of the anomalies.

This argument seems convincing in thinly traded emerging markets such as Jordan, where a number of specific factors delay the flow of information. First, illiquidity affects the market's capacity to accommodate orders (Chordia et al., 2005). Second, a low degree of competition results in the presence of dominant players, who can cause stock prices to move away from their intrinsic value (Mobarek and Keasey, 2000). Finally, a lack of a 'culture of equity' has a tendency to slow the reaction of market participants to information, thus reducing efficiency (Aloui, 2005).

In practical terms, most investors and financial analysts are concerned about the uncertainty of the returns on their investment assets, caused by the variability in speculative market prices (and market risk) and the instability of business performance (Alexander, 1999). Recent developments in financial econometrics require the use of quantitative models that are able to explain the attitude of investors not only towards expected returns and risks but towards volatility as well. Hence, market participants should be aware of the need to manage risks associated with volatility. This requires models that are capable of dealing with the volatility of the market (and the series). Due to unexpected events, uncertainties in prices (and/or returns) and the non-constant variance in the financial markets, financial analysts have started to model and explain the behaviour of stock market returns and volatility using time series econometric models.

For that reason, the subsequent chapter examines the volatility in the Amman Stock Exchange returns using GARCH models. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security's value does not fluctuate dramatically, but changes in value at a steady pace over a period of time.

Table 6.27: Summary of the Results from All Tests used in Chapter Six to Examine the Calendar Effects in the ASE using Gregorian and Islamic Calendar Data

PANEL (A)	Runs Tests, Serial Correlation Tests and Length-of-Runs Tests						
	Runs		Length-of-runs		Serial Correlation		
	Random	Non-Random	Random	Non-Random	Random	Non-Random
Day of the week 1992–1999		X		X		X
Day of the week 1999–2007		X		X		X
Day of the week 1992–2007		X		X		X
Month of the year 1992–1999		X		X		X
Month of the year 1999–2007		X		X		X
Month of the year 1992–2007		X		X		X
Month of the Islamic year		X		X		X

PANEL (B)	Difference of Two Proportions Tests							

Testing the differences between Sunday, Monday and Thursday with other days of the week for the second sample (1999–2007)

	Sunday			Monday			Thursday	
	z	Sig.		z	Sig.		z	Sig.
Monday	1.442	No	Sunday	1.442	No	Sunday	2.98	Yes
Tuesday	2.538	Yes	Tuesday	1.046	No	Monday	1.501	No
Wednesday	1.158	No	Wednesday	0.214	No	Tuesday	0.391	No
Thursday	2.98	Yes	Thursday	1.501	No	Wednesday	1.774	Yes

Testing the differences between Sunday, Monday and Thursday with other days of the week for the main sample (1992–2007)

	Sunday			Monday			Thursday	
	z	Sig.		z	Sig.		z	Sig.
Saturday	1.157	No	Saturday	0.419	No	Saturday	0.355	No
Monday	0.889	No	Sunday	0.889	No	Sunday	1.749	Yes
Tuesday	1.748	Yes	Tuesday	0.813	No	Monday	0.965	No
Wednesday	0.587	No	Wednesday	0.251	No	Tuesday	0.241	No
Thursday	1.749	Yes	Thursday	0.965	No	Wednesday	1.217	No

PANEL (C)	Comparing the Mean Return at the Turn of the Month						

(1)	Gregorian calendar turn of the month (1992–2007)						
	Day-1	Day+1	Day+2	Day+3	Day(-1,+3)	Other Days	Difference
Mean Daily Return	0.00317	0.00183	-0.00019	0.0004	0.00196	0.00033	0.00163
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

(2)	Islamic calendar turn of the month						
	Day-1	Day+1	Day+2	Day+3	Day(-1,+3)	Other Days	Difference
Mean Daily Return	0.00066	0.00062	-0.00359	0.00382	0.00085	0.00054	0.00031
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

7. Chapter Seven: An Examination of the Influence of Islamic Calendar and Social Mood Factors on Volatility

7.1. Introduction

This chapter investigates the relationship between seven mood-proxy variables and stock market returns and also between the mood proxies and volatility. The last two hypotheses of this research are also examined in this chapter; these explore whether or not stock market volatility levels differ during Ramadan and also explore whether volatility levels in stock market returns are affected by social mood effects during this period.

The mood-proxy variables used are constructed from: weather data (temperature, humidity and wind), biorhythmic data (seasonal affective disorder, daylight saving time changes and lunar phases) and belief data (the month of Ramadan). The mood-proxy variables are collected and calculated using a variety of approaches.

It can be noted that high levels of volatility during Ramadan were found in the previous chapter; these findings are consistent with increased synchronization of opinions. This chapter examines the influence of Ramadan on investor mood during different phases of the festival. It considers: the whole month, and the last 20 days, the last 15, the last 10 and the last 5 days of Ramadan. In addition, possible interaction effects between the weather variables and Ramadan, as well as possible interactions between the biorhythmic variables and Ramadan, are also examined.

The previous chapter provided evidence to suggest that the generally positive mood of the population that exists throughout the period of Ramadan has a positive impact on stock prices. This is reinforced by the observation that share trading volumes tend to be higher

during this period. To the extent that Ramadan generates a positive mood, there may be an increased tendency to invest, and the positive mood could cause investors to be less discriminating and less analytical in relation to their investments.

Studies in behavioural finance have found evidence that equity investors might misattribute the source of their moods and allow irrelevant feelings to inform their equity investment decisions. This chapter examines whether Jordanian investors allow weather and biorhythmic variables to influence their financial decisions. It delves beyond this by also examining the influence of possible interactions between Ramadan and: weather variables and biorhythmic variables.

The next section examines the concept of mood misattribution. A brief description of the variables is presented in Section 7.3. This is followed by a consideration of the testing approach. Fifteen different models from the GARCH family are examined in Section 7.4. The next section, Section 7.5, presents the modelling methodology used in this chapter. Section 7.6 presents the results from using a general to specific (GTS) methodology. This is followed by Section 7.7 with an interpretation of the results and Section 7.8, which concludes this chapter.

7.2. Mood Misattribution

Mood affects investment behaviour (Nofsinger, 2002) and it has been suggested that good moods make people less critical, and can lead to decisions that lack detailed analysis. People transmit moods to one another when interacting socially. People not only receive information and opinions in the process of social interaction they also receive moods and emotions.

Moods and emotions interact with cognitive processes when people make decisions. There are times when such feelings can be particularly important, such as during periods of

uncertainty or when the decision is very complex. The moods and emotions may be unrelated to a decision, but nonetheless affect the decision. Moods and motives produced by spiritual factors will affect individual decisions. The general level of optimism or pessimism in society will influence individuals and their decisions, including their financial decisions.

As identified earlier in Chapter Two, there is a distinction between emotions and moods. Emotions are often short term and tend to be related to a particular person, object or situation. Moods are free-floating and not attached to anything specific. A mood is a general state of mind and can persist for long periods. A mood may have no particular causal stimulus and have no particular target (Redhead, 2008).

A positive mood is accompanied by emotions such as optimism, happiness and hope. These feelings can become extreme and result in euphoria. A negative mood is associated with emotions such as fear, pessimism and antagonism. Nofsinger (2005) suggested that social mood is quickly reflected in the stock market, such that the stock market becomes an indicator of social mood. Prechter (1999), in proposing a 'socionomics' hypothesis, argued that moods cause financial market trends and contribute to a tendency for investors to act in a concerted manner and to exhibit herding behaviour.

Many psychologists would argue that actions are driven by what people think, which is heavily influenced by how they feel. How people feel is partly determined by their interactions with others. Prechter's socionomic hypothesis suggests that human interactions spread moods and emotions. When moods and emotions become widely shared, the resulting feelings of optimism or pessimism can cause uniformity in financial decision-making. This amounts to herding and has impacts on financial markets at the aggregate level. It seems likely that such interpersonal transmission of moods coincides with the social interactions at the beginning and end of Ramadan.

This thesis would argue that the impact of Ramadan on trading volumes and returns is possibly a reflection of the increasing importance of social networks and the increased synchronization of opinions. It could be interpreted as showing that when the general investing environment is positive the Ramadan sentiment effect has a magnified positive impact on trading activity. Conversely, when the investment environment is negative the Ramadan sentiment effect magnifies the negative impact on trading activity.

Generally it can be stated that factors that induce a positive mood in people lead them to make more optimistic judgments than if they were in a neutral mood, while factors that induce a negative mood in people lead them to make more pessimistic judgments than if they were in a neutral mood. The finding regarding the influence of irrelevant mood states on decision-making is referred to as 'mood misattribution'.

7.2.1. Weather Variables

Weather is a widely researched source of misattributed mood in psychology. The essential finding in this area is that good weather induces positive mood states and bad weather induces negative mood states (Dowling and Lucey, 2008). Some findings in tests for a possible relationship between equity pricing and weather-based mood-proxy variables include:

- Temperature is positively related to equity returns (Cao and Wei, 2005); temperature may be related to volatility (Kang et al., 2010).
- Wind speed is negatively related to equity returns (Keef and Roush, 2005);
- wind speed is a positively related to volatility (Dowling and Lucey, 2008).
- Humidity appears to have a positive relationship with equity returns (Lucey and Dowling, 2005); humidity is related to volatility (Kang et al., 2010).

Weather and the length of daylight are factors that can affect mood. The effects of such factors on investment decisions have been found in the literature. For instance, Hirshleifer and Shumway (2003) investigated the effects of sunshine on stock market returns. They found stock market returns to be higher during the good weather with annualized returns 24.6% higher compared with the worst weather days.

This can be explained by the fact that, when the weather is good (such as when the sun is shining), people feel good. This may increase optimism and affect investment decisions. It may be the case that investors are more likely to buy shares when the sun is shining. The purchases would cause stock prices to rise. Therefore, it is expected that higher returns will be found during good weather days compared with the worst weather days.

Furthermore, as mentioned earlier in Chapter Two, an explanation has been given by Kaplanski and Levy (2009) that, if seasonal affective disorder (SAD) induces seasonality in returns, and returns are negatively correlated with volatility, then SAD can indirectly create seasonality and volatility in the opposite direction. Therefore, this research assumes that other weather conditions and Ramadan might have a similar indirect effect on volatility. Finally, another explanation for a positive association between bad weather and volatility could be based on psychological studies that link poor mood with an increase in the perceived probability of undesired outcomes (Kliger and Levy, 2003).

