Effect of Regulation, Islamic Law and Noise Traders on the Saudi Stock Market

A Thesis Submitted for the Degree of Doctor of Philosophy

by

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Abstract

Saudi stock market (SSM) has witnessed various market regulations and transformations taking place over the past decade. However, the impact of these reforms on market efficiency has not been addressed in the literature. Furthermore, idiosyncratic features of the market can play an important role on the market performance, yet these features have not been fully investigated. The aim of this thesis is to tackle these issues by empirically examining the market efficiency hypothesis and volatility behaviour of the Saudi stock market. Specifically, in order to better understand the relationship between stock returns and prohibition of interest (*riba*), both conditional and unconditional volatilities are investigated in the context of Islamic law and herd behaviour of noise traders. In Chapter 2 the efficient market hypothesis is tested on the basis of various market efficiency models. Results of both parametric and non-parametric tests reveal that despite the evidence of improved efficiency in the Saudi stock market the weak form of efficient market hypothesis theory is still generally rejected. Chapter 3 considers two types of the generalised autoregressive conditional heteroscedasticity (GARCH) model, a univariate and multivariate GARCH. Specifically, the univariate GARCH model is used to test the seasonality effect of the Ramadan month on each of the five stock market sectors. The multivariate GARCH is used instead to investigate the effect of interest (*riba*) prohibition in Islam on the volatility of the Saudi stock market. A distinction is made between stocks that are in agreement with Islamic *Sharia'a* law and interest paying stocks that are not allowed to devoted Muslim investors. The result demonstrates that the Islamic compliant sectors are more volatile than non-Islamic compliant ones. Further, Ramadan seasonality is more significant for non-Islamic compliant stocks. Chapter 4 investigates market inefficiency by considering two anomalies: investors' herd behaviour and structural breaks in the Saudi stock market. The herd behaviour is investigated by estimating a nonlinear asymmetric cross-sectional absolute deviation model, whereas structural shifts are modelled by estimating a Markov regime switching model. The volatility models considered confirm that both Islamic law and immature behaviour of investors are important factors that contribute to informational imperfectness in the Saudi stock market.

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Contents

Preface

The understanding of stock market movements has been addressed by a large body of applied studies. A fundamental issue considered in the literature is whether or not the stock market price of a firm fully reflects the information available, leading to testing the validity of the efficient market hypothesis (EMH). Stock market efficiency is crucial for both governments and investors owing to the fact that improvement in efficiency can enhance transparency and liquidity, and vice versa.

Fama (1965, 1970) developed a framework of efficient market hypothesis to describe the extent to which the market is informationally efficient. Based on this theory, there are three forms of EMH, of which the weak form is the most widely studied in literature. Under the weak form of market efficiency, current prices fully reflect all information contained in the historical market data, such as security prices and trading volumes. The validity of EMH with respect to stock markets is usually examined in its weak form. Markedly, if such weak form of EMH is supported, stock market prices should then follow a random walk stochastic process. Although existing literature has suggested that mature stock markets can be generally regarded as efficient in the weak form, this form of efficiency has often been rejected for emerging markets.

The lack of efficiency in emerging markets may be owing to market imperfectness, such as thinness, heavy speculation, and insider information. Furthermore, efficiency can be affected by the evolving markets nature, such as the change of market regulations and other features, namely the heterogeneity of market structure and participants. Hence, in order to better explain the relationship between risk and returns in emerging markets, various volatility models have been used in literature in order to address time dependent heteroscedasticity. Most empirical studies utilise the univariate Generalised AutoRegressive Conditional Heteroscedasticity (GARCH) models, as it is considered to be the most efficient way of modelling conditional variances. On the other hand, multivariate GARCH applications— especially for emerging markets—are less common. For example, Worthington and Higgs (2004), amongst others, predict a multivariate GARCH model for three Asian developed equity markets and six Asian developing markets. They confirm the existence of both own-volatility and cross-volatility spill-overs. Moreover, for all markets own-volatility spill-overs are generally higher than cross-volatility ones, especially for the emerging markets. Conditional heteroscedasticity implies that risk is time-varying, and such conditional variance can be driven by market structural breaks. Owing to the sudden shift in macroeconomics policies and financial reform, structural changes are relatively common in emerging markets.

In the empirical literature, the investigation of market structural breaks and financial regime changes has often been carried out by estimating a Markov regime switching model (MRS), as suggested by Hamilton (1989). For instance, Wang and Theobald (2008) investigate the regime-switching volatility of six East Asian emerging markets between 1970 and 2004. Their findings confirm that Malaysia, the Philippines, and Taiwan were characterised by two regimes, whilst the markets in Indonesia, Korea, and Thailand were characterised by three regimes over the sample period. For other non-Islamic and emerging countries, Moore and Wang (2007) test for regime-switching in five new EU member states using weekly data ranging 1994–2006. The authors suggest the number of regimes is between two and three for each emerging market. On the one hand, the existence of excess variability of stock market returns can be interpreted by volatility models; on the other hand, high-price fluctuations can be driven by investors' irrational behaviour—an anomaly that explains the failure of EMH. The herding phenomenon is widely studied in other countries, but not Islamic countries, and certainly not in Saudi Arabia. Two recent examples are Caporale *et al.* (2008) for Greece for the years 1998–2007, and Demirer *et al.* (2009) for Taiwan for the period 1995–2006. They both use the cross-sectional absolute deviation, and go to on to confirm the existence of return dispersion amongst irrational investors. More specifically, the results of Caporale *et al.* (2008), under asymmetric market conditions, indicate that the herd is stronger during periods of a rising market compared with a falling market, whereas Demirer *et al.* (2009) tested a non-linear and asymmetric model for the herd behaviour in 16 of 18 sectors in Taiwan, and stronger herd behaviour during falling market times.

The purpose of this thesis is to focus on the behaviour of the Saudi stock market in terms of market efficiency. The Saudi stock market was established 30 years ago; however, it has only expanded rapidly during the last decade. The massive expansion was triggered by the substantial oil revenue and the repatriation of money after the '9/11' terrorist attacks in New York and Washington DC. Such huge capital influx called for government intervention to improve market efficiency. A first step in this direction took place in 2001, when an electronic trade system was introduced in the stock market. A second major intervention occurred in 2003 with the establishment of a financial regulatory authority independent from the Saudi

Central Bank. These reforms, in addition with a number of other interventions implemented by the government, should have an impact on market efficiency; however, the impact of regulation on the Saudi stock market remains largely unexplored.

A few studies on the Saudi stock market efficiency, prior to the reforms taking place, are Al-Kholifey (2000), who tests the weak form of market efficiency using the daily data of 41 joint companies between 1990 and 1998. In addition, Al-Abdulqader (2002), using weekly closing prices of 45 individual firms during 1990–2000, tested for market efficiency in Saudi Arabia. Using similar investigation methods, both authors reject the EMH. A possible shortcoming of these works is that these studies were undertaken before the dramatic political reforms that took place in Saudi Arabia in the new millennium; therefore, the impact of capital market regulations and other policy interventions were not taken into consideration. The aim of the first part of this thesis is to address these issues.

In the second part of the thesis, the effect of Islamic *Sharia'a* on Saudi stock market volatility is investigated. Such effect is assumed to be vital owing to the fact that Islam prohibits the practice of interest (*riba*), which can subsequently restrain Muslim investors from investing in interest-paying stocks. In addition, the Ramadan effect on stock market returns and volatility—which is somehow related to Islamic *Sharia'a* effect—is investigated.

To the best of the my knowledge, no study carried out thus far investigates the effect of Islamic *Sharia'a* on the Saudi stock market. With respect to the Ramadan seasonality effect, studies by Seyyed *et al*. (2005) and Husain (1998) can be mentioned here: whilst the former examines the effect of Ramadan on the stock volatility in the Saudi market general and sector indices, the latter investigates the seasonality of the Pakistan equity market using GARCH (1, 1). Notably, however, both studies find a statistically significant fall in the level of market volatility for all indices in Ramadan, although such impact can be different across sectors and mean returns. Mustafa (2008) also investigated the pre-Ramadan and post-Ramadan effect on the Karachi stock market, with his result indicating that the Karachi market is of relatively low risk during Ramadan compared with post-Ramadan months.

This thesis extensively investigates the efficiency of the Saudi stock market. The main contributions of this work can be summarised as follows: firstly, in this thesis, stock market data covering new financial regulation are used. As stated previously, research on the Saudi market is not only limited but also outdated, and therefore does not reflect the recent regulatory effect, as well as other important factors. Secondly, with respect to the relevant literature a wider range of econometric models is used in this study. For example, conventional parametric and non-parametric tests for market efficiency are considered. In addition, Granger causality and co-integration models are used to investigate the EMH. Thirdly, the effect of religion on stock returns and volatility is extensively explored.

This thesis is organised as follows:

Chapter 1 is designed to build up a solid background on the development of the EMH theory. The main purpose of this chapter is to review the theory of EMH, and accordingly highlight its implications for stock market analysis. Empirical tests for EMH, including both non-parametric and parametric approaches, are also outlined.

Chapters 2, 3 and 4 contain the main body of research. Chapter 2 focuses on the weak form of market efficiency. Test statistics of the empirical investigation are calculated in order to measure the statistical relation between successive price changes. Importantly, if no relation is found, prices are then said to be random or to follow a random walk model, and are therefore in favour of the weak form of the EMH. The weak form suggests that, in the long-run, no excessive or abnormal profitable investment trading strategy can be derived based on past prices. In an attempt to test for the weak form of market efficiency in the Saudi stock market, six statistical tests are considered for the period before and after market regulation. These are: (i) the test for autocorrelation between 50 individual joint companies and 5 sector indices listed in Saudi stock market; (ii) the Ljung Box test, which tests the joint hypothesis autocorrelation up to a certain number of lags are equal to zero; (iii) the runs test, which detects the randomness of the series according to their actual versus expected number of runs; (iv) the filter rule (Alexander test) that compares any filter size with an intuitive 'buy and hold' strategy; (v) the variance ratio test for the two sub-periods; and (vi) the co-integration hypothesis amongst five sector indices. The chapter results, in general, show improvement in market efficiency compared with previous studies, although the efficient market hypothesis is generally rejected for the Saudi stock market.

Chapter 3 discusses in detail the effects of Islamic *Sharia'a* by modelling the time varying volatility of the Saudi stock market. Islamic *Sharia'a* prohibits the practice of *riba*, and the general rule in Islam is that money must not breed money. In Islam, no distinctions are made between small amounts of *riba* (interest) or large amounts (usury). To investigate the effect of Islamic *Sharia'a* on the Saudi stock market, two conditional volatility models are chosen. The BEKK (Baba, Engle, Kraft and Kroner, 1990) multivariate GARCH (1, 1) model, which is recognised as the first attempt, is the most parsimonious model to measure cross volatility spill-overs compared with the VECH specification. Furthermore, the BEKK model has the advantage that the covariance matrix is always semi-definite. Secondly, a generalised GARCH (1, 1) model is estimated with dummy variables so as to capture the seasonality during Ramadan on the stock volatility. Ramadan is the ninth month of the lunar Islamic calendar, and all adult Muslims are required to fast from sunrise to sunset during this period. The argument put forward in this thesis is that, although there is a slowdown in activity for all sectors, one may expect the non-Islamic-compliant stock market sectors (*Haram* stocks) to be less volatile in the month of Ramadan than Islamic-compliant sectors (*Halal* stocks). One reason for this may be owing to the fact that, during this period, Muslims are more prone to avoiding behaviours that are not in agreement with *Sharia'a* law. In the GARCH (1, 1) specification, Ramadan is modelled as a dummy variable in terms of both mean and the variance of the general, and all five sector indices. Results support the argument that the *halal* sectors are the most volatile sectors in the Saudi stock market.

Chapter 4 further investigates speculative behaviour across different sectors in the Saudi stock market, adopting two different ways: the risk dispersion or herd behaviour, and potential bubble states indicated by regime switching of both means and variances. Specifically, the risk dispersion or herd behaviour is analysed by considering the cross-sectional absolute standard deviations of returns in both bear and bull markets. The number of regimes for the conditional variance of the returns is determined by estimating the Markov switching model of the type, as suggested by Hamilton (1989). Results suggest that the asymmetric herd behaviour is statistically significant across all sector indices, and the herd is more obvious in a bull market. The significance of Markov regimes switching demonstrates the complexity of the volatility structure. Unlike matured stock markets—which usually have two volatility regimes (e.g. high and low states)—the majority of Saudi stock market indices have three states in the volatility equation, i.e. high, medium, and low. Generally speaking, the more volatile sectors, such as Tasi and Service, show both stronger herd behaviour and three regimes. Overall, results suggest that the Islamic religion plays an important role in shaping the behaviour of the financial market in Saudi Arabia: Islamic-compliant sectors are more volatile than non-Islamic-compliant ones, and they show a higher degree of herd behaviour.

The main findings of the thesis are summarised as follows:

1. Compared with previous studies, although improvements of market efficiency following financial reforms have been found, the degree of market efficiency in Saudi Arabia remains unsatisfactory, and the market authority needs to do more work to enhance the efficiency.
2. The result of the third chapter supports the argument that the *halal* sectors are the most volatile sectors in the Saudi stock market. The results also show small differences between stock market sectors.
3. The irrational or herd behaviour amongst investors in the Saudi stock market during the financial crash in 2006 are confirmed. This phenomenon is found to be particularly significant for *halal* and *mixed* (but close to *halal*) sectors, such as Agriculture and Service sectors.
4. The Markov switching model reveals that two regimes in the conditional volatility equation can be identified for the Bank sector only (which, according to *Sharia'a* law, is a *Haram* sector), whereas all other sectors demonstrate a more complicated regime structure of volatility. This finding confirms that Islamic sectors are more risky than non-Islamic ones. Overall, the volatility models utilised in this thesis suggest that Islamic law plays an important role in determining the level of risk within the Saudi stock market.

Chapter 1

Review of Efficient Market Hypothesis

1.1 Introduction

Market efficiency concerns the extent to which stock prices respond to available information about their fundamental values. It is desirable that in an ideal situation all available information should be reflected in a promptly manner and hence price changes should be only the resultant outcome of new information. If market prices do not fully incorporate information, then opportunities may exist to make profit from collecting information. Therefore, investors have great interest in understanding market efficiency and verifying the efficient market hypothesis (EMH).

The efficiency of capital markets is also targeted by governments and market regulators as stock markets are vital for firms to raise capital and resource allocations to boost economy. If a capital market is not efficient, then firms' intrinsic values can be incorrectly priced. Moreover, the mis-pricing may delay or even stop firms' decision on investments. Consequently, the efficiency of capital markets is crucial for a capital market to work properly.

The main purpose of this chapter is to review the theory of efficient market hypothesis and highlight its implications for stock market. Historically, testing market efficiency is closely associated to other mathematical concepts, such as market expectations and martingale. These concepts will be considered in this chapter along with the efficient market hypothesis formulation. Further, implications and empirical tests for efficient market hypothesis will be outlined. More details about efficient market hypothesis applications in the Saudi stock market will be discussed in Chapter 2.

The rest of chapter is organised as follows. Section 1.2 gives a brief discussion of EMH theory; Sections 1.3 and 1.4 discuss its implications and some tests, respectively. Section 1.5 gives a brief discussion of EMH and risk adjusted relationship. Section 1.6 outlines violations of EMH. Finally, a conclusion is given in Section 1.7.

1.2 The theory of efficient market hypothesis

A market is usually referred to informational efficient market, when asset prices incorporate all available information. Although this idea can be traced back to 1900, the term "efficient" emerged for the first time in Fama (1965) seminal paper. Albeit different definitions exist in the literature, there is a consensus regarding the price response to information. The most parsimonious definition of efficient market given by Fama, *et al.* (1969, p.2):

"An efficient market is a market that adjusts rapidly to new information".

From the definition above, it is clear that the concept of the efficient market is closely linked to the information available at the time when market prices should respond to. Thus, we define some statistical concepts before analysing the efficient market hypothesis theory.

1.2.1 Expectation

If x is a random variable, then the expected value of x, in its discrete and continuous form, is defined respectively as

$$E(x) = \sum_{i=1}^{\infty} \pi_i x_i , \tag{1.1}$$

$$E(x) = \int_{-\infty}^{+\infty} x f(x) dx, \tag{1.2}$$

where, π_i is the discrete probability for x_i and $f(x)$ is the continuous probability density function.

1.2.2 Conditional expectation

Let x_t is a stochastic process, the conditional expectation based on the information set Ω_t, can be defined as:

$$E(x_t|\Omega_t) = \int_{-\infty}^{+\infty} x_t f(x_t|\Omega_t) dx_t, \tag{1.3}$$

where, $f(x_t|\Omega_t)$ is the conditional density function. Therefore, the conditional forecast error can be derived as:

$$\varepsilon_{t+1} = x_{t+1} - E(x_{t+1}|\Omega_t). \tag{1.4}$$

1.2.3 Martingale and sub-martingale models

An important mathematical concept related to conditional expectation is that of a martingale. The sequence x_t is called a martingale if for every *t* the following conditions hold:

(a) $E|x_t| < \infty$ and (b) $E(x_{t+1}|\Omega_t) = x_t$.

or equivalently its return, $r_{t+1} = x_{t+1} - x_t$, is zero , i.e.

$$E(r_{t+1}|\Omega_t) = 0 . \tag{1.5}$$

"*A martingale in probability theory classifies observed time series according to the way they trend. A stochastic process is a martingale if its trajectories display no discernible or periodicities".*[Neftci,2000,p.120]. If the asset price follows a martingale process, then conditional on what has happened so far, the expectation of the next price is the same as the current price, in other words, the directions of the future movements in a martingale are impossible to forecast.

An example of a martingale process is the random walk[1].

$p_t = p_{t-1} + \varepsilon_t$, where $\text{cov}[\varepsilon_t, \varepsilon_s] = 0$, for all $t \neq s$. Then

$$E[p_t \mid p_{t-1}, p_{t-2},...] = E[p_{t-1} \mid p_{t-1}, p_{t-2},...] + E[\varepsilon_t \mid p_{t-1}, p_{t-2},...] = p_{t-1} + 0 = p_{t-1}$$

Martingale implies that there is no winning strategies based upon the history and the odds are fair. The origin of martingale process is related to games of chance and it is equivalent to the fair game definition. A fair game is sometimes referred to as a martingale difference, and can be defined as choice that is neither in your favour nor in your opponent's.

A martingale process has always zero drift and hence is not suitable for modelling the prices. Instead, (1.5) can be extended by the following format:

$$E(p_{t+1} \mid \Omega_t) \geq p_t \text{, or equivalently, } E(r_{t+1} \mid \Omega_t) \geq 0, \tag{1.6}$$

then the price, p_t for a security is said to follow a sub-martingale process of a positive drift with respect to the information sequence Ω_t. In other words, the expected value of next period's price, conditional on the information set Ω_t, is always equal to or greater than the current price[2].

According to Fama (1970), an important empirical implication of the sub-martingale model is that no trading rules can beat the simple "buy and hold" strategy based only on the information set[3], Ω_t. Like fair game process the martingale process does not required the returns to be un-serially correlated.

[1] See Greene (2007) for more details.
[2] Similarly, a super-martingale is defined as a process that has a negative drift.
[3] LeRoy (1989) argued that no support was given for this claim by Fama.

1.2.4 Fama's efficient market hypothesis

The definition of Fama (1970) implies that asset prices in an efficient market reflect all past and present information. In other words, the asset price p_t changes between time t and $t+1$ is only driven by the arrival of news during the time interval. Therefore, the stock price p_t evolves as the following equation:

$$p_{t+1} = E_t\left(p_{t+1}\right) + \varepsilon_{t+1}, \tag{1.7}$$

where $E_t\left(p_{t+1}\right)$ is the expected value of the stock price for time $t+1$ given all information available at the time t and ε_{t+1} is the forecast error, representing unanticipated information that is not available at the time t but only come in time between t and $t+1$. Therefore, the expected value of ε_{t+1} at the time t is 0. That is,

$$E_t\left(\varepsilon_{t+1}\right) = 0. \tag{1.8}$$

Equation (1.8) has important consequences as the zero conditional expectation of the error term at the time t indicates that the error is uncorrelated with any information before time t. Also, this orthogonal condition is consistent with the implication that asset prices in an efficient market only reflect all past and present information.

As mentioned earlier, there are many definitions of the efficient market. However, this thesis will be restricted to Fama definitions[4]. For instance, in his first paper, Fama (1965, p.56) defined it as "*a market where there are large numbers of rational, profit-maximizers actively competing with each other trying to predict future market values of individual securities, and where important current information is almost freely available to all participants*".

Moreover, in his second paper, Fama (1970, p.386) defined the efficient market prices where the prices "*fully reflect*" all available information, though he admitted that the term "fully reflect" is rather general as it requires a model that assumes stock price movements follow some kind of repetitive patterns. Since the majority of empirical literature focus only

[4] Campbell, Lo and MacKinlay (1997) cited more recent definition given by Malkiel (1992).

on the weak form of efficiency, martingale, sub-martingale processes are used in literature to model the concept of efficient market.

Following Roberts (1967), Fama (1970) distinguish the degree to which market information is efficient. Specifically, such degree is measured by the following three categories of all relevant information, reflected by asset prices at any point in time[5]. First, weak-form efficiency, where the current prices fully reflect all information contained in the historical returns (mainly security prices and trading volumes). Second, semi-strong-form efficiency, where the current prices fully reflect all information contained in the historical returns plus any information that is publicly available (announcement of annual earnings, dividends, stock splits, etc.). Third, strong-form efficiency, which include weak form, semi-strong form plus any inside private information that some agents or groups can have and is not available for public.

Finally, Fama (1970) concludes that transaction costs, unavailable information and investor inconsistency can contribute to an inefficient market and thus pointed out three sufficient conditions for a fair game to take place in the market. The first condition is the absence of transactions costs in trading securities and hence the information set Ω_t is the same for all investors. The second is that all information is available freely to all market participants. The third is that the all participants have homogeneous expectations and would come to the same conclusions for the same given information Ω_t.

These conditions are hardly achievable in the real world. However, these conditions are sufficient but not necessary and any violation of one or more assumptions will not invalidate the theory. Although significant transaction costs can usually advert market efficiency, they do not always void the market efficiency theory if an appropriate model of normal returns can be set up, i.e. any abnormal return must take account of cost related to transactions/information. In this sense, EMH says that there is no free lunch for excess returns, for example, an investor can still be able to earn gross abnormal profits in an efficient market but has to pay a higher charge/fee that is equivalent to the excess returns to cover the cost of transactions. Overall, the investor’s net profit is still similar to others. For this reason there

[5] Harry Roberts (1967) discerned the three forms of market efficiency, which became the classic taxonomy in Fama (1970). See Fama (1970) for more details.

has been increased interest in finding equilibrium models that can better forecast expected returns on stock markets (Campbell, Lo and MacKinlay, 1997).

1.3 Implications of the EMH

The efficient markets hypothesis rules out the possibility of earning abnormal profits depending on the available information. This has important implications for investors, firms and market regulators.

1.3.1 Implications to investors

The most important implication of the efficient market hypothesis for investor is to trust market prices as prices reflect all available information at any point in time[6]. There is no opportunity for investors to make greater returns given the risk taken. In an efficient market, investors can be rewarded exactly what they pay for on average, e.g. their risk adjusted returns should be the same. For example, a simply passive "buy and hold" investment strategy is enough for an efficient market. If an investor has a well-diversified portfolio, then he/she can hardly outperform the market via any active investment strategies, which are wasteful in efficient markets[7].

As discussed, the efficient market theory is important for investors and analysts as it reveals the relationship between stock prices and its intrinsic values. Generally speaking, efficient market hypothesis implies that the market is arbitrage free in efficient markets.

1.3.2 Implications to firms

The efficient market hypothesis implies that stock markets provide correct signals, e.g. the cost of equity, for real resource allocations and raising capital for new projects of firms. Hence, there is no reason for delays in market issuance for financing physical invest-

[6] Clarke, *et al.* (2001, p.3) mentioned that "*all investments in efficient markets are fairly priced*".
[7] However, the existence of investment managers and different investment strategies do help ensure information cascading quickly, maintaining the status of market efficiency (Cuthbertson and Nitzsche (2004)).

ments as better conditions do not exist and current prices are always right. In the opposite case, if stock prices are not efficient, then profitable investment projects can't be successfully financed by investors. Furthermore, efficiency is an important issue for firms in case of merger and acquisition processes as efficiency helps to achieve these processes in most fair way. Efficient market theory also implies that firm conglomerate formation is not necessary. For example, if a firm can reduce risk of shareholders via conglomeration then shareholders can do so via the constitution of a diversified portfolio of firms. This is a cheaper and more convenient as conglomeration can embedded with other costs and business integration risk.

1.3.3 Implications to governments and market's regulator

The implementation of an efficient market is also the aim for government and market regulators as they should not intervene if the market is efficient.

In an efficient market, since current prices of securities reflect all available information at any given point in time, there is no reason to be concerned about the fact that prices are either too high or too low. However, if the market is not efficient, government needs to ascertain how far the market is on average from efficiency, and then impose appropriate policies to enhance efficiency of the market.

1.4 Test of market efficiency

Tests for market efficiency hypothesis can be carried out in different ways according to efficiency form under consideration. Usually the test starts from the lowest level of weak form to the highest level of strong form. Tests for weak form of market efficiency will be elaborated as the thesis only focus on the market efficiency in the Saudi stock market and only this form will be considered whereas tests for the other two will be briefly mentioned.

1.4.1 Test for weak form of market efficiency

The weak form of efficient market hypothesis has been widely tested and analysed in financial literature. This is because this form has the lowest degree of efficiency and thus it is the pre-requirement for the semi-strong and strong forms of market efficiency.

The random walk model is one of the most common model used in empirical literature to detect the market efficiency. If efficient market hypothesis holds, changes in prices are expected to be random and unpredictable because new information, by its nature, is unpredictable. Therefore stock prices are said to follow a random walk. After Fama's seminal paper, these two terms have often been used interchangeably. According to Fama (1970, p.386):

"*the statement that the current price of a security "fully reflects" available information was assumed to imply that successive price changes (or more usually, successive one-period returns) are independent. In addition, it was assumed that successive changes (or returns) are identically distributed. The two hypotheses constitute the random walk model*".

The martingale was considered a necessary condition for a weak form efficient market (Campbell *et al*, 1997). If all past information has been correctly reflected in prices then it is not possible to profit by trading on it. That is, the expected return conditional on past information is zero, which is consistent with the martingale.

However, it is argued that a martingale with zero drift/expected return can't always reflect the risk held by investors. A rational investor must require a positive return to hold risky assets and the higher the risk, the higher expected to be required. For this reason stock prices are not modelled as martingales. Instead, it is necessary to assume that a random walk model that exhibits an upward drift is more appropriate. Overall, the random walk model includes the properties of martingale/fair game, but it's less restrictive than both models.

Formally, the random walk model can be expressed in three different versions as summarized by Campbell, Lo and MacKinlay (1997). The first form (RW1) given by:

$$p_t = \mu + p_{t-1} + \varepsilon_t \, , \varepsilon_t \sim \mathrm{IID}(0, \sigma^2) \, , \qquad (1.9)$$

where μ is the drift or expected price change, and $\varepsilon_t \sim \text{IID}(0,\sigma^2)$ denotes that ε_t is independently and identically distributed with a 0 mean and a constant variance of σ^2. The logarithm of prices should be used instead of actual prices to prevent a positive probability for a negative price. However, the RW1 is considered unrealistic for stock prices over long time period due to changes of economy, technology, and environment.

The second model (RW2) can be defined as follows:

$$p_t = \mu + p_{t-1} + \varepsilon_t, \ \varepsilon_t \sim \text{INID}(0,\sigma_t^2). \tag{1.10}$$

The model in (1.10) is less restrictive than the one in (1.9) as it relaxes the assumption of identical distribution, i.e. allows for hetroskedasticity or time varying volatility that is widely documented in financial literature. Testing for the RW2 model can be undertaken using technical analysis or non-parametric methods that do not require the identical distribution assumption, such as filter rules, and run tests.

The third random walk model (RW3) is the most general version of random walk model. It allows for dependence in higher moments, but uncorrelated increments. The obvious example of RW3 is the process where:

$$\text{cov}(\varepsilon_t, \varepsilon_{t-k}) = 0, \text{ for all } k \neq 0, \tag{1.11}$$

but its squared increments are correlated, i.e.

$$\text{cov}(\varepsilon_t^2, \varepsilon_{t-k}^2) \neq 0, \text{ for some } k \neq 0. \tag{1.12}$$

The model in (1.12) is the most used model in the recent empirical literature. To test for RW3, the serial correlation, variance ratio test, and long horizon regression are commonly used as inference procedures.

1.4.2 Test for semi-strong form of market efficiency

In a semi-strong efficient market, all available public information such stock splits, earnings and dividend announcements, economic and political news, and even changes in senior management should be reflected quickly in share prices. Since news can't be predicted in advance, tests for the semi-strong form of market efficiency are closely linked to investors' reaction to arrivals of public information by event studies.

Generally speaking, a typical event study process can consist of four steps. Firstly, an event and the study period of the event should be defined. Secondly, stocks associated with the event are identified. Thirdly, the expected return for each of the stocks on the announcement date is estimated. Lastly, the excess or abnormal return for each stock, which calculated based on the differential between expected and actual ones, can be performed and tested by statistical analyses.

If the semi-strong efficient market holds, share prices are expected to react promptly and accurately to public news. Therefore, their actual returns and descriptive statistics such as standard deviations can be computed and compared to the expected ones. Note that even if actual returns exceed expected ones the market under investigation should still be valid for semi-strong market efficiency provided that such abnormal returns are within the announcement period.

1.4.3 Test for strong form of market efficiency

Tests for strong form of market efficiency involve analysing whether investors can earn abnormal profits by trading on non-public, or inside information. However, trading according to inside information is not allowed by law and no investor will admit he is trading according to inside information, which makes any empirical test of strong form impossible. Further, the stock market authority employees are not allowed to invest in the market or give any private information to any person or groups. However, any tests for strong form of market efficiency should always demonstrate that security markets are inefficient in the strong form.

1.5 EMH and risk adjusted returns

EMH does not take account of risk associated with the investments. In this model, abnormal profits are rewarded by excessive risk, not by exclusive market information. Therefore, one way to interpret these market anomalies is that expected returns need to be adjusted for underlying risk. For this reason, the Capital Asset Pricing Model (CAPM) can be used to obtain risk-adjusted returns.

Both the EMH and CAPM are the two pillars in modern asset pricing and allocation theory. As discussed before, EMH suggests that in an informationally efficient market investors can't achieve abnormal returns, e.g. excess profit above the expected return. Therefore, tests for efficient market hypothesis require the determination of expected returns, which can be calculated by an equilibrium model, for example, CAPM[8].

CAPM is a simple, standard one factor model of determining the expected return of a single asset. It states that the expected return of an individual equity is proportional to the covariance of it with the return of the market portfolio. Sharpe (1964), Lintner (1965) and Mossin(1966) assume the existence of lending and borrowing at a risk-free interest and hence the expected return of asset *i*,

$$E(R_i) = R_f + \beta_{im}\left(E(R_m) - R_f\right) \tag{1.13}$$

$$\beta_{im} = \frac{\text{covariance}\left(R_{i,} R_m\right)}{\text{variance}\left(R_m\right)} \tag{1.14}$$

where R_m is the return on the market portfolio, and R_f is the return on the risk-free asset.

It can be seen that the expected return of an individual stock is purely determined by its covariance, or the systematic risk. The CAPM is the basis for measuring the performance of an investor, e.g. the excess return above the market expected return for that risk level[9].

The model is built upon many assumptions, implying the presumed full information efficiency. Combined with the ability to measure the expected return with the associated risk,

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[8] CAPM model will not apply in this thesis due to difficulty of obtaining risk free benchmark in Saudi market, see Section 2-3 for more details.

[9] This measure is called alpha, or Jensen's alpha, which is just the *ex post* estimated alpha.

the CAPM can be used to test the efficient market hypothesis. However, Krause Andreas (2001) among others argued that a critical issue of the CAPM is the aggregation of all risks into a single risk that is the market risk, or β_{im}. This aggregation is useful to some extent in case of well diversified portfolio, but can be problematic for the explanation of specific returns on an individual asset. Hence, CAPM has been extended to multifactor models, such as Ross' Arbitrage Pricing Theory (APT) or Fama-French's three factor model.

Consequently, an alternative is the joint tests of EMH and a market equilibrium model for the risk adjustment return. If abnormal profits can be earned, either EMH or the risk adjusted model should be rejected and usually, the market equilibrium model is more questionable, leading to the no conclusion about market efficiency.

1.6 Market anomalies

Although some financial markets are efficient, particularly in the weak form, the literature also suggests considerable anomalies that indicate potential inefficiencies, leading to the mispricing of shares. Hence, market anomalies are referred to the situation where changes in asset prices can't directly be linked to either existing or new information.

1.6.1 Anomalies of market efficiency

Several market anomalies have been mentioned widely in literature. A case in point is the calendar or seasonality effect. In addition, size effect, value effect, momentum effect and other violations to the efficient market hypothesis are often mentioned in empirical studies. However, if market anomalies do exist, then they not only invalidate the hypothesis, but also suggest that asset returns are predictable and making excess returns are possible.

A well-known model that incorporates market anomalies is the three factor model by Fama and French (1995). In addition to the beta of the standard capital asset pricing model (CAPM). The model by Fama and French combines both the size and value anomaly effect.

The size effect (or small size effect) refers to the negative relation between stock returns and the firm capitalisation where the small company generates more returns than a larger does. The size effect can be measured by the capitalisation differential between small and big firms.

The value effect (or the value versus growth effect) is the situation where the company with a high book-to-market ratio (value stocks) outperforms the company with a low book-to-market ratio (growth stocks). Usually the value effect is measured by high book-to-market ratios minus low ones.

Asset pricing models and market efficiency require that markets are rational and hence the existence of market anomalies can suggest that this assumption is not necessarily valid as market participants can be irrational. If investors are irrational, then their behaviour can impede information cascade among markets. For example, stock market movements can be driven on the basis of investors' herd behaviour instead of market information[10]. Further, volatility plays an important role in asset pricing models. Many economic models assume that the variance and covariance, as measures of volatility, are constant through time. However, empirical evidence rejects this assumption as stock price volatility can be clustered or conditionally time varying. Testing for, and modelling of, time-varying volatility of stock market returns has been given considerable attention in the literature.

1.6.2 Anomalies of herd behaviour

Herd behaviour has been studied by behavioural economics and was recently introduced into finance and return modelling. Particularly in emerging markets, such as the Saudi stock market, herd behaviour is common as the market are dominated by individuals who are inexperienced and often make decisions on the basis of rumours and information publically circulated (internet websites, text messages, friends advice, etc.). Such behaviour can drive the market from one extreme side to the other and may cause the market to overact.

The existence of herd behaviour has a significant impact on efficient market hypothesis and volatility models. If such behaviour is found in the market, this leads to impact nega-

[10] Herd behaviour is considered in Chapter 4.

tively on efficient market hypothesis and create excessive volatility swing that can't be explained by standard volatility models.

1.7 Conclusion

Traditionally, stock markets lead markets among other financial market's instruments. Stock markets help firms to raise capital for funding projects and business expansions. Also, investors can participate in stock markets and share profits of the companies' stock they bought. However, performance of those activities can be dependent on the market efficiency. If stock markets are informationally efficient, then the share prices reflect firms' intrinsic value, which in turn, provides valuable information about firms for investors, shareholders and regulators.

This chapter has provided a broad review of the efficient market theory, including its definition, closely associated concepts, and the most popular forms of the theory developed by Fama (1970). An efficient market implies that its stock prices should always be at their fair values and they only move immediately when their fair values change, reflecting the arrival of new information. Further, the implications of the market efficiency for investors, companies, and regulatory body are mentioned. Finally, the markets anomaly that may invalidate the implementation of the efficient market hypothesis is discussed briefly.

In the next chapter, traditional statistical approaches in addition to more advance econometric tests are performed to assess the effect of the market deregulation on the Saudi stock market.

Chapter 2

The Effect of Regulation on the Saudi Stock Market Efficiency

2.1 Introduction

Publicly traded companies play a key role in the formation and transfer of debt and equity capital in market economies. The operational and informational efficiency of stock markets are largely determined by the number of market participants, the number and capitalized value of securities, and the regulatory and institutional environments of the markets.

As seen in the previous chapter the efficient markets hypothesis implies that asset prices incorporate all available information. From this perspective, market inefficiencies redistribute wealth between well informed investors and less well informed investors. In this respect, financial regulators play a key role in enhancing market efficiency by imposing transparency rules on markets.

Starting from 2001 the Saudi government has undertaken a major effort in regulating and at the same time modernizing the domestic stock market. In the light of these changes a natural question arises: Has market efficiency increased as a result of financial regulator effort? This crucial issue has been only partially addressed by the current literature. Interesting studies on the stock market efficiency in Saudi Arabia have been undertaken by Butler and Malaikah (1992), Al-Razeen (1997), Dahel and Labbas (1999), Al-Kholifey (2000), and Al-Abdulqader (2002). However, no previous empirical work has investigated if increased regulations had a major impact on market efficiency. In particular, the available literature does not provide an unequivocal conclusion in terms of the relationship between the lack of efficiency of the Saudi market and informational or operational aspects of the efficient market hypothesis.

The purpose of this chapter is twofold. First, we address the question of whether or not the Saudi market is weakly efficient after the introduction of major changes in the investment environment. Secondly, we investigate whether regulation has had a role in characterising the efficiency of the Saudi market between the period 2001 and 2008.

To achieve these goals, the Saudi stock market data have been split in two sub-periods. The first sub-period starts from the beginning of 2002 to the first quarter of 2005. This period was characterised by an increase in regulatory activities and an increase in the volume of investors. The second sub-period relates to somewhere around the 2^{nd} quarter of 2005 up to the 2^{nd} quarter of 2008, where the highest level of the Saudi stock index (Tasi) was observed at over 21,000 points and then fell again. Splitting the sample in two periods and analysing the result of each sub-sample will help to detect the effect of regulation on Saudi stock market.