7.2.2. Biorhythmic Variables

Behavioural finance researchers have tested mood-proxy variables developed based on biorhythms, the body's natural biological cycles. These cycles have been linked to mood moderation and fluctuation in the psychological literature. Findings on their relationship to equity pricing include:

- Seasonal Affective Disorder (SAD), also known as winter depression or winter blues, is a mood disorder in which people who have normal mental health throughout most of the year experience depressive symptoms in the winter or, less frequently, in the summer, spring or autumn, repeatedly, year after year (Lurie et al., 2006). Kamstra et al. (2003) examined the influence of SAD in the seasonal time-variation of stock market returns. They provide international evidence that stock market returns vary seasonally with the length of the day.

- Daylight Saving Time Changes (DSTC) can induce depression due to the sleep disruption of losing or gaining an hour of sleep around DSTC events (Monk and Aplin, 1980). Kamstra et al. (2000) examined the influence of DSTC in the seasonal time-variation of stock market returns. They provide evidence of a negative relationship between DSTC and equity returns following a DSTC weekend.

- Lunar phases (LP) are widely linked to depression cycles around full moons (Iosif and Ballon, 2005). LP has been linked to a negative relationship with equity returns around full moon periods (Dichev and Janes, 2003).

7.2.3. Belief Variables

According to Muslim belief, Ramadan was the month in which the first verses of the *Qur'an* were revealed to the Islamic Prophet Muhammad. Fasting in the month of Ramadan is one of the five pillars of Islam. During this month, Muslims do not eat or drink during the daylight hours from dawn to sunset. Furthermore, in the *Qur'an*, God proclaims that *"fasting has been written down (as obligatory) upon you, as it was upon those before you"*. According to the earliest *hadith*, this refers to the Jewish practice of fasting on Yom Kippur.

During Ramadan, Muslims can experience a whole series of emotions. The process of fasting can be of particular significance here. Fasting is meant to teach the person patience, sacrifice and humility, but it also enhances the senses and emotion. Muslims also ask for forgiveness for past sins, and pray for guidance and help in refraining from everyday evils. According to Islam, fasting is one of the activities that increase humanity in society but, from an investor perspective, its significance can be seen in terms of its effect of heightening the senses and making people more emotionally sensitive to the impact of external influences.

Furthermore, Ramadan is associated with increased social interaction, particularly at the end of the period. This suggests there would be a strengthening of social effects on decision-making. The importance of social networks would increase. These developments would intensify herding, and are consistent with the increased synchronization associated with high volatility.

Muslims strive harder in the last 10 days of Ramadan, since the Night of al-Qadr (the anniversary of the night Muslims believe the first verses of the *Qur'an* were revealed to Muhammad by the angel Gabriel) could be one of the odd-numbered days in these last ten (the first, third, fifth or seventh). Muslims often pray extra prayers on this day, particularly the night prayer. They awake, pray, and hope Allah will give them something they may desire.

Some Muslims from each community, those who can afford to devote their time to the remembrance of God, stay in the mosque for the final 10 days of Ramadan. This worship is called *itikaf* (retreat). They observe the fast during the day and occupy themselves with the remembrance of God, performing voluntary prayers and studying the *Qur'an*, day and night, apart from the obligatory prayers which they perform with the congregation. Food and other necessities of life are provided for them during their stay in the mosque, thus they may not

leave the precincts of the mosque except for a genuine religious purpose. By devoting time to remembering God, Muslims hope to receive divine favours and blessings connected with the blessed night.

As identified earlier in Chapter Two, *zakat* and the associated *tazkiyah* principle become increasingly important during the month of Ramadan. As an example, more emphasis is placed on *Zakat al Fater* (where every Muslims should donate a particular amount of money to poor people before the end of Ramadan). The Islamic system aims to eliminate poverty from society, rather than managing the poor. One of the disciples of the Prophet Muhammad, who was one of the Guided Successors, Ali Bin Abi Talib, stated: *"If poverty were a man, I would certainly kill him."*

During Ramadan, particularly during the last ten days of the period, the perspective of investors is expected to be significantly more emotionally sensitive than during other months. Investors may exaggerate the influence of any good or bad news when making financial decisions.

7.3. Data

7.3.1. Equity Data

The data used in this chapter relates to ASE daily closing prices covering the period 1 January 1992 to 31 December 2007 (see Chapter Four for full details). After excluding non-trading days, this provides a total of 3,914 daily observations[50] and 192 monthly observations.

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[50] Number of observations of price index returns is 3912 for the main sample (1992–2007) as first trading day and last trading day are excluded.

As can be seen from Figure 7.1, the daily returns during this period show greater daily volatility towards the end of this period, specifically from 2005 to 2007. It can be noted that in 1992 a 5% limit was imposed on the daily price movements.

Figure 7.1: ASE Daily Returns Percentage from 26/06/1412 to 22/12/1428 (01/01/1992 to 31/12/2007)
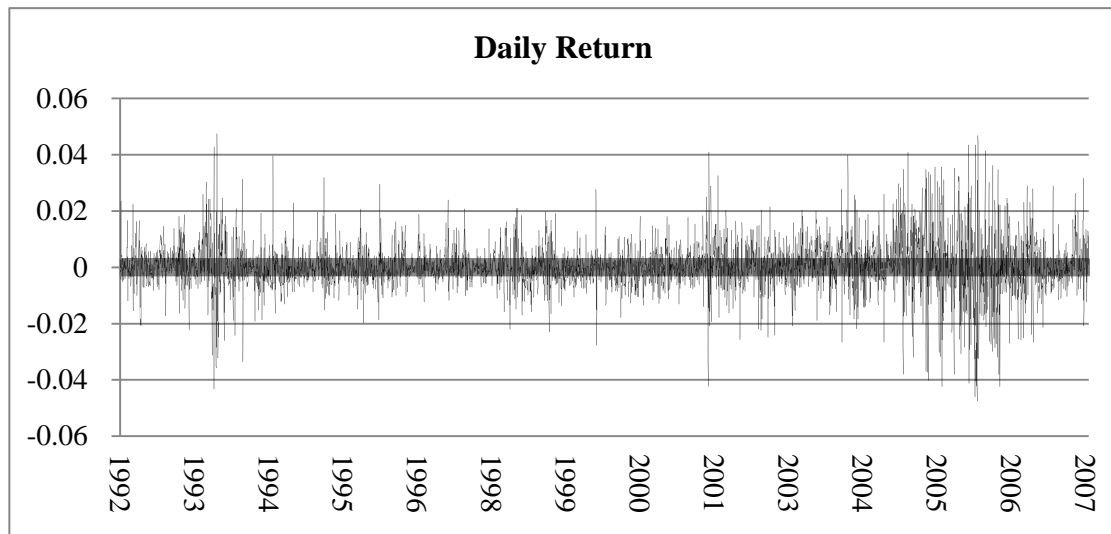
Furthermore, Muslim investors dominate the market, which means that the majority of investors are likely to observe Ramadan. The market was only opened to foreign investors in 1999, yet in December 2006, Muslim Jordanian citizens represented 94% of investors in the market. Of the 6% of non-Jordanian investors, 5.4% were fellow Muslim Arab investors and the remaining 0.6% represented non-Arab investors.[51]

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[51] As at December 2006 there were a total of 151,431 investors registered. These were: Jordanian: 142,071, Arab: 8,289 and non-Arab: 1,017 (AMEINFO, Country Guide, [online] available at https://www.cia.gov /library/publications/the-world-factbook/geos/jo.html [7 December 2010].

7.3.2. Weather Data

Daily temperature, humidity and wind data were obtained from Tutiempo, World Climate Database[52]. The data set runs from 1 January 1992 to 31 December 2007, this provides a total of 5,787 usable daily observations for each weather variable. Summers in Jordan are uniformly hot and sunny and on occasions the winter weather can be cold, with occasional snow on the higher ground. The relatively low levels of rainfall occur mainly in the winter and spring; it usually takes the form of heavy showers. The worst weather is brought by hot, dry winds from Arabia (the Khamsin). These are most likely to blow in early or late summer and last for a day or two at a time. Under these conditions heat stress may be felt[53].

The average temperature in Jordan is 17.5^{o}C. The highest monthly average high temperature is 33°C, in August, whereas the lowest monthly average low temperature is 4°C in January. The driest weather is in June, July and August when an average of 0 mm of rainfall occurs. The wettest weather is in January, when an average of 68 mm of rainfall occurs for a period of ten days. There is an average of six days per year with frost in Jordan; in January there is an average of two days with frost. The average annual relative humidity is 50.5% and average monthly relative humidity ranges from 36% in June to 69% in January. Average sunlight hours in Jordan range between 6.5 hours per day in December and 13.1 hours per day in July. Table 7.1 below provides descriptive statistics for the raw data of the three weather variables.

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[52] Tutiempo, World Climate Database, [online] available at http://www.tutiempo.net/en/Climate_/Amman_Airport/402700.htm [15 July 2010].
[53] BBC News, [online] available at http://www.bbc.co.uk/_weather/world/country_guides/results.shtml?tt=TT002510,[25 July 2010].

Table 7.1: Descriptive Statistics of the Three Weather Variables

	Sample	Min	Max	Mean	Std. Deviation	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
Temp	5798	-2	35	17.75	7.430	-.141	.032	-1.210	.064
High Temp	5798	1	43	23.60	8.338	-.294	.030	-1.040	.061
Low Temp	5798	-5	28	12.34	6.523	-.067	.030	-1.130	.061
Humidity	5787	12	100	54.53	19.908	.228	.032	-.816	.064
Wind	5797	0	58	10.43	6.820	1.240	.032	2.791	.064
Valid N	5787								

The temperature variable is measured in degrees Celsius. The minimum temperature in Amman is -2 ^{o}C in winter, whereas the highest temperature in summer is 35 ^{o}C, with an average temperature throughout the sample of 17.75 ^{o}C.

Histograms Graphs 7.1, 7.2 and 7.3 below show the distribution of the three weather variables; the histogram of temperature is skewed toward high-temperature weather. The humidity variable is the percentage relative humidity[54]. The humidity in Jordan varies throughout the year, moving from 12%, the lowest degree of humidity to 100%. Moreover, there are certain times during the year that Jordan suffers from low humidity. The histogram of humidity ranges between 30% and 70%. The wind speed[55] variable varies between 0 knot and 20 knot, where 0 knot represents no wind and 20 knot represents high wind speed.

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[54] Relative humidity is a term used to describe the amount of water vapor in a mixture of air and water vapor. It is defined as the ratio of the partial pressure of water vapor in the air-water mixture to the saturated vapor pressure of water at those conditions. (http://www.timeanddate.com/weather/jordan/amman, [10 March 2012]

[55] A knot is a unit of measurement for wind speed. Mathematically, one knot is equal to approximately 1.1508 statute miles. (http://www.timeanddate.com/weather/jordan/amman, [10 March 2012]

Graph 7.1: Distribution of Temperature Data
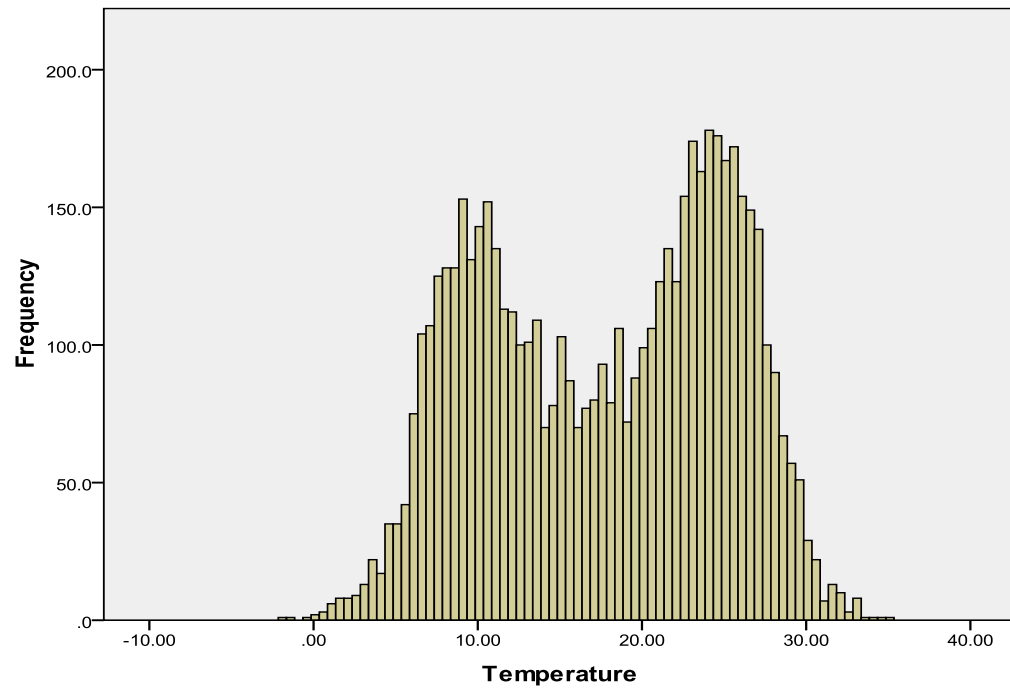
Graph 7.2: Distribution of Humidity Data
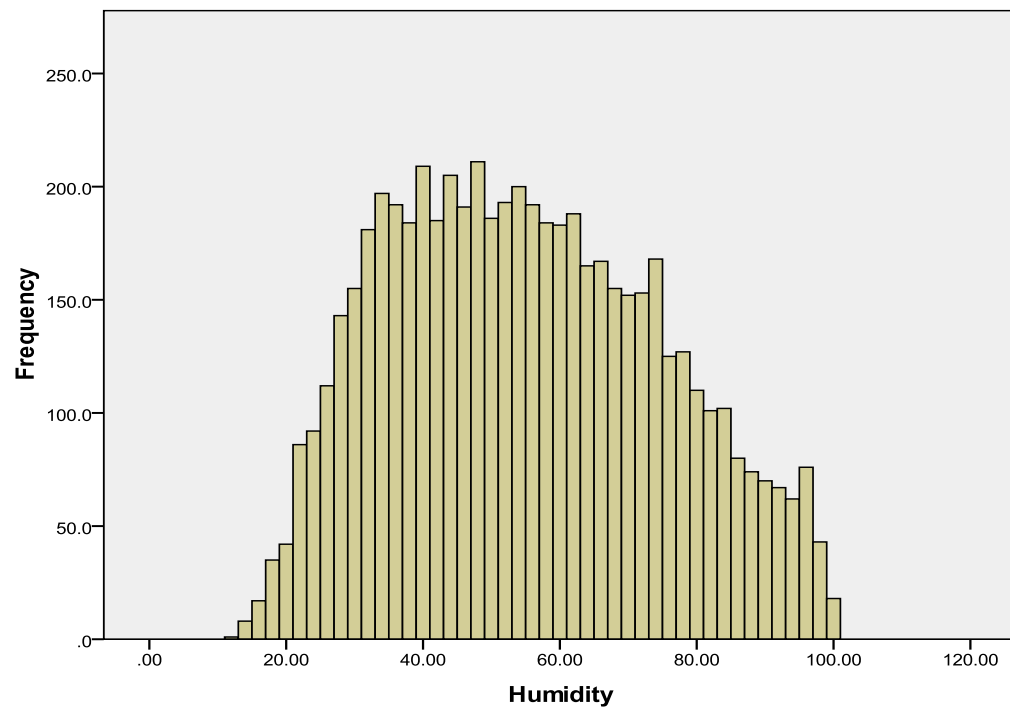
Graph 7.3: Distribution of Wind Data
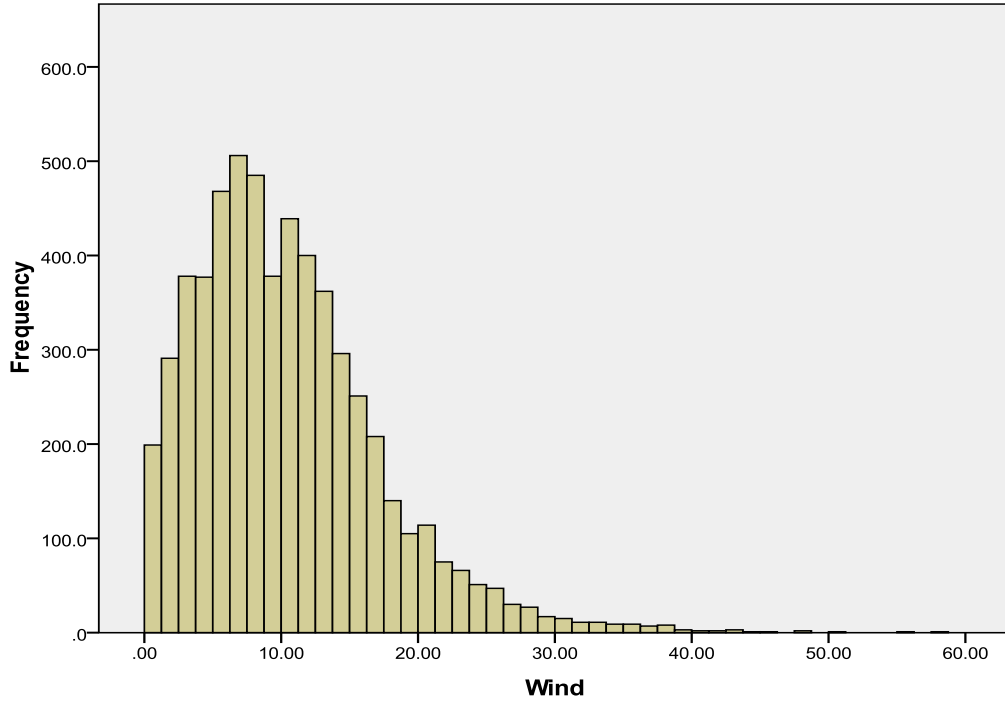
In order to assess the general relationships between stock returns and weather variables, weather variables are converted to dummy variables. Within the weather effect literature, several techniques are used to control for seasonality. This thesis uses the method developed by Kang et al. (2010), which uses a 21-day moving average (MA) and moving standard deviation (MSD) (σ). The weather dummy variable used in the thesis is calculated as follows:

$$MA(W_t) = \frac{1}{21}\left(W_{t-10} + W_{t-9} + \cdots + W_t + \cdots + W_{t+9} + W_{t+10}\right) \quad \text{Equation 7.1}$$

$$\sigma(W_t) = \sqrt{\frac{1}{21}\sum_{i=-10}^{10}\left(W_i - MA(W_i)\right)^2} \qquad \text{Equation 7.2}$$

Where:

W_t is the daily value of the weather variables (temperature, humidity, and wind speed) at time t.

Assuming that extreme temperatures may lead to more significant effects on stock returns than normal temperature conditions, we generated two dummy variables for the temperature variable, depending on the extreme above-average and extreme below-average temperature conditions, as follows:

If $WLT_t = W_t < [MA(W_t) - \sigma(W_t)]$, then $WLT_t = 1$; $= 0$ otherwise and

If $WHT_t = W_t > [MA(W_t) + \sigma(W_t)]$, then $WHT_t = 1$; $= 0$ otherwise

Where

WLT_t is a dummy variable for extreme below-average temperature

And

WHT_t is a dummy variable for extreme above-average temperature

For the humidity and wind we generated one dummy variable for each, depending on the extreme above-average and extreme below-average conditions, as follows:

If $D.WV_t = W_t < [MA(W_t) - \sigma(W_t)]$, then $D.WV_t = 1$; $= 0$ otherwise and

If $D.WV_t = W_t > [MA(W_t) + \sigma(W_t)]$, then $D.WV_t = 1$; $= 0$ otherwise

This produced 625 observations for extreme low temperature, and for extreme high temperature it generated 648 positive (non-zero) observations. The humidity dummy variable is based on 1,381 observations. For the wind dummy variable, 522 non-zero observations were generated.

7.3.3. Biorhythmic Data

Daylight saving time changes (DSTC) occur in the last week of March at Friday midnight (clocks forward), and in the last week of September at Friday midnight (clocks back). A dummy variable was constructed taking a value of one on the first trading day following a DSTC, and zero otherwise. The DSTC dummy variable produced 32 positive observations.

A SAD variable reflecting the length of the night to the mean annual length of twelve hours (Kamstra et al., 2003), SAD_t was calculated as follows:

$$SAD = H_t - 12$$

With $H_t = \begin{cases} 24 - 7.72.\,acros\left(-\tan\left(\frac{2\pi\delta}{360}\right)\tan(\lambda_t)\right) in\ the\ Northern\ Hemisphere \\ 7.72.\,acros\left(-\tan\left(\frac{2\pi\delta}{360}\right)\tan(\lambda_t)\right)\ \ in\ the\ Southern\ Hemisphere \end{cases}$

Equation 7.3

Where:

λ represents the latitude; $\lambda_t = 0.4102.\sin\left\{\left(\frac{2\pi}{365}\right)(julian_t - 80.25)\right\}$;

And

$julian_t$ represents the number of the day in the year.

The SAD dummy variable generated 1,936 observations. Note that by working with hours of night, as opposed to day, the expected impact of the SAD measure on returns will be positive.