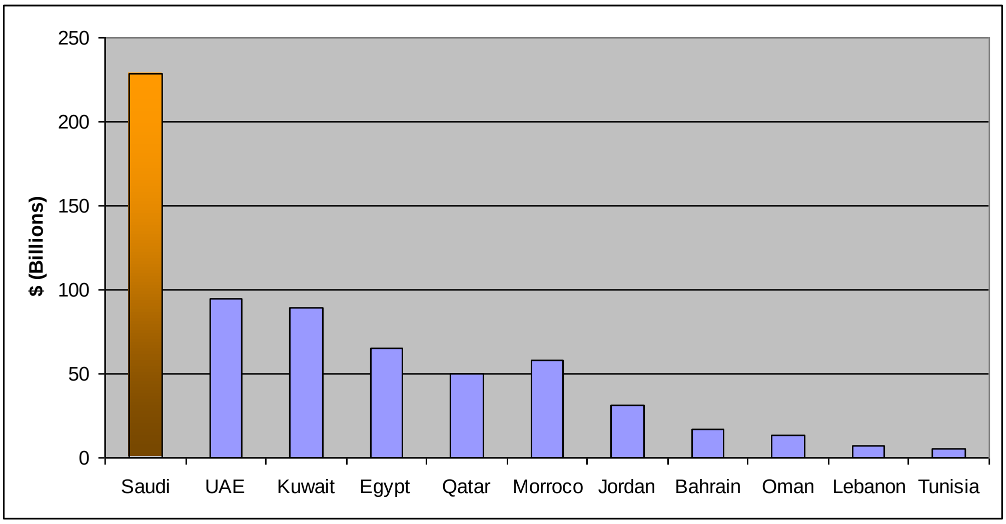
The rest of chapter organised as follows. Section 2.2 provides some background and historical review of the Saudi market. Section 2.3 introduces some issues relating the methodology used to test for the efficient market hypothesis. Section 2.4 explains the tests be used in this study, which is followed by the empirical results in Section 2.5. Finally, some concluding remarks are given in Section 2.6.

2.2 Historical overview of the Saudi stock market

The recent history of Saudi stock market can be divided into two periods: from 1985 to 2001, which we refer to as the pre-boom period, and after 2001 (i.e. the post-boom period) when a sharp increase in market regulations and volatilities was noted.

The pre-boom period is associated with lack of regulations and a steady market growth. After 2001 the Saudi stock market started rising sharply with subsequent unprecedentedly high volatilities. This rapid growth has driven the Saudi stock market to become the largest market in the Arab world. Figure 2.1 report market capitalisation in 2009 in billions of dollars for the Arab world. The Saudi market capitalisation constitutes more than double of United Arab Emirates or Kuwait that come in the second and third positions in term of market capitalisation.

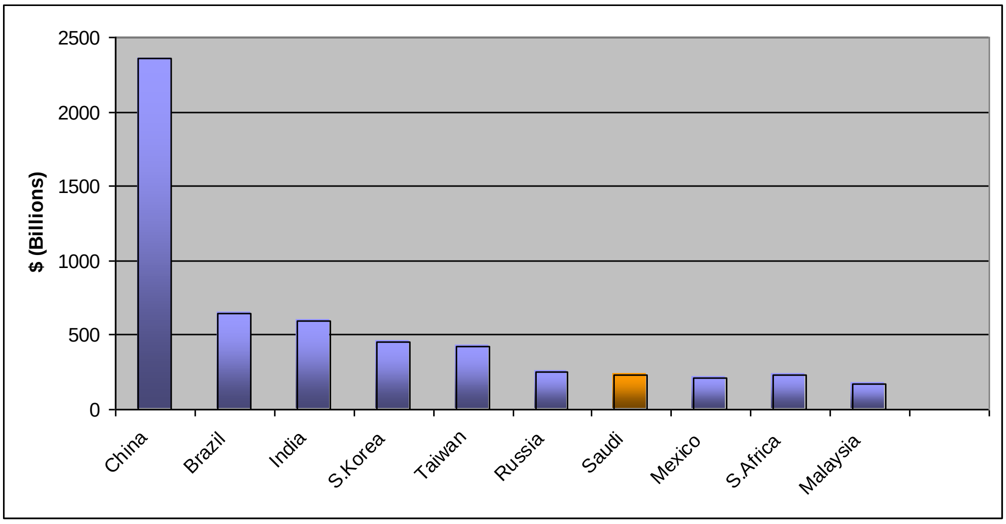
Figure 2.1. Arab market capitalisations, (March 2009).



Source: Tadawul monthly report, March 2009.

However, as shown in Figure 2.2, the Saudi market capitalisation is still small if compared to the other emerging and fast growing markets such China, India, South Korea, and Brazil. The rapid growth of Saudi market after 2001 was not without cost. Structural rigidities, contributed to a substantial run-up in prices in early 2005-2006 followed by the subsequent correction. This prompted fundamental regulatory interventions in the Saudi market. One of the most important interventions was to hand over the market authority from the Saudi Arabia Monetary Agency (SAMA) to the newly-formed Capital Market Authority (CMA).

Figure 2.2. Emerging market capitalisations, (March 2009).



Source: Tadawul monthly report, March 2009.

The establishment of CMA was the cornerstone of the regulation process in the Saudi market. The CMA issued new rules and regulations to protect investors and ensure fairness and efficiency in the market wherever it was needed. It is worthwhile to highlight the key events leading to the establishment of the CMA and some features of the Saudi market which may have initiated the CMA.

2.2.1 The Saudi stock market before 2001

Although the first stock company was established in 1935, the largest increase in market capitalisation occurred in the mid 1970s. This grotwth occurred during the first oil price shock between 1973 and 1982 when a "Saudaisation" of part of the foreign banks capital took place[11].

The striking growth in market capitalisation is reflected in the number of registered trading companies. In particular, in 1975 there were only 14 publicly trading companies. This number slowly increased to 19 by the end of 1981. In 1985 the number of joint stock's companies reached 50 and jumped at 100 companies in 1990.

The Saudi stock market itself was not formally regulated until 1984. After "Souk Al-Manakh" crisis in Kuwait, the Saudi government took serious consideration of the regulation issue. The financial turmoil that started in the neighbouring Kuwait market in 1982 caused a sharp increase in the sovereign debt in Saudi Arabia. As a result, a commission formed jointly by the Ministry of Commerce and Ministry of Finance and Central Bank (SAMA) was established to regulate, monitor and improve the stock market performance. At the end of 1985 there were 78 unregistered brokers working in the market. After just one year of its establishment, SAMA ended the unlicensed brokerage system. Instead, commercial banks took the responsibility of executing trades in the market.

In an effort of regulating the financial market in 1985 the Saudi Shares Registration Company (SSRC) was also established. Under the SSRC supervision, commercial banks were required to establish a new share department. However, lack of coordination between different branches of the same bank resulted in arbitrage opportunities for the investors as the

[11] In 1982, the law restricted bank ownership to be 60% for Saudian and 40% for foreign investors.

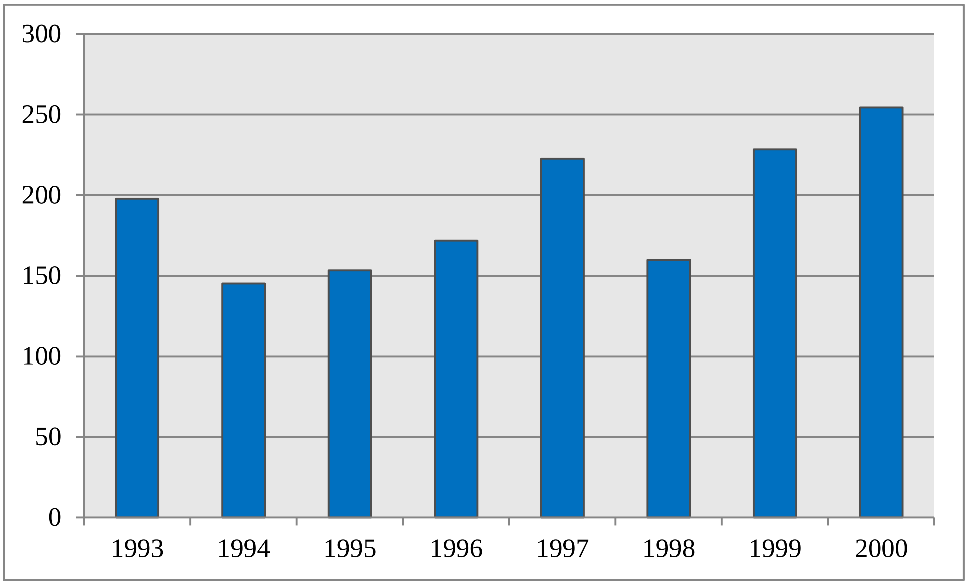
same share could be traded at different prices. Furthermore, it could take up to several days before orders were completed. As a result, some active investors traded for themselves, providing their own ask-bid prices and unofficially becoming market makers.

In August 1990 a major improvement in market efficiency took place in the Saudi market when SAMA introduced the electronic securities information system. The new system connected more than 150 bank branches with SAMA and established 12 central trading units, all of which were connected directly to a central host computer in SAMA's head office in Riyadh. This electronic screen-based system provided investors with instantaneous bid and asks prices, and enabled execution of their orders in real time. The system enhanced the operational quality in the market.

Before concluding this section a brief overview of the Saudi stock market is given. The earliest data about the Saudi stock market can be traced back to February 1985, when the stock index (Tasi) was started with 1000 points. Six industrial sectors were included. The growth of the Saudi market index during 1990-2001 was around 5% per year in average but 13% from 1996 to 2001. The market capitalisation grew from $43 billion to $70 billion in 2001.

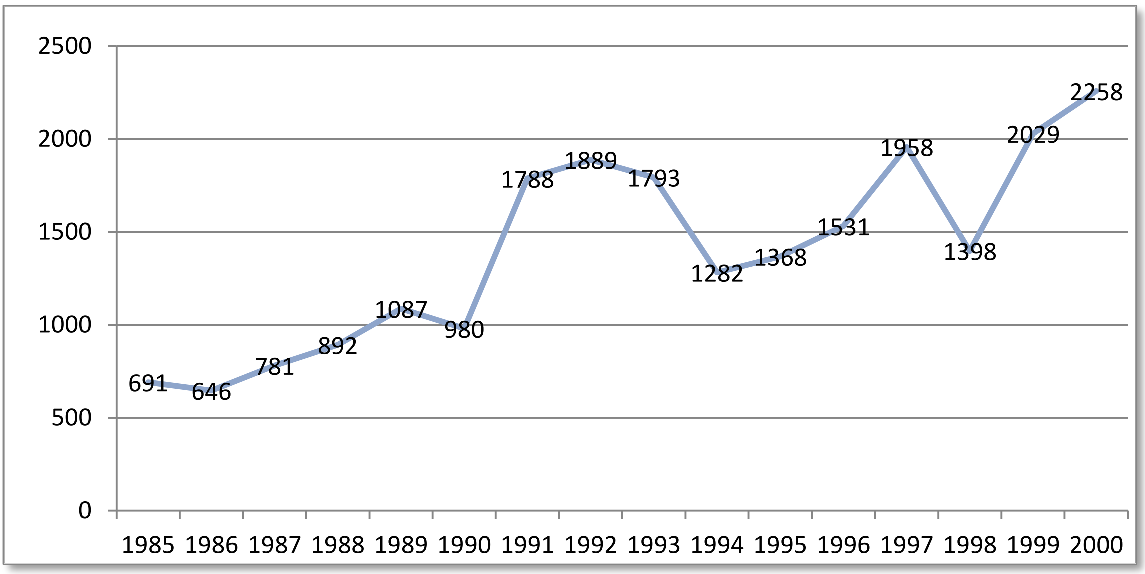
Figure 2.3 shows the market capitalisation in Saudi market before the regulation took place in the market, whereas Figure 2.4 shows the movement of Tasi from the first day of the market opening to the end of 2000.

Figure 2.3. Saudi market capitalisation before the implement of financial regulations,(SR, Billion).



Source: Tadawul annual reports 02, 03, 04, 05, 06, 07, and 08.

Figure 2.4. Tasi movement, (1985- 2000).



Despite the moderate growth during the decade, the stock market failed to convince more investors, resulting in low turnover ratio in the market. For example, in 1998 the turnover ratio was only 26%. This ratio was not only very low compared to either the US market (106%) or Germany (167%) for the same year, but less than the average of the major developing markets which was estimated at about 30%. One particular problem of the Saudi market during this earlier period was restrictions of new Initial Public Offer (IPO) companies. The process of going public could take more than 2 years and the price of company shares was set to be lower than their fair values, which also discouraged many companies from seeking public listing. Another issue was that the government and quasi government funds held half of the total market shares, so that only about fifty percent could be traded in the market at any given point of time[12].

2.2.2 The Saudi stock market post 2001

The Saudi stock market experienced extraordinary growth after the terroristic attacks on the World Trade Centre in New York that happened on September 11th, 2001. This growth was the result of a substantial increase in the oil revenue which boosted the economy of the country. Such rapid expansion leaded to a new important wave of innovations in the stock market.

In order to facilitate the investment environment in the Saudi stock market, the government introduced a modern automated trading system in October 2001, named Tadawul. The new system enabled electronic trading which not only resulted in easier buying and selling, but also greater transparency and speed in processing transactions, ultimately fostering market liquidity, and increasing trade volumes. Furthermore, the government established the CMA in 2003 as the sole supervisor to regulate and monitor market activities, replacing the role of SAMA.

In establishing the CMA, the Saudi government set specific goals to be achieved. Firstly, a process of liberalisation and openness of the Saudi market had to be undertaken. A case in point was opening up to the Gulf Countries Council citizens, the GCC (Saudi, Kuwait, Bahrain, Qatar, Oman and United Arab Emirates); and expatriate (residents) workers within Saudi border. Secondly, the regulation of Saudi stock market was seen as an essential step to foster the government plans of making the Saudi economy and the Saudi market more lucrative for foreign direct/indirect investments. Finally, greater market efficiency was seen as a mean of decreasing the risk of high correlations on unpredictable/unsustainable oil revenue

[12] See Albqami (2000), for more details.

that constitutes 70% of the export revenue and 90% of the government revenue in Saudi Arabia.

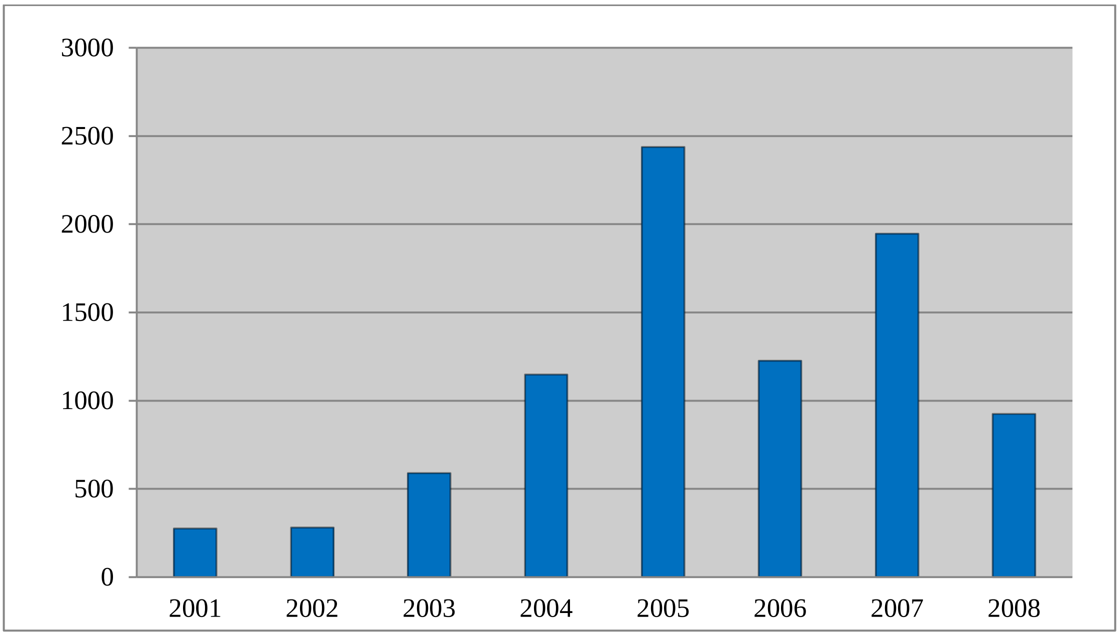
By developing a well-functioning stock market, the ultimate government's target was to keep the national wealth within Saudi borders as well as induce more repatriation funds to flow into the country. The government aim was also to become more competitive with the rich neighbours such as Dubai and Qatar, where important stock market reforms were taking place.

To enhance corporate governance and market efficiency, the CMA issued a number of new regulations. Some of the most important are highlighted below:

1. Market conduct regulations, which prohibited insider trading, manipulative or deceptive actions, and punished for false statements/rumours in the market. This gave the CMA the power to suspend or fine investors for any insider trading.
2. Offers of securities regulations, which reflected all terms and conditions for offers of securities in the kingdom, such as public offering and private placement requirements, information provided to investors, private placement announcements and responsibility for any incorrect documents.
3. Listing rules that set out requirements and served as guidelines for public offerings of securities, (e.g. a financial advisor had to be appointed for an offering).
4. Giving authorisation to specific people to implement regulations which demarcated the responsibility/liability of joint firms' boards and managers. In this way, the CMA had the power to prevent joint firms from possessing other joint firms' shares directly.
5. Introducing securities business regulations.
6. Introducing real estate investment fund regulations.
7. Introducing corporate governance regulations.
8. Introducing investment fund regulations.
9. Introducing merger and acquisition regulations.

Figure 2.5 gives a clear picture of dramatic changes in Saudi stock market capitalisation that jumped quicly from SR 280.73 billion in 2002 to be double in 2003 reaching SR 589.93 billion, which double in 2004 to SR 1.14 Trillion, and exceeding 2.43 Trillion in 2005.

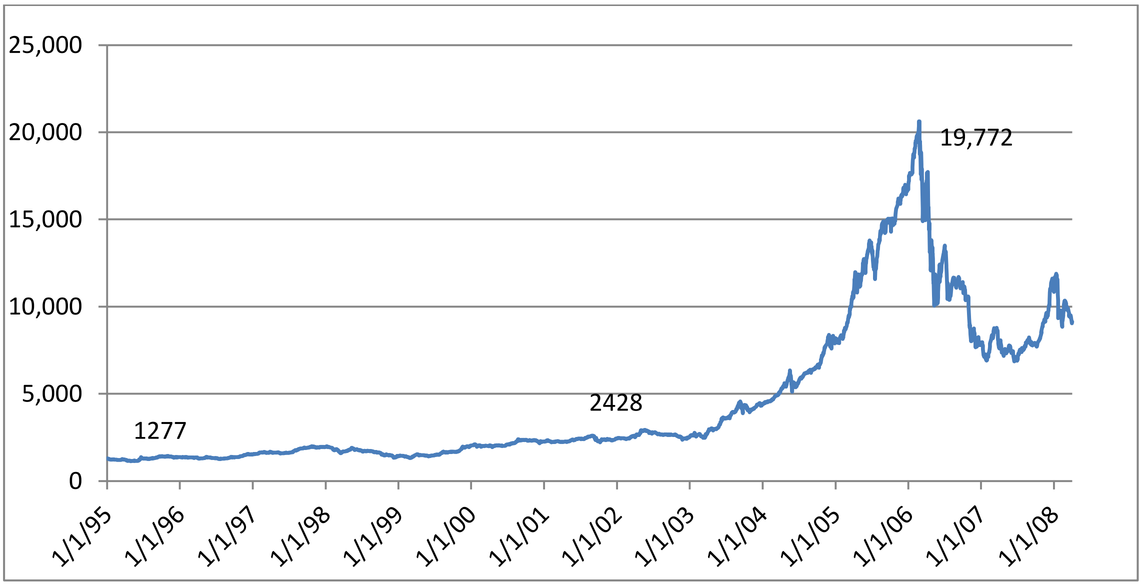
Figure 2.5. Saudi market capitalisation after the implement of financial regulations, (SR, Billion).