The lunar cycle is determined by the relative positions of the earth, the moon and the sun. *New moon* signifies the situation when the moon is directly between the earth and the sun. Since one only sees the part of the moon that reflects light from the sun, one sees very little or

nothing of the moon around the *new moon*. As the relative positions of the sun, the moon and the earth change, one begins to see more and more of the moon. The moon starts growing from right to left until it reaches *full moon*. During *full moon*, the moon is on the opposite side of the earth with respect to the sun, and one sees a full round side of the moon. The growth of the moon from *new moon* to *full moon* is called *waxing* and the mid-point when the moon is half full is called the *first quarter*. During the days after the new moon, but before the first quarter, the moon is called *waxing crescent*, and between first quarter and full moon, it is called *waxing gibbous*. After the full moon, the moon starts to decrease, again from right to left. During the contraction, the moon goes through *waning gibbous*, *last quarter* and *waning crescent*, until it reaches new moon, and the cycle starts again. The lunar cycle has a periodicity of 29.53 days, with the full moon date halfway in between two successive new moons (Dichev and Janes, 2003).

Figure 7.2: Lunar Phases
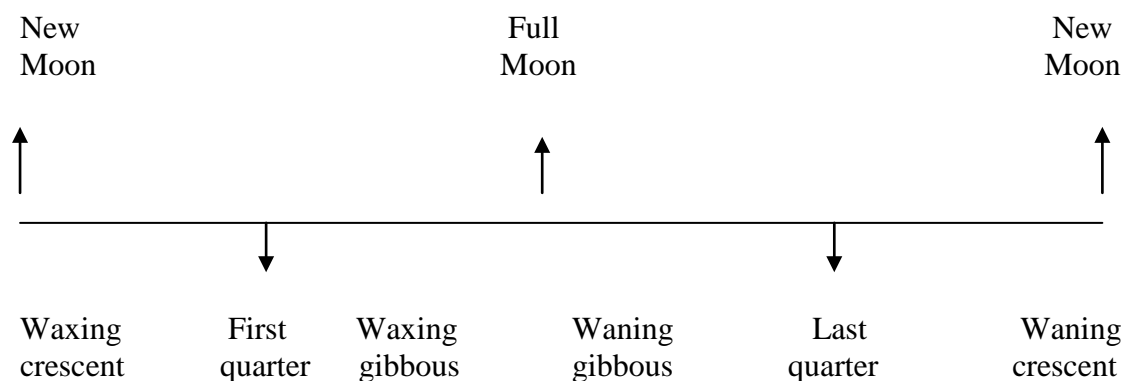
Figure 7.2 above shows each lunar phase (LP), which is used in this research as a variable that varies between 1 (full moon) and -1 (new moon). Each day has a value based on how close it is to a full moon; the LP is calculated as follows:

$$\text{Cosine}\left(\frac{2\pi d}{29.53}\right) \qquad \textbf{Equation 7.4}$$

Where

d is the number of days since the previous full moon.

The window is defined as the full moon date +/-3 calendar days; this offers 7 observations for each month, with a total of 926 observations for the full samples of LPs (see Figure 7.3).

Figure 7.3: Full Moon Windows

Lunar cycle = 29.53 days

New Moon   Full Moon   New Moon   Full Moon

7 days   7 days   7 days   7 days
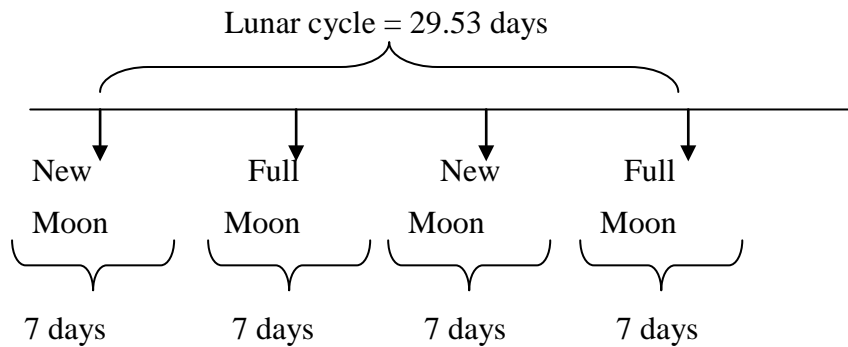
7.3.4. Belief Data

Ramadan is the ninth month of the Islamic calendar, which is a lunar calendar and months begin when the first crescent of a new moon is sighted. Since the Islamic lunar calendar year is 11–12 days shorter than the solar year, Ramadan migrates throughout the seasons. The Islamic day starts after sunset. The actual start and end dates for Ramadan from 1992 to 2007 are shown in Table 7.2 below.

Table 7.2: Actual Start and End Dates for Ramadan (1992–2007)

Gregorian Year	Islamic Year	Start	End
1992	1412	4/3/1992	2/4/1992
1993	1413	22/2/1993	23/3/1993
1994	1414	11/2/1994	12/3/1994
1995	1415	31/1/1995	1/3/1995
1996	1416	21/1/1996	19/2/1996
1997	1417	9/1/1997	7/2/1997
1997	1417	30/12/1997	28/1/1998
1998	1418	19/12/1998	17/1/1999
1999	1419	8/12/1999	6/1/2000
2000	1420	27/11/2000	26/12/2000
2001	1421	16/11/2001	15/12/2001
2002	1422	5/11/2002	4/12/2002
2003	1423	26/10/2003	24/11/2003
2004	1424	14/10/2004	12/11/2004
2005	1425	4/10/2005	2/11/2005
2006	1426	23/9/2006	22/10/2006
2007	1427	12/9/2007	11/10/2007

The Amman Stock Market return data has been adjusted to be aligned with the Islamic calendar (Hijri). This Hegirian calendar is a lunar calendar that has twelve lunar months in a year of normally 354 days. The data corresponds to the Islamic calendar period 26/06/1412 to 22/12/1428. This offers 197 monthly observations. Ramadan is the ninth month of the Islamic calendar. Since the lunar year is approximately eleven days shorter than the solar year, Islamic holy days usually shift eleven days earlier in each successive solar year, such as those in the Gregorian calendar.

If positive mood effects ensure that Islamic investors are more optimistic during Ramadan, then it would be expected that positive returns would be found during this month. It can be identified that a positive return is made during this period (0.13% average daily return). The

t-test presented illustrates that the average daily return during Ramadan is significantly different from the other months of the year.

The Ramadan data was tested using two approaches. In the first approach, a dummy variable was created for each day in Ramadan; a value of one was given for each day of Ramadan and zero otherwise. Similar dummy variables were created corresponding to: the last 20, the last 15, the last 10 and the last 5 trading days in the month of Ramadan. For the whole month of Ramadan dummy variable, 348 positive (non-zero) observations were generated. Whereas, for the last 20, 15, 10 and 5 trading days dummy variables, 340, 255, 170 and 85 positive observations were generated respectively.

For the second series of tests, an interaction term was also tested between Ramadan and each of the weather variables (high temperature, low temperature, humidity and wind), as well as the biorhythmic variables (SAD, DSTC and lunar phases). The resulting seven interaction terms took on a value of one for each day for each interaction and zero otherwise. Additionally, similar interaction effects were tested between the last 10 days of Ramadan and the last 5 days of Ramadan and then compared. Table 7.3 below summarizes the twenty-one interaction terms variables identified.

Table 7.3: Twenty-One Dummy Variables of the Interaction between Ramadan and Other Mood Variables

No	Dummy Variables	No. of Observations
1	Interaction between Ramadan and low temperature	47
2	Interaction between Ramadan and high temperature	48
3	Interaction between Ramadan and humidity	116
4	Interaction between Ramadan and wind	40
5	Interaction between Ramadan and daylight saving time changes	3
6	Interaction between Ramadan and lunar phases	83
7	Interaction between Ramadan and seasonal affective disorder	332
8	Interaction between the last 10 days of Ramadan and daylight saving time changes	1
9	Interaction between the last 10 days of Ramadan and high temperature	23
10	Interaction between the last 10 days of Ramadan and low temperature	27
11	Interaction between the last 10 days of Ramadan and lunar phases	36
12	Interaction between the last 10 days of Ramadan and seasonal affective disorder	160
13	Interaction between the last 10 days of Ramadan and wind	15
14	Interaction between last 10 days of Ramadan and humidity	58
15	Interaction between last 5 days of Ramadan and humidity	32
16	Interaction between the last 5 days of Ramadan and daylight saving time changes	0
17	Interaction between the last 5 days of Ramadan and high temperature	13
18	Interaction between the last 5 days of Ramadan and low temperature	10
19	Interaction between the last 5 days of Ramadan and lunar phases	0
20	Interaction between the last 5 days of Ramadan and seasonal affective disorder	80
21	Interaction between the last 5 days of Ramadan and wind	9

7.4. Testing Approach

Financial research presents considerable evidence that returns are non-normally distributed and characterized by leptokurtosis, skewness and volatility clustering. A common way to capture the above stylized facts would be to model the conditional variance as a GARCH process. The GARCH (p, q) model captures the tendency in financial data for volatility clustering and also incorporates heteroscedasticity into the estimation procedure (see Engle (1982), Bollerslev (1986), Engle and Ng (1993) and Enders (1995)).

Determining the most appropriate GARCH specification for Amman's stock market returns was undertaken by testing the index return against a range of fifteen GARCH specifications and selecting the most appropriate based on the log likelihood ratio test (LLRT) and the AIC test. The LLRT allows the selection of the best GARCH specification, taking into account the principle of parsimony. The range of GARCH specifications covers basic GARCH, exponential GARCH, asymmetrical GARCH and TGARCH. Sub-specifications included the addition of ARCH-in-mean effects, and assumptions regarding error distributions as following either: normal, student's t, or generalized error distributions (GED).

Table 7.4 below presents the result of fifteen models from the GARCH family. These specification tests lead to a diagnosis of the ASE being best specified as an EGARCH (1, 1) with AR (1) and GED error distribution assumption. The model has the lowest LLRT value, although EGARCHM (1, 1) has a LLRT lower than EGARCH (1, 1), yet the conditional variance in the mean equation is not statistically significant. Furthermore, EGARCH (1, 1) has the highest AIC value and lowest number of parameters. The AR (1) specification is also applied for the conditional mean, consistent with the nonsynchronous trading effect.

It is often observed that downward movements in volatility in financial markets are followed by higher volatilities than upward movements of the same magnitude. However, the GARCH model imposes symmetry on the conditional variance structure that may not be appropriate for modelling the behaviour of stock returns. To address this issue, Nelson (1991) proposes the exponential GARCH or EGARCH model. The specification for the higher order conditional variance is:

$$log(\sigma_t^2) = \omega + \sum_{j=1}^{p} \beta_j log(\sigma_{t-j}^2) + \left(\sum_{i}^{q} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} \right) \quad \textbf{Equation 7.5}$$

The left-hand side of the equation is the log of the conditional variance. This implies that the asymmetric effect is exponential, rather than quadratic, and that forecasts of the conditional variance are generated to be non-negative. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$.

After assessing all the evidence, it was decided that a model based on the specification of EGARCH-GED(1, 1) would be the most appropriate one to be applied in this thesis.

Table 7.4: Results of Fifteen Models from the GARCH Family

		GARCH	GARCHM	GARCHM_t	EGARCH	EGARCH_GED	EGARCHM	EGARCHM_GED	AGARCH	AGARCH_t	AGARCHM	AGARCHM_t	TGARCH	TGARCH_t	TGARCHM	TGARCHM_t
Return_1	Y	0.237	0.235	0.232	0.237	0.234	0.228	0.224	0.235	0.237	0.231	0.231	0.237	0.236	0.234	0.232
Constant	X	0.015	-0.001	-0.016	0.025	-0.007	-0.002	-0.023	0.025	0.001	0.007	-0.012	0.020	-0.004	0.002	-0.016
h_t	X		0.038	0.029			0.066	0.040			0.043	0.032			0.045	0.029
alpha_0	H	0.032	0.033	0.030	-0.018	-0.039	-0.018	-0.040	0.032	0.030	0.032	0.030	0.032	0.030	0.032	0.030
alpha_1	H	0.235	0.237	0.269					0.230	0.270	0.232	0.272	0.252	0.267	0.258	0.269
beta_1	H	0.740	0.738	0.731	0.932	0.940	0.930	0.938	0.743	0.730	0.740	0.728	0.742	0.733	0.740	0.731
student-t	df			4.560						4.516		4.543		4.554		4.577
threshold	H												-0.040	-0.002	-0.047	-0.003
asymmetry	H								-0.072	-0.070	-0.074	-0.073				
eps[-1]	H				0.022	0.009	0.024	0.010								
|eps[-1]|	H				0.423	0.426	0.429	0.431								
GED	log(nu/2)					-0.520		-0.519								
log-likelihood		-4325.3	-4323.8	-4176.5	-4317.4	-4167.7	-4314.4	-4166.1	-4320.5	-4174.6	-4318.6	-4173.3	-4323.8	-4177.6	-4321.7	-4176.5
AIC		2.214	2.214	2.139	2.211	2.135	2.210	2.135	2.212	2.138	2.212	2.138	2.214	2.140	2.214	2.140

7.5. Modelling Methodology

David Hendry asks whether econometrics is alchemy or science (Hendry, 1980). He argues that the subject can only be treated as scientific (and therefore credible) if a rigorous methodological analysis is applied. Gilbert (1986) talks about the average econometric regression, where the researcher decides on the theory they wish to 'prove' and manipulates their analysis until econometrically credible results compatible with the desired outcome are derived. Hendry seeks to avoid such abuses by identifying strict methodological 'rules'. He identifies a series of 'model acceptance criteria' and, perhaps most importantly, outlines a process of model reductionism that attempts to minimize the likelihood that the modelling process will be manipulated. He suggests that researchers should follow a general-to-specific (GTS) process of model development that lets the data determine the direction that models develop.

The formulation of a *general* unrestricted model that is *congruent* with the data is accompanied with the application of a *testing down* process, eliminating variables with coefficients that are not statistically significant, leading to a simpler *specific* congruent model that encompasses rival models (see, for example, Hendry and Morgan, 1995, p. 365). This approach has its roots in the work of Sargan (1964); however, it is now most closely associated with David Hendry. Hendry and Mizon (1978) developed and applied the methodology, in particular in a series of influential time series studies of aggregate demand-for-money and consumption functions (Hendry and Mizon, 1978).

Within the context of this thesis, the general model can be seen as encompassing existing models that identify the impact of the weather on social mood and therefore financial market behaviour (for example, Dowling and Lucey, 2008). To these models we add further mood-related variables relating to the impact of Islamic religious holidays on financial market behaviour.

It should be noted that as the GTS methodology is normally applied in a standard-type regression time series context, it needs to be adapted if we want to apply it to the modelling of volatility within a GARCH framework.

The standard approach of testing down the model through the elimination of variables and elements of the lag structure needs to be adapted to our current requirements. Specifically, within the GARCH framework, this means that the mean equation and the volatility equation are treated as separate, where the mean equation can be treated as a 'control' for variables we do not want to examine in the volatility equation (see, for example, Kang et al., 2010). In addition, it should be noted that the modelling of the mean equation is further constrained by statistical requirements in respect to the structure of the residuals.

Table 7.5 below identifies the full set of potential variables before one can start the process of reduction.

Table 7.5: Identification of Potential Variables before Starting the Process of Reduction

No.	Dummy Variables	No. of Observations
1	Return	3912
2	Seasonal affective disorder	1936
3	Humidity	1381
4	Lunar phases	926
5	Day of the week	778
6	High temperature	648
7	Low temperature	625
8	Wind	522
9	Ramadan	348
10	Last 20 days of Ramadan	340
11	Interaction between Ramadan and seasonal affective disorder	332
12	Last 15 days of Ramadan	255
13	Last 10 days of Ramadan	170
14	Interaction between last 10 days of Ramadan and seasonal affective disorder	160
15	Interaction between Ramadan and humidity	116
16	Last 5 days of Ramadan	85
17	Interaction between Ramadan and lunar phases	83
18	Interaction between last 5 days of Ramadan and seasonal affective disorder	80
19	Interaction between last 10 days of Ramadan and humidity	58
20	Interaction between Ramadan and high temperature	48
21	Interaction between Ramadan and low temperature	47
22	Interaction between Ramadan and wind	40
23	Interaction between last 10 days of Ramadan and lunar phases	36
24	Interaction between last 5 days of Ramadan and humidity	32
25	Daylight saving time changes	32
26	Interaction between the last 10 days of Ramadan and low temperature	27
27	Interaction between the last 10 days of Ramadan and high temperature	23
28	Interaction between the last 10 days of Ramadan and wind	15
29	Interaction between the last 5 days of Ramadan and high temperature	13
30	Interaction between the last 5 days of Ramadan and low temperature	10
31	Interaction between the last 5 days of Ramadan and wind	9
32	Interaction between Ramadan and daylight saving time changes	3
33	Interaction between the last 10 days of Ramadan and daylight saving time changes	1
34	Interaction between the last 5 days of Ramadan and lunar phases	0
35	Interaction between the last 5 days of Ramadan and daylight saving time changes	0

As a first step in respect to the model reduction process, we exclude potential variables with a low number of observations to avoid issues relating to test-statistic reliability in the general model. Thus, we excluded the variables shown in Table 7.6 below.

Table 7.6: Exclusion of Variables with Low Number of Observations

No.	Dummy Variables	No. of Observations
1	Interaction between the last 10 days of Ramadan and low temperature	27
2	Interaction between the last 10 days of Ramadan and high temperature	23
3	Interaction between the last 10 days of Ramadan and wind	15
4	Interaction between the last 5 days of Ramadan and high temperature	13
5	Interaction between the last 5 days of Ramadan and low temperature	10
6	Interaction between the last 5 days of Ramadan and wind	9
7	Interaction between Ramadan and daylight saving time changes	3
8	Interaction between the last 10 days of Ramadan and daylight saving time changes	1
9	Interaction between the last 5 days of Ramadan and lunar phases	0
10	Interaction between the last 5 days of Ramadan and daylight saving time changes	0

Therefore, this leaves the remaining variables in Table 7.7 below.

Table 7.7: Remaining Variables after Excluding the Variables with Low Number of Observations

No.	Dummy Variables	No. of Observations
1	Return	3912
2	Seasonal affective disorder	1936
3	Humidity	1381
4	Lunar phases	926
5	Day of the week	778
6	High temperature	648
7	Low temperature	625
8	Wind	522
9	Ramadan	348
10	Last 20 days of Ramadan	340
11	Interaction between Ramadan and seasonal affective disorder	332
12	Last 15 days of Ramadan	255
13	Last 10 days of Ramadan	170
14	Interaction between last 10 days of Ramadan and seasonal affective disorder	160
15	Interaction between Ramadan and humidity	116
16	Last 5 days of Ramadan	85
17	Interaction between Ramadan and lunar phases	83
18	Interaction between last 5 days of Ramadan and seasonal affective disorder	80
19	Interaction between last 10 days of Ramadan and humidity	58
20	Interaction between Ramadan and high temperature	48
21	Interaction between Ramadan and low temperature	47
22	Interaction between Ramadan and wind	40
23	Interaction between last 10 days of Ramadan and lunar phases	36
24	Interaction between last 5 days of Ramadan and humidity	32
25	Daylight saving time changes	32

Potential co-linearity between the remaining variables was then considered and a number of highly correlated variables were eliminated. The month of Ramadan is highly correlated with: interaction between Ramadan and seasonal affective disorder (0.91), the last 20 days of Ramadan (0.96), and the last 15 days of Ramadan (0.95). Furthermore, there is a high correlation (0.93) between Ramadan and the interaction terms between the last 10 days of Ramadan and seasonal affective disorder.

There was also a high correlation between the last 5 days of Ramadan and the interaction terms between the last 5 days of Ramadan and: daylight saving time changes (0.95), lunar phases (0.92), wind (0.95), low temperature (0.94) and high temperature (0.91). Therefore, these variables have been excluded. Table 7.8 below summarizes the remaining variables that were used to develop the general model.

Table 7.8: Variables Used in the General Model

No.	Dummy Variables	No. of Observations
1	Day of the week	778
2	Ramadan	348
3	Wind	522
4	Seasonal affective disorder	1,936
5	Lunar phases	926
6	Low temperature	625
7	High temperature	648
8	Return	3,912
9	Last 10 days of Ramadan	170
10	Last 5 days of Ramadan	85
11	Interaction between Ramadan and low temperature	47
12	Interaction between Ramadan and high temperature	48
13	Interaction between Ramadan and humidity	116
14	Interaction between Ramadan and wind	40
15	Interaction between Ramadan and lunar phases	83
16	Interaction between Ramadan and seasonal affective disorder	332
17	Interaction between the last 10 days of Ramadan and lunar phases	36
19	Interaction between the last 10 days of Ramadan and humidity	58
20	Interaction between the last 5 days of Ramadan and humidity	32

7.5.1. General Model

The general-to-specific methodology directs econometricians to start with a general model containing the relevant information from the data generation process. The general-to-specific approach has a modelling process that starts with a 'general

unrestricted model' (GUM). GUM is the most general estimable, statistical model that can reasonably be postulated initially.