Source: Tadawul annual reports 02, 03, 04, 05, 06, 07, and 08.

Figure 2.6 also shows the general index movement from 1995 until early 2008. It is clear that after 2002 the Tasi experienced an extraordinary growth. It was more or less flat until the end of 2002, then it jumped from 2.518 points at the end of 2001 to 4.437 points at the end of 2003 and it peaked in early 2006 at 21.000 points.

Figure 2.6. Tasi movement (1995-2008).



2.3 Testing for the efficient market hypothesis

As mentioned in Chapter 1, EMH can be investigated by *i*) testing if the random walk model holds, and *ii*) by considering a risk adjusted procedure such as an CAPM type model. Nevertheless, the CAPM model is not suitable for the purpose of this study due to the following reasons. First, the CAPM model requires the availability of a risk free benchmark. Secondly, the CAPM model relies on the assumption of a well-diversified market portfolio. Neither of these is satisfied in Saudi or in general in any Islamic oriented market.

The history of risk free assets in Saudi Arabia can be traced back to mid-1988, when Saudi central bank (SAMA) issued Saudi Government Development Bonds (GDBs). The maturities of these securities were two, three, four, five, and ten years. However, due to Islamic restriction, and improvement of Saudi budget balance sheet, SAMA stopped issuing any risk-free rate instruments by the end of 1997. Instead, the efforts were directed to support the issuance of Islamic *Sukuk* that enjoyed a good public support. *Sukuk* is the plural of *Sakk* which is equivalent in Islamic *Sharia'a* to a conventional bonds. The definition of *Sukuk* according to International Islamic Finance Market Report is *"Certificates of equal value representing undivided shares in ownership of tangible assets, usufructs and services or (in the ownership of) the assets of particular projects or special investment activity".[IIFM,Sukuk report,1st edition,2010]*.

Sukuk are designed in the way that they considered as ownership instruments and not debt instruments, i.e. not paying any interest. Hence, they can't be used as a benchmark of risk free rate[13]. For this reason, risk adjusted returns based upon the CAPM and other models that utilize a risk free rate are difficult to apply in Islamic markets.

The purpose of this study is to investigate if Saudi market efficiency has improved after the introduction of new regulations. To this end, results of studies that took place before market regulation will be compared to our analysis. In order to draw clear inference regarding the effect of regulation on the stock market this study use the same empirical techniques that have been used in previous researches.

[13] Recently, Budd and McCrohan (2012) estimate a four factor CAPM model using returns of the Saudi index. In their paper the authors used the 3-month US T-bills as proxy for the risk free rates in Saudi Arabia. However, I believe that this approach has many shortcomings, therefore I avoid going along that line of research.

Before presenting the empirical results, in this section we briefly report the results of related literature. The first study on efficient market hypothesis in the Saudi stock market was undertaken by Butler and Malaikah (1992) who tested the random walk model on Saudi and Kuwaiti markets. The result showed that all 35 Saudi companies under consideration exhibited statistically significant one lag autocorrelation, while only 36% out of all the 36 Kuwaiti firms in the analysis showed autocorrelation of the same order. Moreover, the runs test suggested that all the Saudi companies violated the no correlation assumption, whereas for 14 Kuwaiti companies only the same was true.

Al-Razeen (1997) investigated the weak form of EMH in the Saudi stock market using weekly data from 1992 to 1995 for 28 joint companies. Employing similar techniques (namely the autocorrelation, the runs and filter rule tests), the author rejected the null hypothesis of no autocorrelation for 60 % of the sample. Al-Razeen also found that for 64 % of the firms the run tests were significantly different from zero.

Dahel and Laabas (1999) conducted a similar analysis on the on the Kuwait, Oman, Bahrain and Saudi markets. This work suggested that only the Kuwaiti market satisfied the assumptions of weak form of market efficiency, whereas the rest of the markets failed to hold.

More recently, Al-Kholifey (2000) used the autocorrelation, runs test, and filter rule test and found that 61% of the sample under consideration revealed statistically significant serial correlation. Moreover, the filter rule results showed that both daily and weekly returns violated the assumption of EMH.

Al-Abdulqader (2002) tested the Saudi market efficiency using weekly closing prices of 45 individual firms from 1990 to 2000. According to his results, the null hypothesis of no autocorrelation was rejected for 51% of the companies. The Ljung-Box test rejected the null hypothesis for 23 securities, whereas the runs test results showed that 24 out of 45 firm returns (53%) were significantly different from zero. Finally, he observed that all examined filters outperformed the buy and hold strategy on average (although differing in numbers with respect to filter size).

Regarding the co-integration test, to the best of our knowledge, no previous studies were undertaken on the Saudi market sectors. However, Al- Suhaibani (2004) used weekly data to investigate the co-integration in 5 GCC markets (namely Saudi Arabia, Bahrain, Qatar, Oman, and Kuwait). The finding revealed bilateral co-integration between Bahrain and Kuwait stock exchanges, between Bahrain and Oman, and between Saudi and Qatar markets.

Jay Squalli (2005) investigated co-integration between the Duabi and Abu Dhabi financial markets in UAE using daily indices from several sectors from September 30, 2001 through July 19, 2005. The result showed that Banking, Service, and the general index are co-integrated whereas the insurance sector was not.

To summarise the existing literature, most studies are based upon data before 2000 and suggest that the weak form of the efficiency of the Saudi stock market does not hold. However, available literature relates to the pre-boom period (i.e. before 2001) of Saudi market history, therefore, the lack of market efficiency can’t be clearly disentangled from informational or operational aspects of the EMH. In addition, no previous study has considered the effect of regulation on the Saudi market. The radical transformation of the investment environment during the recent years calls into question the reliability of previous results. For this reason, in what follows an investigation the EMH has been undertaken again and results will be compared to previous findings.

Before describing the methodology followed in the study, it may be useful to mention some key features of the Saudi stock market. These are:

1. The absence of market makers.
2. Unprofessional investors who can read and analyse available and new information.
3. Lack of researches that conduct and explain the market.
4. Use of insider information by some groups, or investors, and
5. Big portions of non-tradable stocks owned by government and semi-government funds.

As discussed before, this paper will focus only on the weak form of the efficient market hypothesis in the Saudi stock market.

2.4 Methodology

In order to test the weak form of efficient market hypothesis, a number of inference procedures have been commonly used in the empirical literature. In this section we review the test statistics that have been used in related studies.

2.4.1 Serial correlation and Ljung-Box tests

The first test we consider is the autocorrelation or serial correlation test. The k-order autocorrelation coefficient $\rho_{(k)}$ measures the relationship between the stock return at the current time t and the same stock return at previous time $t-k$. Assume that the stock return has finite variances, then the serial correlation coefficient $\rho_{(k)}$ can be calculated as

$$\rho(k) = \frac{Cov(r_t, r_{t+k})}{\sqrt{Var(r_t)}\sqrt{\mathrm{var}(r_{t+k})}} = \frac{Cov(r_t, r_{t+k})}{\mathrm{var}(r_t)} \tag{2.1}$$

where $\rho(k)$ is the autocorrelation coefficient, r_t is the return of a time series at time t, and k is the lag of the period. The standard error of $\rho(k)$ is given as

$$\sigma(\hat{\rho}_k) = \sqrt{\frac{1}{n-k}} \ , \tag{2.2}$$

where n is the sample size. The null and alternative hypotheses are:

H_0: $\rho(k) = 0$ (price changes are uncorrelated)[14].

H_1: $\rho(k) \neq 0$ (price changes are correlated).

[14] Note that uncorrelated random variables are not necessarily independent. To see this, let X be standard normal variable. Since X is symmetric (i.e X and $-X$ have the same distribution), so is X^3, therefore both X and X^3 have an expectation of zero. Thus $\mathrm{cov}(X, X^2) = E(X^3) - E(X)E(X^2) = 0$, but X and X^2 are clearly dependent.

Therefore, the weak form of market efficiency is rejected if $\rho_{(k)}$ is significantly different from zero at the specified significance level. As far as the sign of correlation coefficient is concerned, a positive autocorrelation coefficient indicates either slow adjustment of prices to new information or insider information (note that a positive sign may also be associated to infrequent trade). On the other side, a negative autocorrelation indicates wide fluctuations in the stock price around its intrinsic value, or mean reversion. According to Al-Razin (1997, p.165) "*this behaviour happens as a result of adjustment for capital transactions that create reversals in return series*".

The serial correlation test is an individual coefficient test which depends on the chosen number of lags. Instead of testing serial correlation at a specific lag, the Ljung-Box (1978) statistic can be used to test the "overall" correlation based on a number of lags. The null and alternative hypotheses of this test are:

H_0 : autocorrelation up to certain lags are jointly not different from zero.

H_1: autocorrelation up to certain lags are jointly different from zero.

Formally, the statistic is defined as follows:

$$LB = n(n+2)\sum_{k=1}^{m}\left(\frac{\hat{\rho}_k^2}{n-k}\right) \sim \chi^2(m), \tag{2.3}$$

where m is the maximum lag being considered, n is the sample size and α is the significance level. The LB statistic is asymptotically distributed as χ^2 with m degree of freedom.

2.4.2 The runs test

The runs test, also called Wald–Wolfowitz test, is a non-parametric statistical approach that can be used to test the hypothesis of random walk for a series of successive price changes. Unlike the autocorrelation tests, the runs test requires no assumptions about population distribution. The only assumption needed is that the underlying process is continuous.

A run is defined as a set of sequential prices that are either all above or below the mean or the median of the whole series[15]. In this chapter we categorise a run of share price changes into one of three types according to their signs. Namely, there will be a positive sign when the return is above the median, a negative sign if it is below the median, and 0 if no change from one period to the next one is observed. The difference between the total number of runs (R_a) and the total expected number of runs (R_e) is then compared and tested against the random walk hypothesis. That is, if a large series follows a random walk and is normally distributed, then the difference can't be statistically significant, otherwise, there will be either a negative correlation in the series if R_a is significantly greater than R_e, or a positive correlation if R_a is statistically less than R_e.

Similarly, if the stock market is efficient in the weak form, then the difference between the returns R_a and R_e should not be statistically significant. Otherwise, the market will have either a negative or a positive correlation depending on the sign of the difference between the number of active runs, R_a and the number of expected runs, R_e.

Under the assumption that the sample size is large enough, the total expected number of runs (R_e) follows a normal distribution with a mean of:

$$R_e = \frac{N(N+1) - \sum_{i=1}^{3} n_i^2}{N}, \tag{2.4}$$

and a standard deviation of:

$$\sigma_{R_e} = \left[\frac{\sum_{i=1}^{3} n_i^2 \left[\sum_{i=1}^{3} n_i^2 + N(N+1) \right] - 2N \sum_{i=1}^{3} n_i^3 - N^3}{N^2 (N-1)} \right]^{\frac{1}{2}}. \tag{2.5}$$

[15] The mean is generally effective in measuring the central tendency for symmetrical distributions, but can be inappropriate in the presence of outliers in the sample. See for example Squalli (2005) for details.

where N is the total number of price changes, n_i is the number of each sign price change, $i=1$ for positive changes, $i=2$ for negative changes , and $i=3$ for no changes. Therefore, a standard normal (Z) distribution can be used for the runs test of R_e:

$$Z = \frac{R_a - R_e}{\sigma_{R_e}} \sim N(0,1). \qquad (2.6)$$

Based on the (2.6)[16], the null and alternative hypotheses are constructed as follows:

H_0: the successive of price change is random,(i.e. the difference between R_a and R_e is not significantly different from zero).

H_1 : the successive of price change is not random, (i.e. systematic).

Accordingly, if the calculated Z score is greater than critical value given by an appropriate significance level, we can reject the null hypothesis and conclude that the series of returns can't be predicted. The stock market in that case will not satisfy weak form of market efficiency.

2.4.3 The filter rule test

Fama and Blume (1966, p.226) described the autocorrelation coefficient as "*too unsophisticated to pick up the complicated patterns that the chartist sees in stock prices". Furthermore, they described the runs test as too rigid in determining the duration of increasing and decreasing prices.

As an alternative, Fama and Blume (1966, p.227) suggested to apply the filter rule test as "*a more sophisticated criterion to identify movement in stock prices*". The filter rule as proposed by Alexander (1961) defined as follows:

If the daily closing price of a security moves up at least $x\%$, one should buy the security until the price moves down at least $x\%$ from the previous high, at which time, one simultaneously sell the security and go short. The short position should be hold until the price rises

[16] Note that the Z score can be adjusted for discontinuity by computing $Z = ((R_a + 1/2) - R_e)/\sigma_{R_e}$.

at least $x\%$ above a subsequent low, at which point one should cover and buy. The process is then repeated for a certain period and the performance according to the filter rule is then compared to the buy-and-hold strategy.

The hypothesis of this test is that investor can't earn any abnormal profit using strategy that depends only on the historical prices. In other word, there is no strategy can beat the naive buy and hold strategy if the market is weakly efficient.

2.4.4 The variance ratio test

The variance ratio test (VRT) is based on the random walk model.

Assume that log of stock prices follow a random walk with drift process

$$p_t = \mu + p_{t-1} + \varepsilon_t , \tag{2.7}$$

where the residual $\varepsilon_t \sim N(0, \sigma^2)$ and $E(\varepsilon_t \varepsilon_{t-1}) = 0$. This implies the variance of returns, $p_{t+T} - p_t$ increases linearly over the observed time interval:

$$\mathrm{var}(p_t - p_{t-T}) = T\sigma_t^2 . \tag{2.8}$$

Therefore, if a series follow a random walk model with a drift, the variance of the q - differences should be q times the variance of the first differences. In other words, if the logarithms of the stock prices are generated by a series of non-stationary returns, the variance of the returns should be proportional to the sample interval. Formally, the variance ratio test can be formulated as follows.

Let the variance of the return be

$$\mathrm{var}(p_t - p_{t-q}) = q\,\mathrm{var}(p_t - p_{t-1}), \tag{2.9}$$

where q is a positive integer representing the time internal. Based on Lo and MacKinlay (1988) the estimated variance ratio $\hat{VR}(q)$ can be defined as[17]

$$\hat{VR}(q) = \frac{\frac{1}{q}\operatorname{var}\left(p_t - p_{t-q}\right)}{\operatorname{var}\left(p_t - p_{t-1}\right)} = \frac{\hat{\sigma}^2_{(q)}}{\hat{\sigma}^2_1}, \tag{2.10}$$

where $\hat{\sigma}^2_{(q)}$ is an unbiased estimator of the variance of the q^{th} difference and $\hat{\sigma}^2_1$ is the estimated variance of the first difference. That is,

$$\hat{\sigma}^2_1 = \frac{1}{nq-1}\sum_{t=1}^{nq}(p_t - p_{t-1} - \hat{\mu})^2, \tag{2.11}$$

where $\hat{\mu} = \frac{1}{nq}\sum_{i=1}^{nq}\left(p_i - p_{i-1}\right)$, and

$$\hat{\sigma}^2_{(q)} = \frac{1}{m}\sum_{t=q}^{nq}(p_t - p_{t-q} - q\hat{\mu})^2, \tag{2.12}$$

with $m = q(nq - q + 1)(1 - 1/n)$. Under the homoskedasticity assumption of returns, $\hat{VR}_{(q)}$ is asymptotically normally distributed and the standard normal distributed test-statistic z_q is defined as[18]:

$$\hat{Z}_q = \frac{\hat{VR}_{(q)} - 1}{\left[\phi(q)\right]^{1/2}} \sim N(0,1), \tag{2.13}$$

where $\phi(q) = \frac{2(2q-1)(q-1)}{3q(nq)}$ is the asymptotic variance of $\hat{VR}$ under the assumption of homoskedasticity .

[17] $\hat{VR}(q)$ =1 indicates RW, <1 indicates mean reversion, and >1 indicates mean aversion.

[18] Z(q) test statistic for the variance ratio assuming RW1(RW with constant variance of the innovations).

The variance ratio test, proposed by Lo and Mackinlay (1988) that allows the general heteroskedasticity in the variance of the price increments is given by:

$$\hat{Z}*(q) = \frac{\hat{VR}(q) - 1}{[\phi*(q)]^{1/2}} \sim N(0,1), \tag{2.14}$$

where $\hat{Z}*(q)$ is asymptotic variance of $\hat{VR}$ under the assumption of heteroscedasticity, and

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

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

is the asymptotic variance of $\hat{VR}$ under assumption of heteroskedasticity.

Under the null hypothesis in (2.13) and (2.14) the price increments follow a random walk model and hence under the null hypothesis the stock market is weakly efficient. Otherwise, if the calculated Z_q score is significantly greater than the critical value, then we can reject the null hypothesis and conclude that the stock market does not satisfy a random walk model, rejecting the EMH.

2.4.5 The co-integration tests

Many economic variables tend to move closely together and do not diverge from each other in the long run. The features of this long run relationship in time series can be described in terms of co-integration. The co-integration and common trends in stock prices have been widely used to study stock market co-movements. That is, if there is evidence of co-integration among a number of indices, it suggests that they have a tendency to move together in the long run, even if they experience a short run deviation from their equilibrium path.

Granger (1986) highlighted the fact that a pair of prices can't be co-integrated if the market is efficient because co-integration would signify the predictability of at least one price based on the past prices of the other assets. Two time series are said to be co-integrated if they are non-stationary and integrated of the same order, but a linear combination of them is stationary.

Co-integration analysis can be conducted using Engle-Granger (1987) residual based test or Johansen (1988; 1991) and Johansen-Juselius (1990) maximum likelihood procedure in the multivariate context. Johansen approach will be used in this study to investigate the existence of co-integration among Saudi market's five sectors.

The Johansen approach can be formulated as follow:

Define a vector z_t of n potentially endogenous variables, and model z_t as a standard VAR with k lags, which can be represented as

$$z_t = \mu + A_1 z_{t-1} + ... + A_k z_{t-k} + \varepsilon_t , \tag{2.15}$$

where z_t is a $(n \times 1)$ vector, μ is a $(n \times 1)$ vector of constants, A_i is a $(n \times n)$ matrix of parameters, and ε_t is $(n \times 1)$ vector of error terms assumed to be independent and identically distributed Gaussian process.

By subtracting z_t from both sides, the equation (2.15) can be converted to VECM form as

$$\Delta z_t = \mu + \Gamma_1 \Delta z_{t-1} + ... + \Gamma_{k-1} \Delta z_{t-k+1} + \Pi z_{t-k} + \varepsilon_t , \tag{2.16}$$

where $\Gamma_i = -(I - A_1 - ... - A_i)$, $(i = 1,..., k-1)$, and $\Pi = -(I - A_1 - ... - A_k)$.

Equation (2.16) contains information about both short and long runs adjustment to changes in z_t.

Assuming the rank of $\Pi = r$, and N number of endogenous variables, then r will determine the number of co-integration relations, and possible outcomes are: i) the variables are stationary in levels if $r = N$, ii) none of the linear combinations is stationary if $r = 0$, and

iii) there is r co-integration when $0 < r < N$. If case iii) holds, Π can be decomposed into two matrices α and β, such that

$\Pi = \alpha\beta$, where α represents the speed of adjustment to disequilibrium and β is a matrix of long run coefficients and contains co-integration vectors.