Having eliminated a series of variables and terms prior to the modelling process, the remaining variables are then part of a process of testing down further eliminated variables using a series of statistical tests. For example, with the aid of information criteria such as the AIC and, where appropriate, the chi-square test of normality, some of the statistical tests were utilized. As well, the F-test for ARCH 1-2, the Chow test and the Portmanteau test were also applied in this thesis.

In this chapter, tests are applied to the mood-proxy variables using a range of specifications for each mood-proxy variable with the specific aim of identifying variables relevant to the Amman Stock Exchange. The mood-proxy variables are divided into two groups.

The first group relates to the mean equation (Equation 7.6). This equation consists of weather variables (high temperature (HT), low temperature (LT), humidity (H) and wind (W)), biorhythmic variables (seasonal affective disorder (SAD), daylight saving time changes (DSTC) and lunar phases (LP)). The month of Ramadan (RDN), the first trading day of the week (FDoW)[56] and the first lag of return are included in the mean equation as well.

Mean equation:

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[56] FDoW is included in the mean equation to capture the weekend effect anomalies.

$$R_t = c_0 + c_1 R_{t-1} + c_2 HT_t + c_3 LT_t + c_4 H_t + c_5 W_t + c_6 SAD_t + c_7 DSTC_t +$$

$$c_8 LP_t + c_9 RDN_t + c_{10} FDoW_t + \varepsilon_t$$

Equation 7.6

As mentioned earlier in this chapter, weather and biorhythmic variables are a widely researched source of misattributed mood in psychology. The essential findings in respect to weather are that good weather induces positive mood states and that bad weather induces negative mood states. Positive mood states produce positive returns in the stock market (Dowling and Lucey, 2008; Lurie et al., 2006; Kamstra et al., 2003).

These variables are required in the mean equation to act as a control to identify the impact of Ramadan on the volatility examined in the variance equation. The variance equation (Equation 7.7) contains these variables:

- The last 10 days of Ramadan (R10 days)

- The last 5 days of Ramadan (R5 days)

- The interaction between Ramadan and high temperature (Int. (RDN.*HT))

- The interaction between Ramadan and low temperature (Int. (RDN.*LT))

- The interaction between Ramadan and humidity (Int. (RDN.*H))

- The interaction between Ramadan and wind (Int. (RDN.*W))

- The interaction between Ramadan and seasonal affective disorder (Int. (RDN.*SAD))

- The interaction between Ramadan and lunar phases (Int. (RDN.*LP))

- The interaction between the last 10 days of Ramadan and Lunar phases(Int. (10RDN.*LP))

- The interaction between the last 10 days of Ramadan and humidity (Int. (10RDN.*H))

- The interaction between the last 5 days of Ramadan and humidity (Int. (5RDN.*H))

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i\left(z_{t-i} + \gamma(|z_{t-i}| - E|z_{t-i}|)\right) + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) +$$

$$c_{11} Int.(RDN.* HT)_t + c_{12} Int.(RDN.* LT)_t + c_{13} Int.(RDN.* H)_t +$$

$$c_{14} Int.(RDN.* W)_t + + c_{15} Int.(RDN.* SAD)_t + c_{16} Int.(RDN.* LP)_t +$$

$$c_{17} Int.(10RDN.* LP)_t + c_{18} Int.(10RDN.* H)_t + c_{19} Int.(5RDN.* H)_t +$$

$$+ c_{20} R10\ days + c_{21} R5\ days$$

Equation 7.7

Table 7.9 below presents the results of the general model for the ASE. The form of the model is EGARCH (1, 1) with AR (1). The model is an appropriate fit to the data, since the GED coefficient is significantly lower than 2, confirming that the standardized residuals are fat-tailed.

Table 7.9: General Model Using EGARCH-GED(1, 1) (Estimation Sample: 1992–2007)

		Coefficient	Std.Error	robust-SE	t-value	t-prob
Return_1	Y	0.230713	0.01612	0.0183	12.6	0
Constant	X	-0.012	0.01806	0.02127	-0.564	0.573
Day-of-the-week	X	0.038425	0.0209	0.02457	1.56	0.118
Humidity	X	0.006031	0.01879	0.02307	0.261	0.794
Low Temp	X	-0.04272	0.02655	0.03299	-1.29	0.195
High Temp.	X	-0.03922	0.02222	0.02594	-1.51	0.131
DSTC	X	0.038565	0.0315	0.03663	1.05	0.293
LP	X	-0.00898	0.02135	0.02491	-0.36	0.719
SAD	X	0.007701	0.01991	0.02382	0.323	0.746
Wind	X	0.010578	0.02761	0.03428	0.309	0.758
Ramadan	X	0.053459	0.02579	0.03167	1.69	0.092
Intr.R*LP	H	-0.01457	0.1398	0.1718	-0.0848	0.932
Intr.R*Wind	H	-0.11846	0.1822	0.2026	-0.585	0.559
Int.R*Hum.	H	0.079914	0.1273	0.1496	0.534	0.593
Intr.R*Low Temp	H	-0.08484	0.167	0.1762	-0.482	0.63
Intr.R*High Temp	H	-0.30069	0.1556	0.1724	-1.74	0.081
Last 10 days of Ramadan	H	0.08009	0.1482	0.1685	0.475	0.635
Intr.R10*LP	H	-0.08783	0.2748	0.3476	-0.253	0.801
Int.R10*Hum.	H	0.091655	0.3167	0.3413	0.269	0.788
Last 5 days of Ramadan	H	0.060562	0.2172	0.255	0.237	0.812
Int.R5*Hum.	H	-0.18248	0.3485	0.3503	-0.521	0.602
alpha_0	H	-0.03832	0.009255	0.01028	-3.73	0
eps[-1]	H	0.007946	0.0155	0.0152	0.523	0.601
|eps[-1]|	H	0.425434	0.03614	0.04759	8.94	0
beta_1	H	0.940978	0.01047	0.01315	71.5	0
GED	log(nu/2)	-0.51833	0.03087	0.03188	-16.3	0
No. of observations 3912, no. of parameters 26						
AIC.T 8365.88812 AIC 2.13851946						
Descriptive statistics for scaled residuals:						
Normality test: Chi^2(2) = 335.31 [0.0000]**						
ARCH 1-2 test: F(2,3882)= 2.8017 [0.0608]						
Portmanteau(780): Chi^2(779)= 834.52 [0.0821]						

The diagnostic tests indicate that the residuals are non-normal, which is usually the case in financial time series data. In addition, as expected, there was excess kurtosis

and thick tails in the distribution in the residuals. Consequently, it is important to be careful when examining diagnostic tests such as the t-test. There was no serial correlation found (Portmanteau test), which is probably because the model included the first lag of returns. The model (the general model) is statistically significant.

7.5.2. Testing Down

As part of the process of testing down four steps are applied as follows:

1. We ascertain that the general statistical model is congruent with the evidence through the application of relevant tests (such as information criteria-based tests and F-tests).

2. We eliminate a variable that satisfies the variable elimination selection criteria; specifically, one variable with low t-value is excluded each time.

3. We verify that the simplified model remains congruent with the evidence.

4. We continue performing steps 2 and 3 until none of the remaining variables can be eliminated.

For a given data set, the selection criteria are largely based on summary statistics from residuals computed from a fitted model. Information criteria (for example, AIC) based on the residual variance are used as part of the process of testing down to find the model that has the smallest residual variance (Vogelvang, 2005, p. 344). It is essential to emphasize the importance of considering only model reductions that do not fail diagnostic tests in order to retain congruence.

Through this process, we arrived at the specific model presented in Table 7.10 below.

Table 7.10: Specific Model Using EGARCH-GED(1,1) (Estimation Sample: 1992–2007)

		Coefficient	Std.Error	robust-SE	t-value	t-prob
Return_1	Y	0.23094	0.01549	0.01708	13.5	0
Constant	X	-0.0116843	0.01764	0.02001	-0.584	0.559
Day-of-the-week	X	0.0373462	0.02257	0.02662	1.4	0.161
Humidity	X	0.005284	0.01895	0.02283	0.231	0.817
Low_Temp	X	-0.0424811	0.02653	0.03293	-1.29	0.197
High_Temp.	X	-0.0392045	0.02382	0.02741	-1.43	0.153
DSTC	X	0.0404381	0.033	0.03818	1.06	0.29
LP	X	-0.00863413	0.02153	0.02521	-0.343	0.732
SAD	X	0.00755867	0.01978	0.0237	0.319	0.75
Wind	X	0.0110343	0.02754	0.03416	0.323	0.747
Ramadan	X	0.0544467	0.02746	0.03147	1.73	0.084
Intr.R*Wind	H	-0.105421	0.1527	0.1581	-0.667	0.505
Intr.R*High_Temp	H	-0.287318	0.1477	0.1542	-1.86	0.062
last_10_days_of_ramadan	H	0.0978141	0.04804	0.04516	2.17	0.03
alpha_0	H	-0.038172	0.009241	0.0102	-3.74	0
eps[-1]	H	0.00800525	0.01547	0.0151	0.53	0.596
|eps[-1]|	H	0.427679	0.03597	0.0468	9.14	0
beta_1	H	0.940625	0.01045	0.01302	72.3	0
GED	log(nu/2)	-0.518528	0.03079	0.03178	-16.3	0
No. of observations 3912, no. of parameters 19						
AIC.T 8353.15568 AIC 2.13526474						
Normality test: Chi^2(2) = 337.53 [0.0000]**						
ARCH 1-2 test: F(2,3889)= 2.8516 [0.0579]						
Portmanteau(780): Chi^2(779)= 833.60 [0.0855]						

7.6. Results

Using general-to-specific methodology has enabled us to reduce the number of variables in the variance equation of the EGARCH (1, 1) model, without impacting the reliability of the model. The results in respect to the mean equation indicate that the first lag of return is significant at 99% and that the month of Ramadan is significant at 90%. However, other mood variables (weather and biorhythmic) were not found to be significant and neither was the day-of-the-week-effect.

7.6.1. Interpretation of the Results in the Mean Equation

The relationship between Ramadan and mood has not been researched before in the literature. However, the expectation was that we would find a positive relationship between Ramadan and market return. This is so because, although during Ramadan the act of fasting means that Muslims spend the daytime feeling hungry (which is expected to have a bad influence on investor mood), this is more than offset by the positive impact of religious beliefs.[57] This drives investors to feel positive when they are trading during the holy month. The positive coefficient value in the equation (0.05) supports this expectation with 90% level of confidence.

With respect to variable DSTC, the expectation is of a negative relation between DSTC and market return. The coefficient found (0.04) contradicts this expectation and indicates that Jordan's DSTC has a positive impact on investor's mood. However, this is not found to be statistically significant but this finding is consistent with those of Luisa et al. (2009) for Germany.

With respect to lunar phases, the expectation is that the relationship would be a negative relation. The coefficient found (0.008) contradicts this expectation; however; it is not statistically significant.

SAD is theoretically expected to show a positive relationship between hours of darkness and stock market return.[58] The result (0.007) from the Amman Stock Exchange returns supports the positive relation between hours of night and the index return; however, it is not statistically significant.

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[57] Prophet Mohammad mentions that God said "Every good action is rewarded by ten times its kind, up to seven hundred times, except fasting, which is for me, and I reward it."

[58] Note that by working with hours of night, as opposed to day, the expected impact of the SAD measure on returns will be positive.

As for the first trading day of the week, the return for Monday (the first trading day of the week) has in other studies been found to be greater than the returns for other days of the week (French, 1980). The coefficient found (0.037) is consistent with these studies; however, it is not statistically significant.

The impact of wind on social mood has not been researched as widely as other weather variables; Keef and Roush (2005) found wind to be negatively related to mood. Our result (0.011) contradicted this expectation, although it is not statistically significant.

According to US weather observing practice, gusts are reported when the peak wind speed reaches at least 16 knots and the variation in wind speed between the peaks and lulls is at least 9 knots. The duration of a gust is usually less than 20 seconds.

However, in Jordan, the maximum wind speed during our sample is 15.1 knots, which indicates that Jordan does not have wind gusts. Therefore, the relationship between market return and wind may not necessarily be negative.

High and low temperatures are related to aggression (Rotton and Cohn, 2000). The negative emotion of aggression leads to some of the same action tendencies as positive emotions (Lerner and Keltner, 2001). Thus, high and low temperatures cannot be classified in the same category as high cloud cover, which is related to the negative emotion of depression (Dowling and Lucey, 2008).

Therefore, it is expected for one to find a negative relation between low temperature and market return, whereas high temperature is expected to have a positive relationship to market return. The results do indicate that low temperature is negatively related to market return (-0.042); however, this is not statistically

significant. Conversely, high temperature has been found to be negatively related to market return (-0.039), even though it was expected to have a positive relationship. However, the high temperature coefficient is not statistically significant.

As for humidity, since Jordanian weather is dry, it was expected that a positive relation between humidity and market return would be found. Lucey and Dowling (2005) found a positive relationship between extreme low humidity and equity return. The result of this research indicates that humidity is positively related to market return (0.005), although this result is not statistically significant.

7.6.2. Interpretation of the Results in the Variance Equation

The alpha coefficient is -0.038. This implies the existence of the ARCH process in the error term; it is statistically significant at 99% level of confidence. The returns exhibit time-varying volatility clustering; this indicates that periods of volatility are followed by periods of relative calm. The alpha sign is negative as a result of not imposing restrictions on the coefficient of the EGARCH model.

The beta coefficient is 0.940, which indicates that the variance is dependent on its moving average; it is statistically significant at 99% level of confidence. The sum of alpha and beta is close to unity, which implies that volatility shocks are quite persistent. The sum of these coefficients (0.902) indicates that a large positive or a large negative return will lead future forecasts of the variance to be high for an extended period. Since the sum is high, the response function to a shock is likely to die away slowly.

The GARCH coefficient (beta) is larger than the ARCH coefficient (alpha), which indicates that the conditional variance will exhibit reasonably long persistence of volatility.

The exponential GARCH (EGARCH) model of Nelson (1991) was used to identify the possibility of leverage effects. Even if the ARCH and GARCH models are successful in estimating and forecasting the volatility of the financial time series data, they cannot capture some of the important features of the data such as leverage effects, where the conditional variance tends to respond asymmetrically to positive and negative shocks in returns.

The result from EGARCH (1, 1) in this study indicates that the Amman stock market investors respond differently to bad news compared to good news (0.008); however, this is not statistically significant. The size effects, however, (0.427) are statistically significant at 99% level of confidence. This indicates that large positive and negative shocks will increase volatility in the Amman stock market.

No research has been found in the literature that used mood proxies in a mean equation and variance equation at the same time. Previous research has examined the relation between mood proxies and returns or variance. Therefore, three different variables have been included in the variance equation compared to the variables used in the mean equation, in order to identify if the volatility responds to mood proxies as the return.

The variables are: the interaction between Ramadan and wind, the interaction between Ramadan and high temperature, and the last 10 days of Ramadan (whether or not these variables result in a negative or positive relationship associated with above or

below-average volatility that has been tested). The results indicate that the last 10 trading days of Ramadan is statistically significant with 99% level of confidence, and interaction between Ramadan and high temperature is statistically significant with 90% level of confidence.

The result indicates that the last 10 trading days of Ramadan have a positive relation with volatility with the coefficient (0.097), with a significant 99% confidence level. This suggests that Muslims become more optimistic during Ramadan, particularly on odd days, as they expect that one of those nights could be the Night of Al-Qadr.

The interaction between Ramadan and high temperature was expected to be a positive relationship (if Ramadan did element the influence of high temperature). However, the results indicate that the interaction between them has a negative relation in the variance (-0.287). This significance level is 90%.

Furthermore, the interaction between Ramadan and wind was expected to be a negative relationship. The result confirms this (-0.105) but it is not statistically significant.

7.7. Interpretation of the Results According to the Interaction between Ramadan and Weather Mood Factors (High Temperature and Wind)

As mentioned earlier in Chapter Two, the principles of the Islamic economic paradigm are to achieve the creation of human-centric economics. Ahmad (1980), Chapra (1992), El-Ghazali (1994) and Sirageldin (2002) presented work that used, in varying degrees, an axiomatic approach to rationalize the existence of an Islamic political economy by treating the Islamic ethos as an ideal through which social and economic policies are assessed. An example of this is 'unity', or *zakat,* which

indicates the vertical dimension of the Islamic ethical system. This is particularly important during the month of Ramadan for every Muslim. This can possibly explain the behaviour of Muslims investors in Jordan during this period as the stock market can be viewed as a direct index of social mood given that it reflects the combined level of optimism or pessimism in society at a given time (Prechter, 1985, 1999; Nofsinger, 2005). The fact that weather and biorhythm variables can affect investor mood has been documented in the literature. To this, we need to add religious belief-related variables, as is suggested from the results in the previous chapter, and examine how these factors interact with other mood-influencing variables.

If there were many different mood-affecting variables, as the evidence suggests, it would be unsurprising if they were to interact with each other. For example, one might hypothesize that the negative impact of hunger during Ramadan could interact with the negative impact of very hot weather.

Although it was found in the previous chapter that, overall, Ramadan was found to generate more optimistic expectations about the future, the ways in which Ramadan interacts with other mood-influencing variables means that the outcome is not as clear cut as the results presented in Table 7.9 and 7.10 show in relation to both the mean model and the variance.

The results presented in Tables 7.9 and 7.10 above identify that Ramadan generates a positive return in the mean equation with a coefficient of 0.054, which is statistically significant. These support the findings in the previous chapter, where it was argued that, although during Ramadan Muslims experience daytime hunger, this is more than offset by the positive influence Ramadan has on the social mood due to their religious

beliefs. If investors are more optimistic during Ramadan, they may be more inclined to buy stocks during this month, since the coefficients remain positive in both models.

During Ramadan, Muslims can experience a whole series of emotions. The process of fasting can be of particular significance here. Fasting is meant to teach the person patience, sacrifice and humility, but it also enhances the senses and emotions. Muslims also ask for forgiveness for past sins, pray for guidance and help in refraining from everyday evils, and try to purify themselves through self-restraint and good deeds. According to the Islamic religion, fasting is one of the activities that increase humanity in society; however, from an investor perspective, its significance can be seen in terms of its effect of heightening the senses and making people more emotionally sensitive to the impact of external influences.

The results show that the last 10 days of Ramadan have a positive impact in the variance and it is statistically significant with a coefficient equal to 0.097. This may be explained as a result of Jordanian investors exaggerating the impact of their beliefs in Night of Al-Qadr (the night Muslims believe the first verses of the *Qur'an* were revealed to Muhammad by the angel Gabriel, which could be one of the odd-numbered days in these last ten). Therefore, the last 10 days of Ramadan have a positive impact in the social mood in Jordan. This positive impact may cause the investors to be overconfident and to misinterpret the amount of risk being undertaken (being subject to or influenced by an illusion of knowledge bias). Consequently, Jordanian investors who overestimate the accuracy of their forecast underestimate the risks taken. This will trigger more trading in the ASE and in turn increase the volatility during this period of Ramadan. Increases in volatility are considered in the models produced by Engle (1996) and Dufour and Engle (2000).

Narrow framing bias is another explanation for the last 10 days of Ramadan, as investors become more focused on short-term investment, even when the investment horizon is long term. The implication is that, if Jordanian investors focus on short-term volatility on the last 10 days of Ramadan to deter their investment more than in any other period, investors might overestimate stock market returns and therefore the volatility will be increased by the end of Ramadan.

Furthermore, the interaction between Ramadan and high temperature has a negative impact on the variance and is statistically significant with a coefficient equal to -0.287. Therefore, if Ramadan falls during pessimistic periods, such as high temperature, the result will exaggerate the pessimistic effects in the investor mood. In addition, that means the social mood will be at a low point. The combined factors of high temperature and the uncertainties people face make them less likely to trade. Therefore, the market swings less, resulting in a reduction in trading values. Reduction in trading values can result in a lower level of volatility, which is consistent with the results found by Engle (1996). He found that volatility correlated with trading intensity. In effect, he found that the less intense trading is and therefore the longer the duration between trades, then the less volatile a market is likely to be. This is supported by a recent study by Dufour and Engle (2000), who found that, as the time duration between trades decreases, the price impact of trades and the speed of price adjustment of trades increases; i.e. in effect, volatility may increase in response to higher trading volumes. If such a relationship exists in the Jordanian market it might very well be the case that the negative interaction effect on volatility between Ramadan and hot weather might be explained by the fact that their combined effect possibly causes trading volumes to fall.

7.8. Conclusion

It has been documented in the literature that financial market data are characterized by thick tails, volatility clustering, leverage effects and non-trading period effects. This chapter examined the volatility and the return in the Amman Stock Exchange, taking into account the influence of investor mood.

The mood-proxy variables were constructed from weather data (temperature, humidity and wind), biorhythmic data (seasonal affective disorder, daylight saving time changes and lunar phases) and belief data (the month of Ramadan). This chapter intensively examined the influence of Ramadan on investor mood by examining different sub-periods: the whole month and the last 10 days of Ramadan. It also examined the interaction between the weather variables and Ramadan.