The Johansen approach includes two test statistics used to determine the co-integrating rank: The first is the Trace statistic which tests the null hypothesis that the number of distinct co-integrating vectors are less than or equal to r against the alternative of more than r co-integrating relationships; the other is the maximum eigenvalue statistic[19] which tests the null hypothesis that there are r co-integrating vectors against the alternative of $r+1$ co-integrating vectors. The trace test is given by:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \log(1-\hat{\lambda}_i), \tag{2.17}$$

where T is the total number of observations, and λ_i are the estimated eigenvalues. The maximum eigenvalue test is given by:

$$\lambda_{\max} = -T \log(1-\hat{\lambda}_{r+1}). \tag{2.18}$$

After the number of co-integrating vectors has been determined, the second step involves testing for linear restrictions in order to draw inferences regarding the elements of the co-integrating vectors that generate the long-run model[20]. Note that in this thesis we are only interested in establishing the co-integrating rank as this is enough to invalidate the EMH hypothesis, therefore testing for linear restrictions is not considered here.

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[19] The critical values of these two statistical criteria have been calculated by Osterwald-Lenum (1992) and extended by MacKinnon, *et al.* (1999).

[20] For more details see Boutillier and Cordier (1996), and Canepa (2009).

2.5 Data and empirical results

The data used in this study consist of daily closing prices of 50 joint companies listed in the Saudi stock market. The period covered is from 1st of January, 2002 to 4th of April, 2008. All data were obtained from Tadawul, the stock market company. The dataset was adjusted for any stock splits, and then a natural logarithmic transformation was calculated to generate the time series of continuously compounded returns. In particular, the natural logarithm of the returns were calculated as:

$$R_{i,t} = \left(\ln \frac{P_{i,t}}{P_{i,t-1}} \right),$$

where $P_{i,t}$ and $P_{i,t-1}$ are the price of share i at time t and $t-1$, respectively.

Both individual prices and sector indices were considered in the empirical analysis. Using returns of individual stocks allows comparing our results with previous studies: if changes in regulations were effective one should see an impact on stock market efficiency (see for example Butler and Malaikah (1992), Al-Razeen (1997), Al-Kholifey (2000) or Al-Abdulqader (2002). However, individual share prices can be easily influenced by their idiosyncratic components and thus statistical test results can be distorted. In order to avoid this problem the EMH was also tested considering the five main sector indices in the Saudi stock market.

Table 1A provides the summary statistics for the daily return series of the 50 individual companies listed in the Saudi market. From the Table 1A, it appears that the mean return on the individual share is small and varies from 0.0016 for Eastern Agriculture (Agriculture sector) to -0.0000889 for Samba (Banking sector). Also, the mean of most companies as well as the Saudi market average is close to zero with just only 8 companies having negative averages.

The observed differences between maximum and minimum returns can be attributed to big fluctuations in the Saudi market during period under consideration. In terms of the standard deviation, most of returns are accompanied by high risk. For example, standard deviations range from 0.02 for Ribl (Banking) to 0.069 for Savola (Industrial Sector). The Banking sector is less volatile when compared to other sectors.

The skewness coefficient measures the degree of symmetry of the distribution. A value of close to zero indicates that the data are symmetrically normally distributed. From the Table 1A, it appears that 94% of the securities are left skewed.

The kurtosis coefficient is a measure of how peaked a distribution is and in the case of a Gaussian distribution takes a value of 3. From Table 1A the stock market data under consideration are highly fat-tailed; all 50 security returns show kurtosis values greater than 3. In particular, for 9 companies out of 50 the kurtosis coefficient exceeds 100. For 21 of the securities, the value exceeds 10 and for 20 securities returns have kurtosis values between 4 and 10. The results also suggest that the Banking and Cement sectors are highly skewed and fat-tails. The non-normality of the stock market returns is also confirmed by the Jarque – Bera statistics[21], which are presented in the last column of Table 1A.

To detect the impact of the Saudi market regulation, the sample has been divided into two sub-periods. The first period contains data from January 1st, 2002 to February 15th, 2005 (44 months) and the second covers the period from Feb 16th, 2005 up to April 4th, 2008 (44 months). The EMH has been investigated by calculating the test statistics described in Section 2.4 for the two sup-periods and then the results have been compared in order to draw conclusion.

2.5.1 Result of serial correlation and Ljung-Box tests

To test the weak form of efficiency in Saudi stock market the autocorrelation test has been calculated with up to 15 lags for daily returns of all 50 individual companies. At a given lag, if the corresponding correlation coefficient ρ is found to be (statistically) equal to zero, the price of share returns are considered to be uncorrelated. Thus, the corresponding stock price series is assumed to follow a random walk.

Tables 2A and 3A report the results of the autocorrelation test statistics. From these tables a number of points can be made:

[21] The Jarque – Bera is a test for normality of the returns. Under the null hypothesis skewness and the kurtosis are zero.

i) Regardless the sign, the null hypothesis of no correlation at lag one is rejected for 17 companies in the first period (i.e. 34% of the firms in the sample), whereas we reject the null hypothesis for 29 companies in the second period (i.e. 58%). Therefore, the second period displays evidence of greater return predictability than the first period. Comparing the results in both tables with related early empirical studies a clear pattern toward market efficiency emerges. Comparing these results with the previous literature, Butler and Malaikah (1992) found that the hypothesis for autocorrelation could not be rejected for all thirty five companies in their sample. The proportion was 60% in Al-Razeen (1997), 61% in Al Kholaifey (2000) and 51% in Al-Abdulqader (2002).

ii) Negative signs dominate in the first period autocorrelation coefficients for one and two lags (28 and 38 companies out of 50 show negative signs at one lag and two lags, respectively). In contrast, positive signs dominate in the second period autocorrelation analysis at one lag (i.e. 48 companies out of 50 have positive signs at one lag). However, the signs changed to negative at two lags for 31 companies out of 50. Negative first order serial correlation comes from 'thin' market, errors in prices; whereas positive first lag autocorrelation arises from slow adjustment to new information and insider information. However, both signs mean that the market under consideration is less efficient and both signs are noticeable in emerging markets' studies.

iii) Comparing average autocorrelations across the five different sectors, the Banking sector's average autocorrelation did not change between the two periods. However, the Cement sector average autocorrelation did change from a rejection of the null hypothesis in first period to the acceptance of the null hypothesis in the second period. For the remaining three sectors, there was no autocorrelation in the first period, but a conclusion of rejection of the null hypothesis in the second period (possibly due to heavy speculation).

The Ljung-Box result

Instead of testing correlations at each distinct lag, the Ljung-Box (LB) tests the joint hypothesis that all the ρ_k up to k lags are equal to zero. From the last columns in Tables 2A and 3A, the null hypothesis of no autocorrelation for 17 of the 50 companies (34% of companies) could not be rejected. In the second period, the null hypothesis for 42 of the companies (84%) was rejected; only 8 companies (16%) show significant correlations in this period. On average, both Bank and Agriculture sectors in the first period show certain correlation, but the opposite is true for all five sectors in the second sub-period. These findings support the conclusion of the first lag autocorrelation results that the first period was closer to the definition of efficiency (in the weak form) than the second period.

On the aggregate levels Table 4A shows that the null hypothesis of no autocorrelation up to 15 lags can't be rejected in bank and cement sectors at 5% significant level in the first sub-period. However, the null hypothesis is strongly rejected for all 5 Saudi market indices in the second sub-period. This findings on the sectoral levels are in parallel line with the results of individual companies. Overall, the empirical analysis highlights that the first-sup period was closer to the weak form of market efficiency that second sup-period. Also, it's noticeable from Table 4A that there exists dominance of negative signs in the first sub-period data whereas positive correlations appear more frequently during the second sub-period. It is known that a positive sign can be attributed to slower price corrections to new information and this evidence was noticeable in the second sup-period in Saudi market.

2.5.2 Result of runs test

To investigate the weak form of EMH in the Saudi stock market the runs test has been calculated. Tables 5A and 6A show negative runs, positive runs, total runs and expected runs in the 3rd, 4th, 5th and 6th columns for two sub-periods respectively. The runs are provided with the corresponding medians, Z-statistics and *p*-values for each runs test in the last two columns.

The null hypothesis for this test is that there is temporal zero correlation or weak form efficiency in the series. In the first period, the test shows that the actual number of runs is bigger than the expected ones in 33 firms which indicate negative correlation. These findings are in agreement with the results of the autocorrelation analysis where 28 out of 50 companies show negative autocorrelation coefficients.

Table 5A also shows that only 15 companies out of 50 have correlations significantly different from zero. Therefore, the null hypothesis of no correlation is rejected at the 5% level for these 15 companies (30% of the companies). In contrast with the first period, the second period shows that the actual number of runs (R_a) is smaller than the expected number of runs

(R_e) in 35 cases; this indicate positive correlations. This finding is also consistent with the results of the serial correlation test, where 48 companies were found to have positive autocorrelations at lag 1 in the second period.

Comparing to the previous research, our result shows a clear tendency of the Saudi market toward efficiency. For example, Al-Razeen (1997) rejected the null hypothesis of no correlation for 64% of his sample, and Al-Kholiefy (2000) rejected the null hypothesis for 29 out 41 companies (70%).

Finally, Table 7A shows the runs test results when sectoral levels are considered. Comparing to the first sub-period, the main difference between two panels is that the number of runs became smaller in the second sub-period. This can be attributed to the market being sluggish during the second sub-period after bubble. The cement sector is the only sector during two sub-periods whose successive price changes can be treated as random. The industrial sector was to be more stable in the second period. This indicates that returns on this sector can be deemed to follow a random walk only in the second period, but the weak form of market efficiency for this sector should be rejected for the first period. For the other three sectors, (namely Bank, Service and Agriculture) their random walk hypothesis should be rejected at the 5% significance level. These results reveal clearly the divergence of the Saudi market from weak efficiency according to this non-parametric test.

2.5.3 Result of the filter rule test

The weak form of EMH assumes that an investor can't obtain abnormal profits from knowledge of historical share prices. The filter rule is a non-statistical test that uses technical rules and compares them to the buy and hold strategy[22]. That is, if the market is efficient (in the sense of weak form of EMH) then no other mechanism can beat the simple buy and hold strategy.

In this test, the daily closing prices were used and four small size filters were chosen (0.1%, 0.5%, 1%, and 5%, respectively) then the outcomes of these filters were compared

[22] The "buy and hold" strategy is the difference between purchasing and selling price plus any dividend of the share.

with a simple buy and hold strategy. Further, no transaction costs or short sales position were taken in account. Tables 8A and 9A report 1st and 2nd sub-periods filter rule test results. From these tables it emerges that:

i) There is evidence of a sector effect for Banking and Cement. These sectors are in favour of a buy and hold strategy. If one takes transaction costs in consideration, the buy and hold strategy is more profitable than any filter in both sectors.

ii) From Table 8A it appears that only 5 out of 50 companies in the sample (10%) show negative returns when the filter strategy was used. The small number reflects the upward movements in the Saudi stock market during the first period.

iii) In general, small differences were noticed between buy and hold returns and filter returns regardless of its size. The difference is about 2% for most companies on behalf of filters. In the small companies the filter strategy beats buy and hold returns. For example, Industrial companies yield 2% with buy and hold strategies compared to returns of 13%, 13%, 12% and 8% with a 0.1%, 0.5%, 1%, and 5% filter strategy, respectively.

iv) 21 companies were found to be in favour of buy and hold strategy (42%), if the transaction cost[23] is taken into account, then another 13 companies will be added to be in favour of the buy and hold strategy. This is because the extra profits between filter rules and the buy and hold strategy are eliminated by the transaction cost.

In conclusion, 34 out of 50 companies show evidence of supporting the buy and hold strategy. These companies account for 68% of the total companies being investigated in the study. Therefore, there is strong evidence of improvement of the market efficiency during the first period.

Based on result of Table 9A, all 50 companies are in favour of the filter strategy in the second period except Sabb bank. A total of 31 companies have negative buy and hold returns. This situation reflects the effect of the bubble that the Saudi market experienced at the beginning of 2006. However, the collapse of the market during this period makes it difficult to judge what strategy is better. Generally speaking the Banking and Cement sectors are more profitable (i.e. less losses) when buy and hold was used during this period. Both sectors represent a total of 17 companies (34%) of the total number of companies in this sample.

[23] The minimum cost is Saudi Riyal 12 for any transaction under SR 10.000, then 0.0012% for all other transactions.

Comparing our results with previous studies, evidence suggests that our findings differ from Al-Kholaify (2000) and Al-Abdulqader (2002), where the number of companies in favour of the buy and hold strategy were 0% and 25% respectively.

Using the same settings, the buy and hold was compared against filter rules at the aggregate levels. At first glance, Table 10A shows that the results are similar to those non-parameter tests, such as runs tests. For example, the weak form of market efficiency can always be rejected for all five sectors during the second sub-period as the buy and hold strategy is always underperformed compared to the Alexander's filter rule, implying such trading strategy can achieve higher profits than the passive investment strategy that is based upon the assumption that returns are not predictable. On the other hand, it is interesting to see the cement sector in the first sub-period appears to favour the buy and hold strategy, which consistently outperform the filter rules with all the four filters (0.1%, 0.5%, 1% and 5%). This suggests that the cement sector is weakly efficient in the first sub-period. For the bank sector, its profit based upon filter rules is only less than that of the buy and hold strategy when the filter is set to 5%.

Overall, based on the data of both individual prices and sector indices, the main conclusion of the filter rule test is that the Saudi market diverged from efficiency in the second period compared to the first period. This finding is reasonable if one takes into account the bubble effect mentioned earlier. However, the result of the first period shows good improvement of Saudi market efficiency comparing to Al-Kholaify (2000) and Al-Abdulqader (2002) findings.

2.5.4 Result of variance ratio test

If the return follows a random walk model, then the increments in the variance are linear in the sampling interval. In other words, if the logarithms of the stock prices are generated by a random walk process, then the variance of the returns should be proportional to the time interval.

The variance ratio test is a powerful test used to test the hypothesis of the stock prices follows a random walk process under the assumption of homoskedasticity and heteroskedasticity. The test was calculated for the 50 joint companies' closing prices in the two sub-periods.

To facilitate comparisons with other studies, we use a common lag selection of 2, 4, 8, and 16. As reported in Tables 11A and 12A, the null hypothesis of a random walk is rejected at the 5% level of significance with an aggregation value q of 2 for 13 of the companies in the first period (26%). This is true under either homoscedastic or heteroskedastic assumptions. At lag $q = 4$, the null hypothesis was rejected for 15 companies, however, the null hypothesis fails to reject when aggregation values of $q = 8$ and $q = 16$ were used.

In the second period, the null hypothesis was rejected in 25, 22 and 19 cases when using 2, 4 and 16 lags, respectively. Comparing two sup-period results, we notice an improvement of efficiency in the Saudi market in Banking and Cement sectors over the time. In contrast, we failed to reject the null hypothesis for Industrial, Service, and Agriculture sectors under both the assumptions of homoskedasticity and heteroskedastic at $q = 2$.

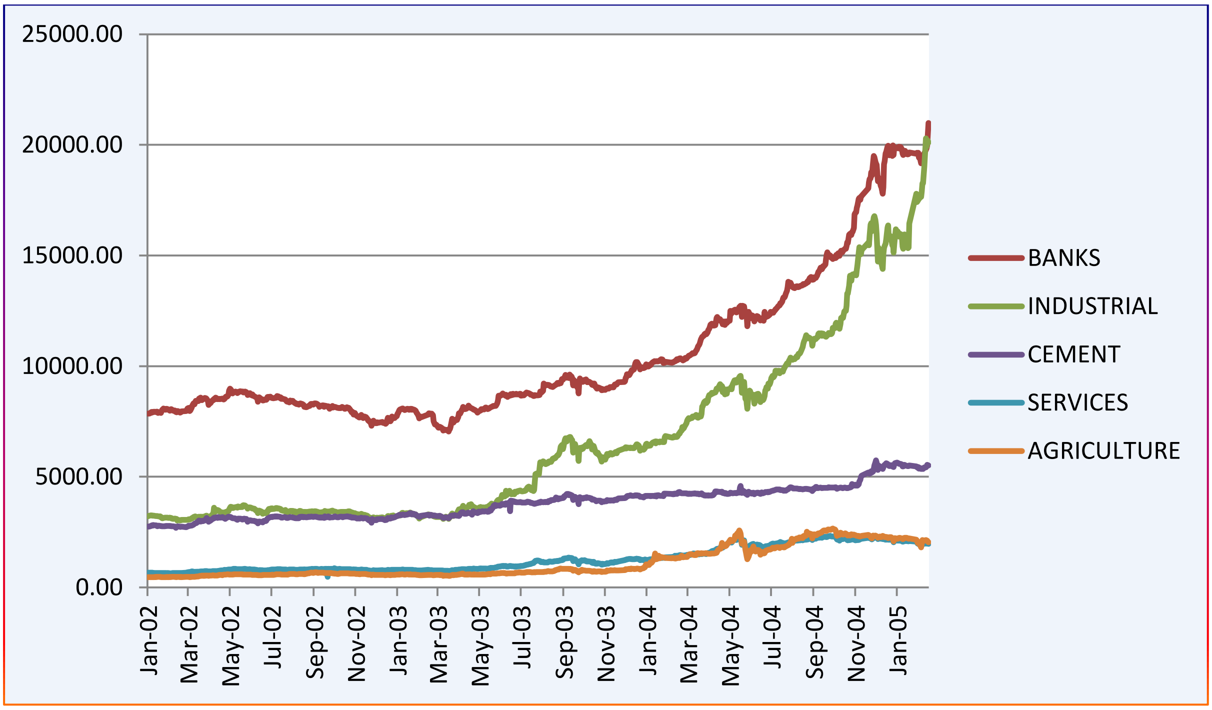
In addition to test the variance ratio statistic for each individual company, the same test was applied to five Saudi market sectors in both sub-periods. The results are reported in Table 13A.

According to this test, the null hypothesis that the price increments follow a random walk process is rejected at aggregation values of q equals to 2, 4, 8, and 16 in both samples at a significance level of 5%. The result reveals clearly that the weak form of efficient market hypothesis is not valid in the Saudi market. However, the results are consistent with the results of the other test statistics. The autocorrelation test rejected the null hypothesis of zero correlation at lag 1 for 17 (34%) companies in the first period and rejected the null hypothesis for 29 (58%) companies in the second period. Based on the filter rule test we noted that the Banking and Cement sectors were the most stable sectors among 5 sectors being investigated in this study.

2.5.5 Result of the co-integration tests

In this section, the co-integration analysis of five sector indices is carried out using the daily closing price of these sectors with 935 observations for each sector. Since co-integration tests require series to be non-stationary, we apply the Augmented Dicky Fuller test (ADF) and Philips-Perron test (PP) to determine if the series are of type I(1). Both tests were carried out with an intercept and no trend. In some cases an intercept and a trend were included in the model. Figure 2.7 suggests trends in Banking and Industrial sectors.

Figure 2.7. First period sectoral indices.



First period

The observations covering the first period in the study are from 1st of January 2002 to 15 of February 2005. Tables 14A and 15A summarise ADF and PP test statistics, respectively. From these tables the null hypothesis of unit roots can’t be rejected at the 1% and 5% significance levels in any of 5 sector indices. However, the first differences of all 5 sectors are stationary even at the significance level of 1%. These results suggest that the five sectors of the Saudi stock market are individually integrated of the order I (1).

The Johansen maximum likelihood procedure was carried out to test the null hypothesis of no co-integration between five indices. Tables 16A and 17A summarise the likelihood ratio based of both trace and maximum eigenvalue statistics. The trace test indicates one co-integrating vector at the 5% level. This implies that there exists one long-run equilibrium between the indices across the sectors in Saudi market. The max-eigenvalue test indicates one co-integration above the 5% level but at 10% significance level.