This chapter followed the GTS and the three golden rules of econometrics suggested by Hendry (1980) of 'test, test and test'. The specific model developed divided the variables into two groups. The first group consisted of weather variables (high temperature, low temperature, humidity and wind), biorhythmic variables (seasonal affective disorder, daylight saving time changes and lunar phases) and the month of Ramadan, as well as the first trading day of the week. These variables were included in the mean equation.

The results indicate that the religious holiday of Ramadan is important in explaining both the returns on the Jordanian stock market and the volatility. This is due to social mood effects and possibly how these interact with other mood-influencing variables.

8. Chapter Eight: Conclusion

8.1. Summary of Research Findings and Research Contribution

The research undertaken has aimed to contribute to the debate in relation to the market efficiency of the Amman Stock Exchange (ASE). Random walk and calendar anomaly effects have been found. Behavioural finance concepts and ideas were used as a theoretical basis along with an application of the Islamic ethical paradigm. The research looks beyond informational efficiency and develops a number of 'novel' contributions to research in this area in terms of both the empirical findings and the interpretation of these findings in terms of behavioural finance. The thesis examines the relationship between seven behavioural mood-proxy variables and stock market returns. It also examines the associated levels of volatility that appear to be particularly high at the start and at the end of the Ramadan holy festival. Additionally, it examines interesting interactions between mood-related Ramadan effects and mood-related weather and biorhythmic effects.

The empirical results (shown in Chapter Four and Five) show that the market capitalization weighted price index of the Amman Stock Exchange during the period 1992–2007 does not follow the random walk hypothesis. Furthermore, day-of-the-week effects have been found in the ASE, especially for the first day of the week (weekend effects). Moreover, January effects or turn-of-the-year effects are still valid in the main sample (1992–2007), as well as in the two sub-samples.

The results show that Ramadan is the only month where the average daily returns are both statistically different from the other months in the year and also positive. During Ramadan, average daily returns were positive and were 0.1340%. The associated

standard deviation was 0.715% which has a coefficient of variation of 5.3. This indicates that there exists relatively high volatility over this period.

This provides evidence to suggest that the generally positive mood of the population that exists throughout the period of Ramadan has a positive impact on stock prices. If the social mood is positive, investors are more likely to have optimistic expectations about future stock performance. This is reinforced by the observation that share trading volumes tend to be higher during this period.

High levels of volatility at the beginning and at the end of Ramadan were found. This is consistent with increased synchronization of opinions. Increased synchronization is accompanied by a period of greater intensity of herding.

By employing a buy-and-hold strategy of buying on the last trading day of the month before Ramadan and selling on the last trading day of Ramadan, an investor could gain 1.87% average excess returns. These are, however, lower than the 2.10% transactions costs, which means that trading on this effect would not be profitable.

8.2. Behavioural Finance Interpretation of the Findings

The results verify that there is evidence from a behavioural finance perspective that there are *systematic biases* in the way investors think in Jordan. This research has found a number of systematic biases that affect investors. These include herding, social mood, synchronization, hindsight bias, illusion of knowledge, narrow framing and overconfidence. All of these biases interfere with the process of rational decision-making that is assumed by the *efficient market hypothesis*.

Mood and emotions may have a role in investment decision-making in Jordan. It has been found that low temperature is strongly negatively correlated with stock returns. Presumably low temperature causes investors to be unhappy and makes them feel less favourably towards investments. Therefore, emotions and moods may be irrelevant pieces of information that become reflected in the Jordanian price index.

Good moods make people less critical, which can lead to decisions that lack detailed analysis. The result shows that Ramadan is strongly positively correlated with stock returns, which indicates that these mood factors affect investment behaviour. Optimism bias may explain this phenomenon, as optimism reduces critical analysis during the investment process and causes investors to ignore negative information.

Another explanation is herding bias. It appears that during Ramadan Jordanian investors become more sociable with each other, which is part of the increase in ethics-based behaviour in Muslim society during the month of Ramadan. For example, as Muslims move toward *zakat*, the performance a good deed becomes an increasing focus. Generally, people in a peer group tend to develop similar tastes, interests and opinions. Social norms emerge in relation to shared beliefs. These social norms include beliefs about investing. The social environment of an investor influences investment decisions.

Furthermore, the illusion of knowledge is the tendency for people to believe that additional information always increases the accuracy of their forecasts. Some information is irrelevant, or may be beyond a person's ability to interpret, yet the person may still regard the information as improving their ability to forecast. This is found in the last 10 days of Ramadan. If investors in Jordan believe in the Night of

Al-Qadr,[59] then they are likely to be influenced by the illusion of knowledge bias, which causes investors to be overconfident and to misinterpret the amount of risk of an investment. Jordanian investors who overestimate the accuracy of their forecast underestimate the risks undertaken.

Narrow framing bias is another explanation for the last 10 days of Ramadan, as investors become more focused on short-term investment even when the investment horizon is long term. The implication is that, if Jordanian investors focus on short-term volatility during the last 10 days of Ramadan to deter their investment more than in any other period, investors might overestimate stock market returns and this therefore increases the volatility by the end of Ramadan.

This research examined a mixture of mood variables together to illustrate the impact of mood proxies on the stock market. Mood variables, such as Ramadan, may produce a positive mood, which has been found to generate more optimistic expectations about the future. Other mood variables might generate a negative mood, such as bad weather. Bad moods are expected to lead investors to be more pessimistic about the future of their investments.

New mood variables were created in this research such as; the interaction between Ramadan and high temperature, low temperature, humidity, wind, SAD, DSTC and lunar phases, to determine whether or not the impact generated by Ramadan is subject to elimination or exaggeration if Ramadan falls in the same period as other mood variables. Fama (1998) argued that, in the long run, bad news offsets good news.

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[59] Night of Al-Qadr: the night Muslims believe the first verses of the *Qur'an* were revealed to Muhammad by the angel Gabriel, which could be one of the odd-numbered days in these last ten.

Therefore, this research sought to examine whether variables that produce good mood could be eliminated by the other variables that produce bad mood in the long run.

This is the first research that uses mood proxies in the mean equation and variance equation simultaneously. Previous research has examined the relation between mood proxies and returns or variance. Therefore, three different variables were included in the variance equation compared to the variables used in the mean equation, in order to identify whether the volatility responds to mood proxies as well as the return.

The variables included: the interaction between Ramadan and wind, the interaction between Ramadan and high temperature and the last 10 days of Ramadan. Whether or not these variables have a negative or positive relationship are associated with above or below-average volatility that have been tested. The result indicates the last 10 trading days of Ramadan is statistically significant with 99% level of confidence and interaction between Ramadan and high temperature is statistically significant with 90% level of confidence.

The result indicates that the last 10 trading days of Ramadan have a positive relation with volatility with a coefficient of 0.097 with 99% confidence. Muslims become more optimistic during Ramadan, particularly during the odd-numbered days as they expect that one of those nights could be the Night of Al-Qadr.

The interaction between Ramadan and high temperature is expected to have a positive relationship if Ramadan did element the influence of high temperature. However, the result indicates that interaction between Ramadan and high temperature has a negative relationship in the variance (-0.287) with 90% level of confidence.

Furthermore, the interaction between Ramadan and wind is expected to have a negative relation if Ramadan did not element the influence of wind. The result indicates that interaction between Ramadan and wind have a negative relationship in the variance (-0.105), although not statistically significant.

The results also revealed that, in Jordan, Ramadan generated positive mood effects. Moreover, it appears that if Ramadan falls in periods associated with poor weather, such as high temperature, the result will exaggerate the pessimistic effects in the investors' mood. The combined factors of high temperature and the uncertainties people face make them less likely to trade and therefore the market is less volatile, resulting in a reduction in trading values.

Reduction in trading values can result in lower level of volatility that is consistent with the results found by Engle (1996) and Dufour and Engle (2000). They found that, as the time duration between trades decreases then the price-impact of trades and the speed of price adjustment to trades increases; i.e. in effect volatility may increase in response to higher trading volumes. If such a relationship exists in the Jordanian market it might very well be the case that the negative interaction effect, on volatility between Ramadan and hot weather might be explained by the fact that their combined effect possibly caused trading volumes to fall.

The potential influence of social mood in Jordan during Ramadan is even greater among non-professionals who have little, or no, understanding of pricing models and financial analysis. Trading in the ASE is considered thin. It lacks trading mechanisms and instruments such as short selling. Additionally, there is a lack of derivatives, and the limitations imposed on margin trading make it difficult to implement efficient diversification procedures, which hinders its liquidity and efficiency.

Therefore, Jordanian investors have a tendency to follow the judgments and behaviour of others. Investors may follow each other without any obvious reason. Such behaviour results in a form of herding, which may help to explain the optimistic effects during Ramadan that cannot be dismissed, even if it is interaction with other mood variables.

Jordanian investors are subject to more psychology biases than Western investors. This research argues that Islamic ethics, as represented by Islamic beliefs (such as the month of Ramadan), has an influence on the financial decisions of ASE investors. Religious belief in Jordan may influence investor behaviour; investors may feel happier when they follow their religious beliefs, particularly during Ramadan.

This happiness may cause investors to be in a good mood. If the investors are in a good mood during Ramadan, their expectations about future prices will be optimistic. Therefore, investors will be willing to buy shares during this month to make more profit according to their optimistic expectations about future prices. The increase in share-buying during Ramadan will provide an indicator to other investors about the optimistic future expectations and then more investors will buy shares. As a result, the shares will be overpriced and the returns during this month will be positive.

Nevertheless, lack of institutional investment increases the influence of psychological biases. Trading in the Western market is well established and builds on well-qualified firms who have the ability to put considerable effort into collecting and analysing market information; in addition, most investors are institutional investors (70% of investors in the UK market are institutional investors). In Jordan, the portfolio trades firms are not well known, and the firms that are known do not have a good reputation

amongst investors. Therefore, the majority of Jordanian investors are individual traders.

8.3. Recommendations for Further Research

Although this research has provided valuable insight, further research could address several issues identified in the results of this study. Further research may attempt to extend the empirical samples to include other Islamic countries, such as Bahrain. Bahrain, which has stricter religious observance rules than Jordan, may have a stronger Ramadan effect on investors. In addition, other countries where Islamic religion plays an important role in the economy, such as Bahrain, should be examined to determine whether Ramadan has a general influence on Islamic investors' behaviour or not.

For developed countries, this research can be extended by examining the impact of other religions, such as Judaism and Christianity, on investors. Effects of religious days on investor mood, such as the effects of Yom Kippur (Jewish holy day), can be examined.

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