Second period

The observations covering the second period in the study are between 16th of February, 2005 and 4th of April, 2008. Tables 18A and 19A report the ADF and PP test results. The null hypothesis of unit roots can't be rejected at all significance levels for any of the 5 sectors. However, differences of all 5 sectors are stationary at all significance levels suggesting that the five sectors of the Saudi stock market are individually integrated of order I (1).

The Johansen's multivariate model was applied on the second period data. Tables 20A and 21A report both trace and maximum eigenvalue tests. Clearly, statistical significance of both trace and maximum eigenvalues suggest that there is no significant co-integration relationship in the second period. The result of co-integration test contradicts with the previous 5 tests. However, this may result from different dataset being used in co-integration test, as it can be attributed to speculation behaviour that changed after the bubble to concentrate on small companies which have less weight in the indices.

2.6 Conclusion

In this chapter an empirical evaluation of the impact of regulation on the efficiency of the Saudi stock market is presented. Data from a total of 50 individual joint companies across five sectors trading over a seven year period between 2002 and 2008 were used to determine the efficiency of the Saudi market. The sample was divided into two sub-samples in order to detect the effect of regulation of the stock market that took place during this period. Important insights can be drawn from this investigation.

The results from this analysis show that when comparing the pre-2001 period with the post-2001 period, an improvement in efficiency took place in the Saudi stock market. For example, efficiency as measured by the autocorrelation was observed as a result of the regulation occurring in the post 2001 period. The autocorrelation fell from 100% since the earlier study of Butler and Malaikah (1992) to 46% in this study (average of two sub-periods). Furthermore, the value was lower compared with 60% of Al-Razeen (1997), 61% of Al Kholifey (2000) and 51% observed by Al-Abdulqader (2002).

Greater efficiency was observed in the first sub-period, (i.e. from the beginning of 2002 to the first quarter of 2005), where most regulator activities were taking shape. Consequently, the Saudi market performance was more stable during this first sub-period compared to the second sub-period of post 2005 (second quarter) to the second quarter of 2008. This is not surprising if one takes into account the instability due to the bubble effect the Saudi market experienced at the beginning of 2006.

At the sector level, the co-integration results show the convergence of the Saudi market toward efficiency. However, the contradiction between individual and aggregate levels may reveal the behaviour of speculation that concentrates in the small companies which have slight effect on the index. This behaviour was noticeable after the bubble in Saudi market.

Negative factors such as the herd behaviour, absence of institutional investments, and lack of experienced participants still affects the market. As the market becomes more mature, these factors should have less and less impact, so that the Saudi market should converge toward efficiency.

The large amount of non-tradable shares owned by the government or semi-government funds constituting 65% of the total market shares should be reviewed. The proportion of tradable shares should be increased above the current level of only 45%. This would minimize speculation and restrict the monopolistic influence of the large shareholders, ultimately enhancing efficiency. The openness of the market to direct foreign investment is needed to improve the market efficiency. Further, an upgrade of the market to international standards requires allowing the derivative transactions in the market. This is likely to form part of a strategy towards greater efficiency and stability in the Saudi market.

Another conclusion that can be drawn from the results of this study is that de regulation and using the modern operation systems can improve the operational efficiency.

Finally, since the regulation is a continuous process, further accumulation of data and research is required to revisit and determine the market efficiency.

Chapter 3
The Effect of Islamic *Sharia'a* on Saudi Stock Market Volatility

3.1 Introduction

The role of beliefs, social norms and values has not been widely studied in financial literature; however, it seems intuitive that individuals operating in different social environments would exhibit different behaviour. Ultimately, markets do not make decisions, but people do, and interactions amongst individual choices, corporate culture, and social norms are unavoidable.

Prior research suggests links between individual religiosity and risk aversion. For example, Miller and Hoffmann (1995) report a negative correlation at an individual level between religiosity and attitude towards risk. Similarly, Osoba (2003) utilises individual panel data to show that risk-averse individuals attend church more often than risk-seeking individuals. Hillary and Hui (2009) examine whether religion affects corporate behaviour in the US, and subsequently found that firms located in counties with a higher level of religiosity display lower degrees of risk exposure. Extant literature also acknowledge that religiosity and social norms have some bearing on investment decisions of institutions, such as pension plans and corporate-decision making in general.

In this paper, we endeavour to add to the existing body of knowledge by focusing on the relation between religion and financial markets. This study focuses specifically on the Islamic religion, and examines the market effects of ethical norms in the novel setting of stock markets.

Importantly, Islamic religion imposes several restrictions on individual investment choices. Most notably, the prohibition of investing in 'sin stocks' (i.e. publicly traded companies involved in producing alcohol, tobacco, and gaming, etc.), and interest-bearing securities. We postulate that, in countries where religion plays a significant role in dictating individual behavioural codes and social norms, the portfolio selection of stocks is affected.

In an attempt to investigate the market effects (if any) of ethical norms, we focus on a country wherein religion constitutes an integral part of society, namely Saudi Arabia. This country is an ideal setting in which to study this phenomenon for several reasons. Firstly, Muslims constitute 97% of the population. Markedly, Saudi Arabia is a conservative society that has adopted the most austerely puritanical form of Islam. The country plays a central role in the international Muslim community as the host of the two holy cities of Makkah and Medina, which is paramount to the country's overall identity. Secondly, although the industry of Islamic finance services is expanding rapidly in the homeland of Islam, non-*Sharia'a*-compliant stocks are available on the market, and there is no legal obligation to trade in *Sharia'a*-compliant securities; thus, portfolio selection is left entirely to market participants, and any moral obligation depends on the ethical attitude of market makers. Finally, as a result of its development and the peculiarity of the Saudi economy, the Saudi stock market has several characteristics that make it unique amongst emerging-market bourses. Market capitalisation and trading volume have multiplied by some orders of magnitude in the last few years, yet the majority of investors are individuals as opposed to institutional. Furthermore, foreign investment is very limited, as GCC national and other Arab residents account for a small proportion of buy and sell transactions, whereas the non-Arab resident proportion is close to zero.

In an attempt to better understand why this country fits the purpose of this chapter, we briefly provide some details of the sphere of influence of Islamic religion on the Saudi society below:

- Politics: Saudi Arabia's government takes the form of Islamic monarchy. In 1992, the Basic Law of Government declared the Qur'an the constitution of the country, governed on the basis of Islamic law. In general, religious scholars play a crucial role in a number of fields of government; these include the judicial system, education, and scientific research.
- Education: The study of Islam dominates the Saudi educational system. A large part of the curriculum, at all levels, is devoted to the study of Islamic religion, and the application of Islamic tradition to everyday life is at the core of the curriculum. Religion is also a compulsory subject for all university students.
- Cuisine: Islamic dietary laws are enforced: pork is not consumed, and other animals are slaughtered in accordance with Islamic prescriptions. Furthermore, alcoholic beverages are prohibited.

- Culture: There are many limitations on behaviour, and dress codes are strictly enforced—both legally and socially.

It is clear from the few highlights noted above that religion plays an integral part of everyday life in the country, determining much of the interaction within the society. The peculiarity of the Saudi society, together with recent developments of the Saudi stock market, constitutes a rare opportunity for a social scientist to observe a phenomenon in an almost lab-like experiment, wherein the effect of ethical norms on financial markets can be tested: starting from 2001 onwards, first-time national individual investors (i.e. non-institutional or non-professional mutual fund managers) entered a 'conventional' (i.e. not only Islamic finance-oriented) and relatively thin stock market in a large number, and started trading massively. A natural question arises at this point: Is stock market volatility affected by this type of social environment? In other words, is there any market effect derived from the religious prescriptions? These are the issues that this chapter will seek to address.

Under Islamic law (*Sharia'a*), usury or interest, termed *riba* in the Arabic language, has been explicitly forbidden for its followers. Although the law against *riba* is difficult to enforce directly, a certain level of social pressure is applied in the form of regular Friday sermons or reminders and warnings by religious authorities through television, radio, and/or newspapers.

According to Islamic *Sharia'a* law, stocks can be divided into three categories. The first are those stocks termed *halal* or lawful. Such stocks are fully *Sharia'a*-compliant in every respect. A *halal* stock implies that the company's activities are lawful under *Sharia'a*, and the sources of its funding are also *halal*. A good example in the Saudi market would be most shares in the Agricultural sector. The second is '*mixed*' shares, which is the case where a company's business activity is *halal*, according to *Sharia'a*. However, the sources of its funds for some activities are not considered lawful. Investment in this kind of stock is considered *halal*, although investors must relinquish a portion of their dividend equal to the earnings from those activities that are earned from non-lawful stocks. Examples of this type of stock in the Saudi market are securities traded in the Industrial, Cement, and Service sectors. The third are the forbidden stocks, termed *haram*. The activities of such companies involve paying or taking interest. The buying or selling of this type of stock is forbidden under Islamic law. A case in point is stock traded in the Banking sector where *riba* is paid or taken explicitly.

To the best of the writer's knowledge, no research has been carried out previously with the objective to understand the relationship between interest prohibition and market volatility. This chapter will therefore be the first attempt at addressing this issue.

In order to explain how religion affects stock market volatility, a multivariate approach is adopted. More specifically, the diagonal Baba-Engle-Kraft-Kroner (1990) (BEKK) multivariate generalised autoregressive conditional heteroskedastic (GARCH) (1, 1) model is estimated to simultaneous measures, and compares the five sectors' volatility according to Islamic code (i.e. *halal*, *haram*, and *mixed*). In addition, in the second part of this chapter, the Ramadan effect on the Saudi five sectors will be investigated. Notably, during the month of Ramadan, the stock volatility is expected to fall. Quantifying the fluctuation of the *halal* and *haram* stocks during this period has not been addressed before. This will be investigated using a GARCH (1, 1) model with the Ramadan month as a dummy variable.

The rest of this chapter is organised as follows: In Section 3.2, a brief background of *riba* and its relationship with the financial market is provided, followed by a related literature review; Section 3.3 presents the methodology, followed by the empirical result in Section 3. 4; Section 3.5 provides a description and related literature concerning Ramadan seasonality in the Saudi stock market, followed by empirical results; and finally, some concluding remarks are given in Section 3.6.

3.2 *Sharia'a* law and stock market volatility

Before presenting the results of the empirical investigation, a brief background of *riba* in the context of Islamic *Sharia'a* is provided. The relationship between *riba* and the financial market is also discussed.

3.2.1 Riba and *Sharia'a* law

The primary source of *Sharia'a* law is the *Qur'an*—the sacred text revered by Muslims. The *Qur'an* is the basis for any legal rulings in Islam. The secondary source for deriving legal rulings comes from the sayings or practices (*Sunnah*) of the Prophet Mohammad[24], believing Muslims are required to consider their conduct, whether business-related or otherwise, in the context of these two primary sources of *Sharia'a*.

The evidence for complying with the *Sharia'a* is found in the *Qur'an* in Chapter 33: '*It is not fitting for a believer, man or woman, when a matter has been decided by Allah and His Messenger to have any option about their decision'* [25] [Ahzab (The Confederates), verses, 36]. More explicitly, regarding *riba*, the *Qur'an* states: '*Those who devour usury will not stand except as stands one whom the Satan by his touch has driven to madness. That is because they say, 'trade is like usury', but Allah has permitted trade and has forbidden usury'* [Al-Baqara (The Cow), verses, 275]; and also: 'oh *you who believe , remain conscious of Allah, and give up all outstanding gains from Usury, if you are (truly) believers*' [Al-Baqara (The Cow), verses, 278].

The sayings and practices (*Sunnah*) of the prophet Mohammad are recorded in books known as *hadith* (meaning narrations). In the *hadith*, Mohammed cautioned his followers from receiving *riba*: '*cursed the devourer of usury, its payer, its scribe and its two witnesses*', [Darul-Uloom, (n.d.), p3]. He also stated that they were equal in sin. Mohammed also said, *'Usury has got seventy divisions. The easiest division of them is a man marrying his mother*', [Darul-Uloom, (n.d.), p3].

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[24] Muslims refer to the prophet with the term 'peace be upon him' which will be implied but not stated in the remainder of this chapter.
[25] There are many *Qur'an* translations; however, the translation in this part follows the translation by Yusuf Ali.

The word *riba* comes from the Arabic language meaning ‘to increase’ or ‘to exceed’. *Riba* in an Islamic context is defined as ‘*a loan with the condition that the borrower will return to the lender more than the quantity borrowed*’ [Maishanu and Bello (2004), p. 3]. In this sense, *riba* refers to the act of lending money at any rate of interest, even small, where the rule in Islam is that money must not breed money. Another definition is that *riba* ‘*technically refers to the premium that must be paid by the borrower to the lender along with the principal amount as a condition for the loan or for an extension in its maturity*’ [Zahid Zamir (2007), p. 4].

Under *Sharia’a*, earning from lending money is deemed immoral, and it is emphasised that wealth should be generated from trade or investment. However, there are several social and economic reasons advanced as to why the *Sharia’a* forbids the practices of paying interest:

1. *Riba* is considered to facilitate the rich lender wrongfully acquiring wealth from the poor borrower.
2. *Riba* allows the lender to increase his/her wealth without performing any labour, and therefore hinders productivity; thus, there is no real increase in economic activity.
3. *Riba* makes the lender wealthier and the borrower poorer. As a result, rich people can take advantage of poorer people because only the rich could benefit because they are more likely to have the money to lend.
4. *Riba* sets unfair conditions for the borrower, whereas, on the other hand, the lender makes unfair profits from the borrower.
5. *Riba* creates unfairness for the lender during high-inflation periods, where the returns are expected to be less than the inflation rate.
6. *Riba* is likely to cause economic instability, enhanced inflation, and negative growth.
7. *Riba* is a pure gain without any loss for the lender; therefore, all the risk is taken by the borrower, rather than sharing the risks and benefits.
8. *Riba* is considered the main source of inequality and unfairness in terms of resource allocation between individuals.

3.2.2 Relationship between financial market and *riba*

In the Saudi stock market, there are five main business sectors: Banking, Industrial, Cement, Service, and Agriculture[26]. The Banking sector comprises nine commercial banks, of which only the Alrajhi bank is considered to be an Islamic bank; the remaining eight banks are traditional banks. With respect to *riba*, investment or speculation is permitted in Alrajhi shares, and forbidden for the remaining eight banks. The obvious reason for this is that these banks practice borrowing and lending with *riba* explicitly.

The Industrial sector includes 23 joint companies. Most of these companies are *mixed*, and a few are considered lawful (*halal*). According to highly regarded religious authorities, such as Al-Shubily (2007), investors in these shares must waive an amount of 3%–10%, on average, of their dividend per share in order to purify any gains received. A list of definitely lawful, definitely unlawful and *mixed* stocks (companies) is provided by Al-Shubily and Al-Osaimi lists[27]. The document is reviewed each year and made available on websites for public benefit. Owing to the large number of joint (*mixed*) firms in this sector and the existence of some *halal* firms, this sector is viewed as being the second most active sector after the Service sector.

Figure 3.1 compares the percentage of shares traded across all five sectors. The Service sector, followed by Industrial, dominates the market. These sectors constitute, in total, approximately 70% of all shares traded. The Banking companies' shares decreased gradually from 2002 onwards, whereas the Agriculture companies' shares increased consistently over time.

[26] Insurance, Electricity, and Telecom sectors are not considered here as each of these sectors have one company only.
[27] These two lists are highly regarded among Saudi investors and probably the most trusted for the Saudi stock market.

Figure 3.1. The percentage of share traded per sector.

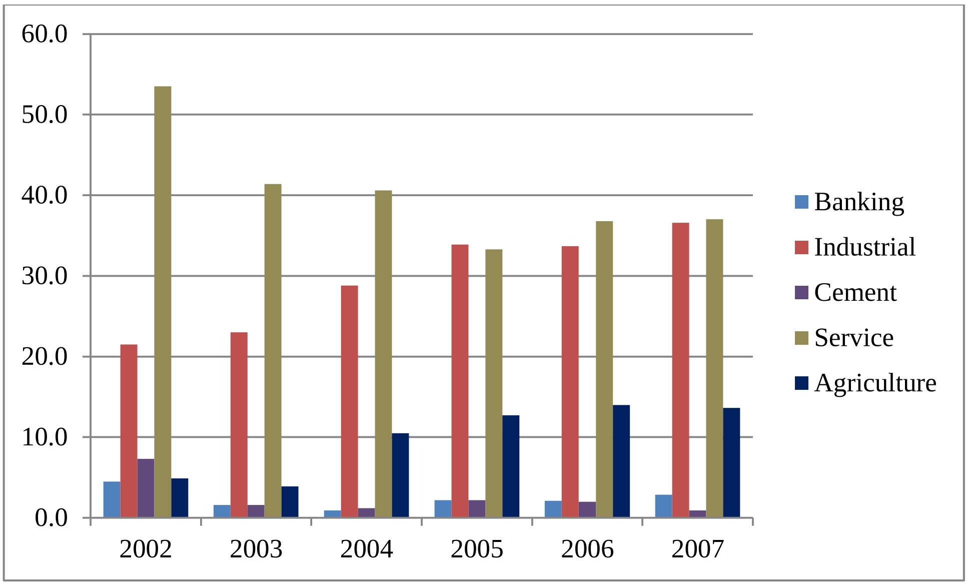
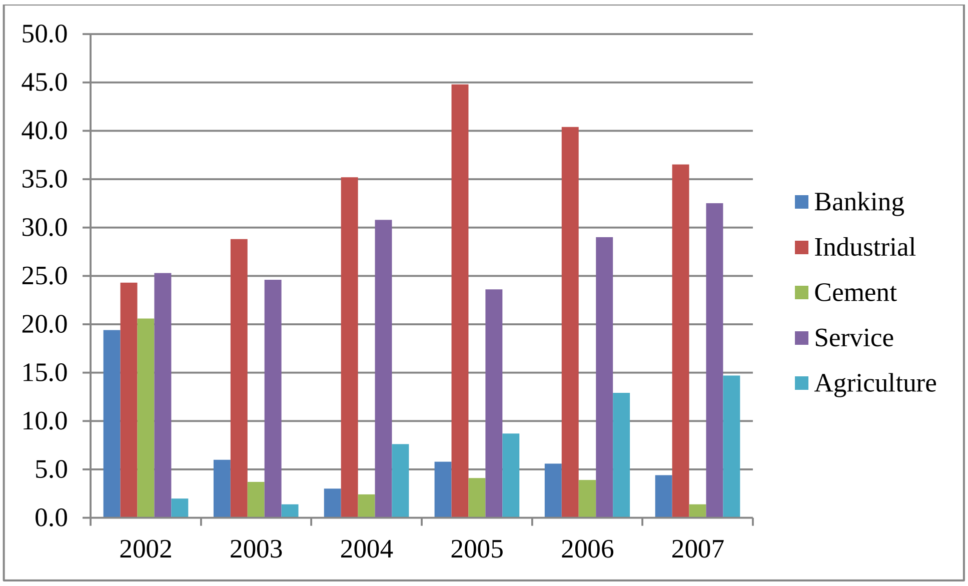


Figure 3.2 displays the dominance of the Industrial sector, followed by Service sector, in terms of the total market value spent in the market during the last seven years. The activity of both sectors may be attributed to the large number of companies listed in these sectors, in addition to the large number of speculators seeking to maximise their gain in these sectors. According to *Sharia'a* law, the speculator is required to pay a religious tax, known as *Zakat*, equal to 2.5% of the net earnings from speculation by the end of year (accumulative gain in one year). If the investor does not earn any dividend, he/she is then not required to pay anything but the *Zakat*.

Figure 3.2. The value traded of each sector as a percentage of the total market value traded.



The Cement sector has eight firms, which are of a *mixed* type. According to Al-Osaimi's 2008 list, the investor is required to waive 6.83% of his dividend if he invests in Yaunbu Cement Company, for example. In the case of Al-Sharqia Company, as much as 15.28% of the dividend is required to be paid in order to purify capital gains. Markedly, the larger the amount paid in a given sector, the more likely the sector is to be forbidden, although the activity itself is permitted. As a result, many investors avoid investing in such companies. Like the Industrial sector, speculation in the Cement sector is allowed, and speculators are required to pay the *Zakat* only if they did not take any dividend.

The Service sector contains 22 joint companies, 14 of which are *Sharia'a*-compliant, with eight categorised as *mixed*. The percentage that an investor has to waive to clear dividends in this sector is very small compared with the Cement sector. According to Al-Osaimi's list (2008), the investor has to alienate 0.02% of the dividend in the Eamar Company and 0.61% in the Mubarad Company. If one includes speculation reasons as permissible for this sector, it may be possible to shed some light on the reasons behind the sector being the most active in the Saudi market.

The Agricultural sector includes nine joint firms. All companies are lawful (*halal*). This sector should be the most preferred sector for investment and speculation owing to the fact that the sector is pure *halal*, and if the share price increases, the speculator can then sell the stock and make capital profit; if, on the other hand, the share prices fall, the speculator can wait and take some pure *halal* dividend.

From Figure 3.1 and Figure 3.2, it can be seen that number of shares traded in the Bank sector decreased gradually from the start of the market boom period, from 4.5% of the total market shares traded to 2.1% by the end of 2007. It is also noticeable that, within the Banking sector, during the middle of the market boom period between 2004 and 2006, shares traded at the lowest levels. In contrast, the Agriculture share trade increased rapidly from 4.9% to 14% of the total market shares traded, which may suggest some evidence that investors in the Saudi stock market prefer the *halal* sector, whilst trying to distance themselves from the *haram*.

For the *mixed* sectors, it is clear from the graphs the dominance of the Service sector on the Saudi total market shares traded, followed by the Industrial sector. This is not surprising if one considers that such sectors together constitute more than half of the total number of joint firms listed in the Saudi market. This is in addition to the large number of *halal* companies in these sectors, as well as the relatively smaller percentage that investors have to alienate in order to 'purify' their dividend. The Cement sector is closer to *haram* as the firms fund their activities with *riba* loans. The investors are required to waive approximately 10%, on average, of their dividends in this sector. This reason may explain the fall in the percentage of the total market shares traded in this sector, with figures decreasing from 7.3% in 2002 to less than 1% in 2007.

Another reason that may explain the high demand for *Sharia'a*-compliant stocks is that 35 of the 53 mutual funds in the Saudi market are restricted to *Sharia'a*-compliant shares. The negative effect of such restrictions of mutual funds is the creation of the crowded-out phenomenon on the limited number of shares available. Importantly, this can cause the price of such stocks to inflate and subsequently fall sharply, as experienced during the crash in the beginning of 2006.

In summary, there is a good degree of evidence favouring Islamic-compliant shares as being preferred by investors in the Saudi stock market; however, one may expect such stocks to be more volatile compared with non-*Sharia'a*-compliant shares.

Like many other emerging markets, the Saudi market is characterised by high return volatility. This is coupled with a thin stock market and low proportion of institutional investors. Furthermore, the market was dominated by speculation during the period under consideration, where 77% of the market participants entered the market after 2003.

3.2.3 Review of related literature

It is clear in the literature that variances of stock returns are time-varying. Also, mean returns tend to cluster. In order to capture the characteristics of financial time series, the Autoregressive Conditional Heteroskedasticity (ARCH) models are commonly used in empirical works. The ARCH model was first introduced by Engle (1982), and since then, numerous extensions have been proposed in the literature.

A useful extension of the ARCH and GARCH models that allow for the possibility of capturing interactions between the volatility of a number stock market returns is the multivariate GARCH model. This framework has been adopted with the objective to investigate the own and spill-over volatility in emerging and advanced markets. For example, Nekhili and Naeem (2009) utilised BEKK-MGARCH in order to investigate volatility amongst six GCC countries, namely Saudi Arabia, Kuwait, Qatar, Bahrain, Oman and the UAE. Their results showed high own-volatility spill-over, as well as a high degree of own-volatility persistence in the GCC markets.

Hammoudeh *et al*. (2009) examined the own-volatility in the Service, Industrial, and Banking sectors in four GCC economies (Saudi Arabia, Kuwait, UAE and Qatar). Their findings suggested that the Saudi sectors had the least inter-sector spill-overs, whereas Qatar had the most. The author’s empirical tests showed that, in all four countries, the Banking sectors were found to be the least sensitive amongst the three sectors in relation to its own past volatility.

Malik and Hammoudeh (2007) examined the volatility and shock transmission amongst US equity, the global crude oil market, and the equity markets of Saudi Arabia, Kuwait, and Bahrain. The authors found that all four equity markets received volatility from the oil market, but not vice versa with the exception of the Saudi market. In the case of the Saudi market, the result showed a significant level of volatility spill-over from the Saudi market to the oil market.

Worthington and Higgs (2004) used an MGARCH approach to examine the transmission of equity returns and volatility amongst nine Asian equity markets. Three of these markets were developed (Hong Kong, Japan and Singapore), and six were developing markets (Indonesia, Korea, Malaysia, Philippines, Taiwan, and Thailand). The main findings were that the own-volatility spill-overs were generally higher than cross-volatility spill-overs for all markets—particularly for the emerging markets.

The methodology adopted in this instance is different from previous efforts in that the writer examines the dynamic relationship between stock market returns and return volatility with the use of a more parsimonious diagonal BEKK-GARCH model. Using this model, the examiner tests not only how rapidly stock-return innovations originating in one sector transmit to the other market, but also the covariance between the mean returns of different stock market sectors is analysed. Before presenting the results of the empirical investigation, the GARCH-BEKK model is discussed briefly below.

3.3 The multivariate GARCH model

As discussed previously, a multivariate GARCH model is more informative than the univariate model as it allows the examination of not only the conditional variances but also the conditional covariance, i.e. the volatility spill-over across different indices. Therefore, the BEKK representation of multivariate GARCH model, as proposed by Baba *et al.* (1990), is chosen in this study. The multivariate GARCH model allows the simultaneous estimation of the conditional variances for the multivariate series of returns. The BEKK representation of multivariate GARCH enables the prediction of a parsimonious model to capture interaction between conditional covariances of returns. With regard to other representations, such as the VECH, for example, the specification of a BEKK model guarantees the semi-positive definiteness of its covariance matrix process.

The first step in the estimation is to identify the specification of the mean equation with the use of the simple Box-Jenkins techniques. The following mean equation was selected and estimated for each sector's own returns and the returns of other sectors lagged one period.

$$\mathrm{R}_t = \alpha + AR_{t-1} + \varepsilon_t,\ (\varepsilon_t \mid \Omega_{t-1}) \sim N(0, H_t), \qquad (3.1)$$

where R_t is a $n \times 1$ vector of daily returns at time t for each sector, and A is a $n \times n$ matrix of parameters associated with the lagged returns.

The diagonal elements of the matrix A measure the effect of own past returns, whilst the off-diagonal elements capture the returns across sectors, or return spill-over. The $n \times 1$ vector of random errors, ε_t, is the innovation for each sector at time t with its corresponding $n \times n$ conditional variance-covariance matrix, H_t. The parameter vector α, represents the long-term drift coefficients and the market information available at time $t-1$ is represented by the information set Ω_{t-1}.

The BEKK representation assumes that the variance-covariance matrix H_t has the following form:

$$H_t = B'B + C'\varepsilon'_{t-1}\varepsilon_{t-1}C + G'H_{t-1}G\,, \qquad (3.2)$$

where B is a $n \times n$ lower triangular matrix of constants; the elements c_{ij} of the symmetric $n \times n$ matrix C measure the degree of innovation from sector i to sector j, which shows how the conditional variances are correlated with past squared errors. The elements g_{ij} of the symmetric $n \times n$ matrix G indicate the persistence in conditional volatility between sectors i and j, which shows how past conditional variances affect the current levels of conditional variances. For the bivariate case, Equation 3.2 can be expressed as:

$$\begin{bmatrix} H_{11t} & H_{12t} \\ H_{21t} & H_{22t} \end{bmatrix} = B'B + \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1t-1} & \varepsilon_{1t-1}\varepsilon_{2t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon^2_{2t-1} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} H_{11t-1} & H_{12t-1} \\ H_{21t-1} & H_{22t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \qquad (3.3)$$

After expanding the right-hand side of Equation 3.3 through matrix multiplication, Equation 3.3 takes the following form:

$$\begin{aligned} h_{11t} &= b_{11}^2 + c_{11}^2\varepsilon_{1t-1}^2 + 2c_{11}c_{21}\varepsilon_{2t-1} + c_{21}^2\varepsilon_{2t-1}^2 \\ &\quad + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} \\ h_{12t} &= b_{11}b_{21} + c_{11}c_{12}\varepsilon_{1t-1}^2 + (c_{12}c_{21} + c_{11}c_{22})\varepsilon_{1t-1}\varepsilon_{2t-1} + c_{21}c_{22}\varepsilon_{2t-1}^2 \\ &\quad + g_{11}g_{12}h_{11,t-1} + (g_{11}g_{21} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} = h_{21t} \\ h_{22t} &= b_{12}^2 + b_{22}^2 + c_{12}^2\varepsilon_{2t-1}^2 + 2c_{12}c_{22}\varepsilon_{1t-1}\varepsilon_{2t-1} + c_{22}^2\varepsilon_{2t-1}^2 \\ &\quad + g_{12}^2 h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2 h_{22,t-1} \end{aligned} \qquad (3.4)$$

In Equation 3.4, the full BEKK GARCH (1, 1) contains 65 parameters which are difficult to interpret, and mostly out of the scope of this study; therefore, we will restrict Equation 3.3 by using the diagonal representation suggested by Bollerslev *et al*. (1988). The diagonal BEKK significantly reduces the number of parameters to be estimated to 25 parameters, whilst simultaneously maintaining the advantage of the positive definiteness of the conditional covariance matrix. This is considered sufficient for the purposes and objectives of this paper.

In the diagonal representation, we restrict the off-diagonal elements in C and G to zeros. Consequently, each conditional variance depends only on the past values of itself, and its own lagged squared residuals, whereas the conditional covariance depends on the past values of itself and the lagged cross-product of residuals. In the restricted model of Equation 3.3, we have, $c_{12} = c_{21} = g_{12} = g_{21} = 0$. Hence, Equation 3.4 simplifies to:

$$
\begin{aligned}
h_{11t} &= b_{11}^2 + c_{11}^2 \varepsilon_{1t-1}^2 + g_{11}^2 h_{11,t-1}, \\
h_{12t} &= b_{12} + c_{11} c_{22} \varepsilon_{1t-1} \varepsilon_{2t-1} + g_{11} g_{22} h_{12,t-1} = h_{21t}, \\
h_{22t} &= b_{11}^2 + b_{22}^2 + c_{22}^2 \varepsilon_{2t-1}^2 + g_{22}^2 h_{22,t-1}.
\end{aligned}
\tag{3.5}
$$

The parameters b_{ij} , c_{ij} and g_{ij} can’t be interpreted on an individual basis. Instead, the functions of the parameters forming the intercept terms and the coefficients of the lagged variance, covariance and error terms appearing in Equation 3.5 are of interest.

The model in Equation 3.5 can be estimated by maximum likelihood, and the log-likelihood function for the multivariate GARCH model is given by

$$
L(\theta) = -\frac{T_n}{2} + \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T} (\ln|H_t| + \varepsilon_t' |H_t^{-1}| \varepsilon_t), \tag{3.6}
$$

where n is the number of sectors, T is the number of observations, θ is the vector of parameters to be estimated, and the random errors are assumed to be normally distributed.

The BHHH (Berndt, Hall, Hall and Hausman, 1974) algorithm was used to calculate the maximum likelihood parameter estimates and their corresponding asymptotic standard errors (see Higgs and Worthington [2004] for further details).

Finally, in order to check for model misspecification, the portmanteau test by Ljung and Box (1978) was used. The statistic is given by:

$$Q = T(T+2)\sum_{j=1}^{p}(T-j)^{-1}r^{2}(j)\,, \qquad (3.7)$$

where $r(j)$ is the sample autocorrelation at lag j calculated from the noise terms and T is the number of observations. Q is asymptotically distributed as χ^2 with $(p-k)$ degrees of freedom, and k is the number of explanatory variables.

3.4 Data and empirical results

The data set comprises daily observations on the closing values listed on the Saudi stock market for the five sectors (Banking, Industrial, Cement, Service, and Agriculture). The data set was gathered from the Saudi Capital Market Company, covering the period January 1, 2002–April 4, 2008. Using daily data is preferable to weekly or monthly data as the former can catch the transient responses for innovations that may last for a short time.

The returns series are defined as the natural logarithm of the daily prices:

$$R_{i,t} = \left(\ln \frac{P_{i,t}}{P_{i,t-1}}\right),$$

where $R_{i,t}$ is the return of index i in day t, $P_{i,t}$ and $P_{i,t-1}$ are the quotes of the daily closing index.

The main summary statistics are presented in Table 3.1. The mean, median, minimum, maximum, standard deviations, skewness, kurtosis, the Jacque-Bera statistic and its associated *p*-values are reported. The mean returns for the five sectors are positive, ranging from a maximum 0.001186 (Industrial) to a minimum 0.000456 (the Cement sector). The positive sign reflects the high growth in the Saudi stock market during the period of study. From Table 3.1, it is interesting to note that the prohibited (*haram*) sector, i.e. Banks, and one sector close to prohibition, i.e. Cements, have the smallest mean values compared with the others.

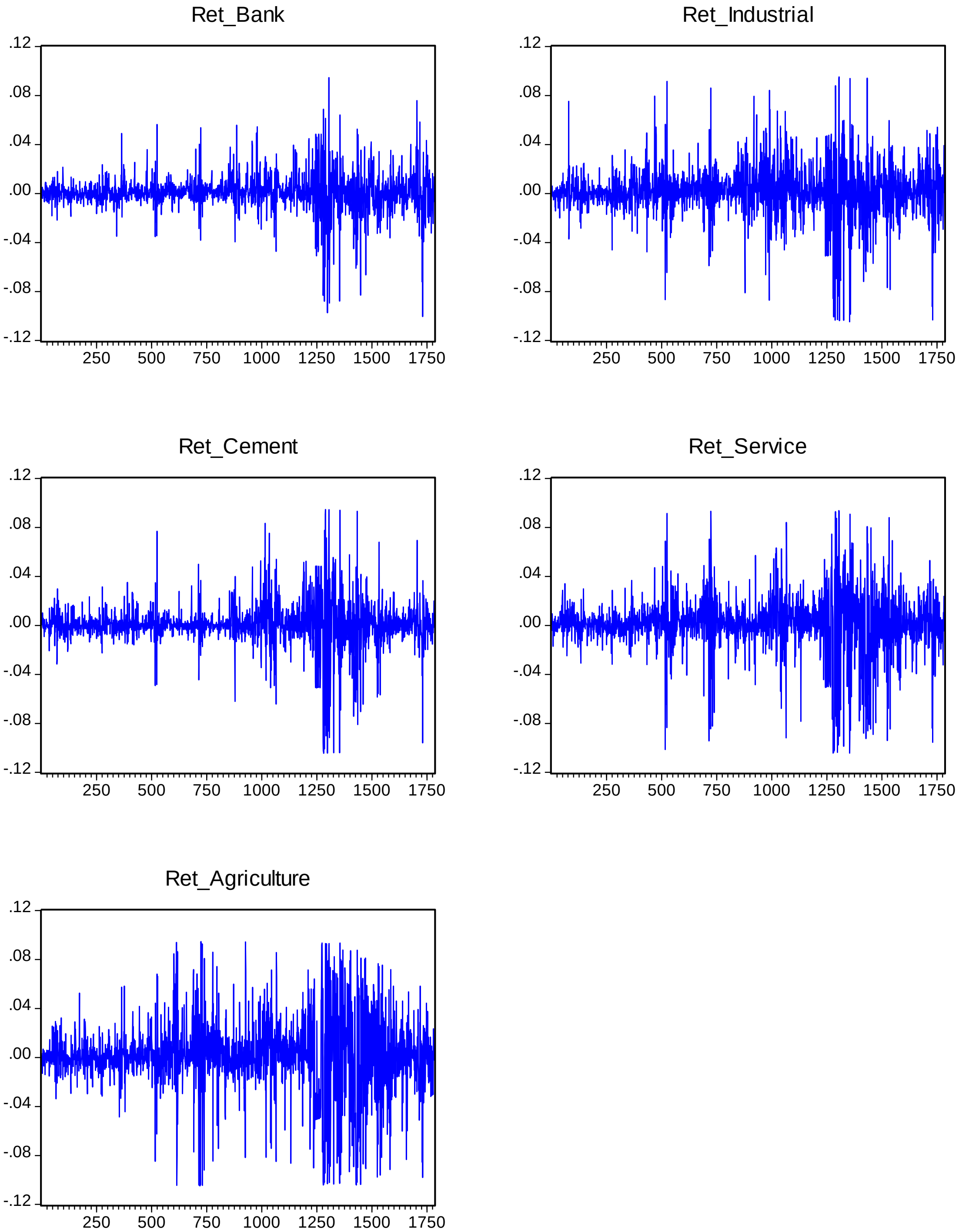
Table 3.1. Summary statistics of the daily returns for five Saudi market sectors.

	Mean	Median	Std. Dev.	Skewness	Kurtosis	J-Bera	*p*-value
Bank	0.0006	0.0003	0.0152	-0.5983	11.6982	5717.6	0.000
Industrial	0.0012	0.0014	0.0215	-0.4786	8.1611	2043.5	0.000
Cement	0.0004	0.0004	0.0186	-0.5736	12.0238	6137	0.000
Service	0.0006	0.0016	0.0244	-0.8299	7.5457	1736.9	0.000
Agriculture	0.0011	0.0009	0.0313	-0.4463	5.4624	508.7	0.000

According to the sample standard deviation, the prohibited stocks in the Banking sector and the ones close to prohibition in the Cement sector are the least volatile amongst the five sectors. Indeed, volatility, as measured by standard deviation, is ranked perfectly from maximum to minimum according to their compliance with the *Sharia'a*. Agriculture is the most volatile sector (0.03133), followed by Service (0.02436), Industrial (0.02148), Cement (0.0185), and Banks (0.0151).

The volatility of returns can be seen from a plot of the daily return of five sectors, as shown in Figure 3.3. At first glance, it can be clearly seen that the *Sharia'a*-compliant sectors are more volatile compared with non-*Sharia'a*-compliant. Furthermore, there is negative skewness for all sector returns, thus indicating data non-normality. All series were found to be leptokurtic, i.e. fatter tails and a higher peak, with the kurtosis statistics greater than 3. Excess kurtosis in stock return has been well documented in many equity market studies in both developed and emerging markets. In the last two columns of Table 3.1, the Jarque-Bera statistics and corresponding *p*-values reject the null hypothesis that the returns are normally distributed for all series.

Figure 3.3. Daily returns of five Saudi market sectors.



Empirical results

In this section, the effect of *riba* prohibition on Saudi stock market volatility is investigated. Prior to estimating the multivariate GARCH model, a preliminary investigation has been undertaken with the estimation of a univariate GARCH (1.1) model.

The estimating procedure for the univariate GARCH model for each of the six sector return time series has been carried out as following: first, an appropriate ARMA model for the mean equation has been specified such that there are no any serial correlations in its error terms; second, a univariate GARCH (1, 1) for the variance equation has been estimated, with the estimated coefficients and standard errors for the univariate GARCH (1, 1) model for the five major sectors of the Saudi stock market presented in Table 3.2.

Table 3.2. Estimated coefficients for univariate GARCH(1,1) model.

		Bank	Industrial	Cement	Service	Agriculture
Mean eqn.	C	0.001017 (0.000279) ***	0.001153 (0.000302) ***	0.000305 (0.000141) **	0.001343 (0.000402) ***	0.000272 (0.000573) ***
	AR(1)	-0.625635 (0.182653) ***	0.845748 (0.056376***	-0.213722 (0.122372) *	1.338611 (0.026058) ***	0.037205 (0.011975) ***
	AR(2)	0.149569 (0.040228) ***	NA	-0.448420 (0.080958) ***	-0.431769 (0.035689) ***	0.860758 (0.049936) ***
	AR(3)	0.056311 (0.027411) **	0.037081 (0.016910) **	-0.726686 (0.119998) ***	0.056556 (0.015303) ***	NA
	MA(1)	0.772164 (0.181407) ***	-0.847836 (0.055037) ***	0.210364 (0.117404) *	-1.317749 (0.014587) ***	NA
	MA(2)	NA	NA	0.430360 (0.078176) ***	0.376181 (0.018975) ***	-0.824634 (0.055874) ***
	MA(3)	NA	NA	0.751870 (0.116019) ***	NA	NA
Variance eqn.	C	2.79E-06 (3.56E-07) ***	4.93E-06 (1.49E-06) ***	3.68E-06 (8.01E-07) ***	7.96E-06 (2.05E-06) ***	1.94E-05 (4.27E-06) ***
	ARCH(1)	0.168967 (0.012396) ***	0.186062 (0.027819) ***	0.280461 (0.039514) ***	0.225193 (0.033417) ***	0.314864 (0.043924) ***
	GARCH(1)	0.835976 (0.008836) ***	0.829577 (0.020108) ***	0.754396 (0.025594) ***	0.786740 (0.022657) ***	0.718379 (0.027618) ***

Note: Univariate GARCH(1,1) is regressed assuming Generalized error distributions (GED) and standard errors are given in parenthesis. ***, ** and * indicate the significance level of 1%, 5% and 10%, respectively. NA denotes that the corresponding lag is not applicable.

From Table 3.2, it appears that all five sectors exhibit strong conditional heteroscedasticity, with all ARCH and GARCH coefficients statistically different from zero—even at 1% level. However, it is clear that the combination of ARCH and GARCH effects are greater than the unity, thereby indicating that the estimated conditional heteroscedasiticity is unstable. The excessive conditional volatility of one sector can be driven by the co-movements of the other sectors, and, if this is true, such univariate GARCH models can't correctly reveal the conditional co-variances in the Saudi stock market. Consequently, it is essential that such univariate GARCH models be extended to a multivariate GARCH (MGARCH) framework, enabling the effect of volatility spill-over and correlation transmission to be examined.

Further, testing for the effect of *riba* prohibition in Islamic *Shara'a* requires the examination of co-movement amongst the five sectors. In this sense, the univariate GARCH (1,1) models presented in Table 3.2 are not very informative. Similarly, when using a Markov switching regime model, the mutual effects across different sectors would not be taken into account. As the purpose of this study is to investigate whether *haram* sectors are isolated from other *halal* and *mixed* sectors, the multivariate GARCH model has been adopted.

A possible shortcoming of the multivariate GARCH model is that it requires the estimation of a large number of parameters. In order make the model more parsimonious without losing information, a diagonal BEKK model has been predicted.

The estimated coefficients and standard errors for the conditional mean return equations of the multivariate GARCH (MGARCH) model are presented in Table 3.3. The diagonal parameters are all significant, meaning that all sectors reported significant own return spill-over (affected by its own lags). The effect of own-lagged in the Bank sector is the highest (0.1164), followed by Service (0.1056), then Cement (0.102). Markedly, Industrial (0.085) and Agriculture (0.070) have the smallest estimated coefficient.

Table 3.3. Estimated coefficients for conditional mean return equations.

	Bank i=1	Industrial i=2	Cement i=3	Service i=4	Agriculture i=5
Cons.	0.0019 (0.3568)	-0.0015 (0.5094)	0.0015 (0.4396)	0.0019 (0.5734)	0.0024 (0.7336)
$a_{i,1}$	0.1164*** (0.0353)	-0.0269 (0.0503)	-0.0081 (0.0434)	-0.0359 (0.0566)	0.0476 (0.0724)
$a_{i,2}$	0.0383 (0.0260)	0.0859*** (0.0372)	-0.0194 (0.0321)	-0.0304 (0.0418)	-0.0021 (0.0535)
$a_{i,3}$	-0.0193 (0.0313)	0.0064 (0.0447)	0.1023*** (0.0386)	0.1284** (0.0503)	0.0409 (0.0644)
$a_{i,4}$	0.0169 (0.0301)	-0.0261 (0.0429)	0.0313 (0.0370)	0.1056** (0.0483)	0.0926 (0.0618)
$a_{i,5}$	-0.0319 (0.0186)	-0.0064 (0.0266)	-0.0477** (0.0229)	-0.0251 (0.0299)	0.0707* (0.0383)

Note: asterisks indicate significance at *10%, **5% and *** 1% level.
Standard errors are given in the parenthesis.

The own-mean spill-over implies that an increase of SR 1.00 in the Banking sector today, for example, will result in an increase in its price of SR 0.11 over the next day. Furthermore, in all five sectors, the own-mean spill-overs are found to be positive, therefore reflecting the positive direction of the Saudi market during the period under consideration.

Regarding the cross return spill-over, only two sectors—namely Cement and Agriculture—show significant cross return spill-over, i.e. affected by lagged returns of other sectors. The mean return for Agriculture is influenced positively, as was mentioned previously, by its own lagged return, and negatively by the lagged returns of the Cement sector. The negative cross mean return effect implies that, when the Cement returns fall, investors tend to hedge themselves in the Agriculture sector, but not vice versa.

On the other hand, the Cement sector is influenced positively by its own lagged return, and positively with the lagged return of the Service sector. Again, the effect is in one direction, and not mutual between the two sectors. However, the positive sign of this cross mean effect means that both sector returns go in the same direction. This relationship may be attributed to the fact that the Service sector contains many construction and building companies.

It is important to mention that the Bank sector—notably the forbidden sector—is independent and isolated from all other *mixed* and *Sharia'a*-complaint sectors in terms of cross return spill-over. This result supports the hypothesis that any price change in the Banks index does not cause other indices to move up or down, and vice versa.

The estimates of the conditional variance covariance equations from the analysis are presented in Table 3.4. In this table, the *b*'s in the first five rows refer to the intercept in the GARCH equations; the *c*'s are the (ARCH) effects or innovation transmission degrees; the *g*'s are the (GARCH) effects that provide estimates of the persistence in conditional volatility transmission. The diagonal BEKK is used to effectively investigate the effects of the lagged own innovations or shocks, and lagged own persistence on the current own volatility of five sectors listed in Saudi capital market.

Table 3.4. Estimated coefficients for variance covariance equations.

	Bank (j=1)		Industrial (j=2)		Cement (j=3)		Service (j=4)		Agriculture (j=5)	
	Est. co-eff.	Std. err.	Est. co-eff.	Std. err.	Est. co-eff.	Std. err.	Est. co-eff.	Std. err.	Est. coeff.	Std. err.
b_{1j}	0.0019	0.0004	—	—	—	—	—	—	—	—
b_{2j}	0.0009	0.00021	0.0019	0.0003	—	—	—	—	—	—
b_{3j}	0.0006	0.0001	0.0005	0.0002	0.0016	0.0002	—	—	—	—
b_{4j}	0.0009	0.0002	0.0006	0.0002	0.0004	0.0001	0.0018	0.0003	—	—
b_{5j}	0.0006	0.0002	0.0004	0.0003	0.0004	0.0002	0.0007	0.0004	0.0024	0.0010
c_{1j}	0.298***	0.043	—	—	—	—	—	—	—	—
c_{2j}	—	—	0.281***	0.018	—	—	—	—	—	—
c_{3j}	—	—	—	—	0.32***	0.028	—	—	—	—
c_{4j}	—	—	—	—	—	—	0.274***	0.022	—	—
c_{5j}	—	—	—	—	—	—	—	—	0.268***	0.0618
g_{1j}	0.947***	0.016	—	—	—	—	—	—	—	—
g_{2j}	—	—	0.959***	0.0055	—	—	—	—	—	—
g_{3j}	—	—	—	—	0.94***	0.010	—	—	—	—
g_{4j}	—	—	—	—	—	—	0.959***	0.0074	—	—
g_{5j}	—	—	—	—	—	—	—	—	0.9633***	0.019

Note: asterisks indicate significance at *10%, **5% and *** 1% level.

From Table 3.4, the following may be inferred:

i. Own-innovation spill-overs in all sectors are large and significant, therefore indicating the presence of strong ARCH effects.

ii. Own-innovation spill-over effect in the Banking sector (*haram*) and Cement sector (close to *haram*) are higher than the *halal* sectors, as well as those sectors close to *halal*. The own-innovation spill-over effects in descending rank are Cement (0.32), Bank (0.29), Industrial (0.28), Service (0.27) and Agriculture (0.26).

iii. The large own-shock effect in Cement and Bank sectors may be attributed to the high price of these sector shares, and sharp increase then decrease these prices before and after the bubble.

iv. The small own-innovation effect in *halal* and *mixed* sectors compared to *haram* sector indicates the significant congestion of these sectors owing to high demand on these sector shares; thus, the effect of the market boom was limited compared with the *haram* sectors as the boom started earlier in the *halal* sectors. Owing to daily price restriction to move 10% only, these sectors continued increasing at a steady and gradual pace, at approximately 10% on a daily basis.

v. Volatility persistence (g's in Table 3.4) is very high for all sectors, thereby indicating the presence of strong GARCH effects. The lagged own-volatility persistence ranges from 0.9633 in the agricultural sector to 0.941 in Cement. This outcome strongly supports the argument that the volatility in the Saudi market ranges in an ascending way from *halal* to *mixed* to *haram* sectors. This can be attributed to the continuity of trading/investing in *halal* sectors in all market events, or circumstances that prolong the persistency in such sectors. In contrast, however, the persistence in the *haram* sectors falls quickly owing to lesser demand and lesser trade during the shock in these sectors.

Coming to the results of the misspecification tests, the Ljung-Box Q statistics in Table 3.5 show an autocorrelation in the Agricultural sector, whereas the other four sectors reveal no evidence of autocorrelation in the standardised residuals. Autocorrelation in Agriculture may attribute to the effect of outliers. In general, since the Ljung-Box statistic does not provide evidence of a linear relationship in the standardised residuals in four of the five sectors, we may therefore conclude that the VAR–MGARCH model is well specified.

Table 3.5. Ljung-Box *Q* statistics result.

	Bank	Industrial	Cement	Service	Agriculture
L-B statistic	7.1730	1.9564	9.0398	10.0304	18.1901
p-value	0.2081	0.8551	0.1075	0.0744	0.0027

Another misspecification test is the stationarity for the second moments of the standardised residuals in the MGARCH (1,1) model; this is undertaken by ADF unit root test. The results of this test are reported in Table 3.6. It is evident that the null hypothesis of the unit root can be rejected—even at the conservative 1% statistical significance level—thus indicating that the second moments of the standardised residuals are stationary.

Table 3.6. ADF unit root test result.

	Bank	Industrial	Cement	Service	Agriculture
ADF test statistic	-10.11406***	-10.03996***	-7.585105***	-7.872874***	-8.988523***

Note: asterisks indicate significance at *10%, **5% and *** 1% level based upon MacKinnon (1996) one-sided *p*-values.

3.5 Ramadan effect on stock volatility

Stock market seasonality is a documented phenomenon in finance literature. Variations in trading activity resulting from 'January effects', 'Monday effects', and 'Year-end effects' are all well-known concepts in stock markets. In this regard, Ramadan can be analysed in the context of calendar effect, contextualised in an Islamic environment.

The Islamic lunar year comprises 12 months, each of which lasts either 29 or 30 days. Ramadan is the ninth month of the Islamic calendar, and is a time at which all adult Muslims are required to fast from sunrise to sunset. During Ramadan, eating, drinking and smoking are included in some of the forbidden acts, along with other immoral acts, such as dishonesty, deception, etc. However, an exemption from fasting for the sick or travellers is available.

In general, with the start of Ramadan, Muslims increase pious activities, such as offering extra prayers and charity. As a result of this, economic activities tend to slow down during the Ramadan month, and business hours are reduced to 5 working hours per day. Importantly, stock market activity is not excluded from the impact of Ramadan: although the usual business hours of stock market during Ramadan do not change, during this period, trading volumes and liquidity are at their lowest levels. In general, stock turnover is minimal and the market indices fall.

3.5.1 Related literature

The Ramadan effect on stock volatility has been investigated in few empirical works. The results of some of these studies are reviewed below:

An early work was carried out by Husain (1998), which investigated the month of fasting's effects on Pakistan equity market using GARCH (1, 1), subsequently establishing a significant decline in stock return volatility during this month, although the mean returns did not show any significant changes.

Mustafa (2008) investigated the Ramadan and post-Ramadan effect on the Karachi stock market. His results indicated that the Karachi market is at a relatively low risk during Ramadan, compared with post-Ramadan months, such as the month of Shawal—the month immediately following Ramadan.

Bialkowski *et al.* (2009) studied the effect of Ramadan in 14 Islamic countries, finding that 11 of the 14 countries had higher average returns during Ramadan, and significant decreases in volatility in 13 of the 14 countries.

Seyyed *et al*. (2005) examined the effect of Ramadan on the stock volatility in the Saudi market's general and sector indices. The empirical analysis suggested a significant fall in the level of market volatility for all indices—statistically significant at both the 5% and 1% levels—with the only exception witnessed in the Agriculture sector.

Alper and Aruoba (2001) investigated the Ramadan effect on the Turkish stock market. In contrast with other related studies, the stock indices considered by the authors did not exhibit any significant Ramadan periodicities.

Finally, Al-Ississ (2009) examined the effects of Ramadan on the daily indices returns in 17 Muslim countries between 1988 and 2008. His results showed that, whilst Ramadan's last five odd days have a positive significant impact, the last 5 even days do not show statistical significance.

3.5.2 The empirical results

Most of the empirical works reviewed above utilise dummy variables in the mean equation to detect the Ramadan effect on returns. In this work, the writer is interested in analysing the effect of Ramadan in both the mean returns and volatility; therefore, a Garch model is proposed with the aim of investigating the joint effect of Ramadan on mean and variance of stock returns. Furthermore, owing to autocorrelation and heteroskedasticity problems in regard to time-series data, the traditional regression model used in the previous studies is not appropriate as it is recognised as potentially resulting in misleading results. The GARCH model, as first introduced by Bollerslev (1986), overcomes the problems associated with the traditional linear regression model, and is therefore preferred in this work.

The following GARCH (p, q) model is chosen to estimate the Ramadan effect on Saudi stock market return.

$$R_t = \lambda_0 + \alpha_1 D_{ramadan} + \sum_{i=1}^{m} \phi_i R_{t-i} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t \,,\ \ \varepsilon_t \mid \Omega_{t-1} \sim N\left(0, \sigma_t^2\right) \qquad (3.8)$$

where $D_{ramadan}$ =1 for the daily sector return during the month of Ramadan and 0 otherwise.

The terms of the autoregressive moving average model ARMA(m,n) in equation (3.8) were included to eliminate the autocorrelation and the specific order was evaluated using serial correlation LM test. The structure of GARCH (p , q) model used to estimate the parameters of variance equation is:

$$\sigma_t^2 = \beta_0 + \beta_1 D_{ramadan} + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j \sigma_{t-j}^2 \qquad (3.9)$$

The order of m and n was chosen according to SIC (Schwartz Information Criterion) and β_0 , γ_i , and δ_j are parameters to be estimated. The values of p and q are > 0, define the order of the process and β_t is the parameter describing the Ramadan effect on the volatility returns.

Ramadan statistics:

Figure 3.4 shows the average number of stocks traded (in millions) in Ramadan versus non-Ramadan periods, i.e. all the other trading days of the year. The Ramadan effect on the number of shares traded in the market is obvious where four of five sectors' trading falls during the Ramadan month. The exception to this is the Service sector, where the number of shares traded in the month of Ramadan exceeds those outside of Ramadan; this may be explained by the fact that the Service sector dominates in terms of market activity during the period under consideration. Another reason for this may be that many of the *halal* companies' prices reach their lowest point, and investors may therefore buy as many stocks as they can during the fall in price associated with Ramadan.

Figure 3.4. The average number of share traded in Ramadan versus non-Ramadan, (2002-2008).

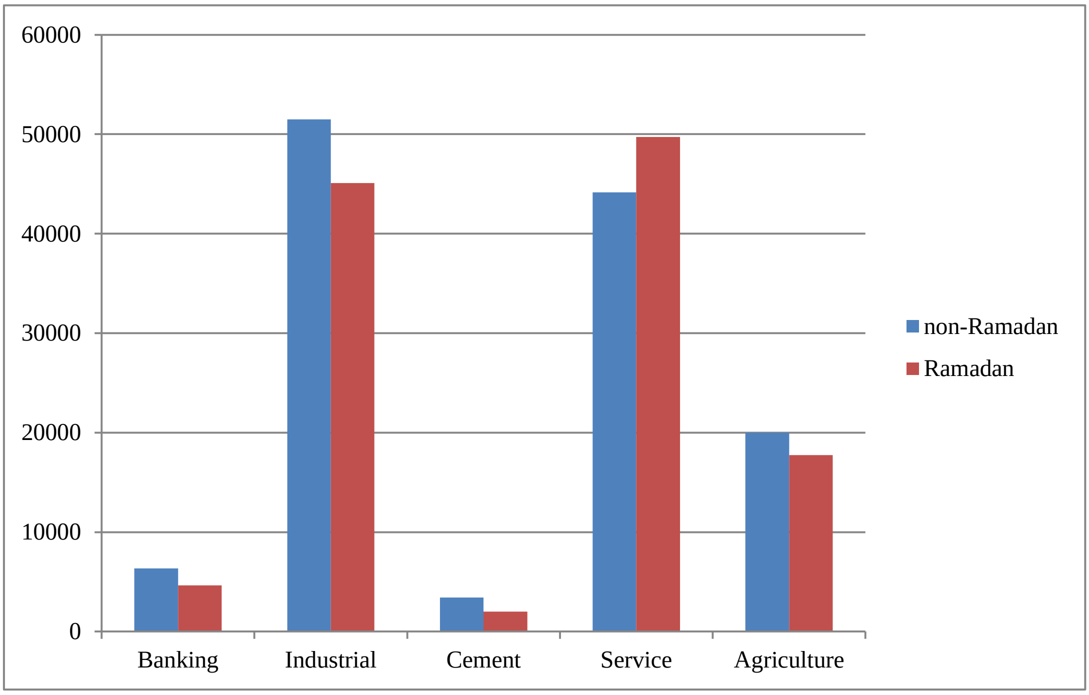
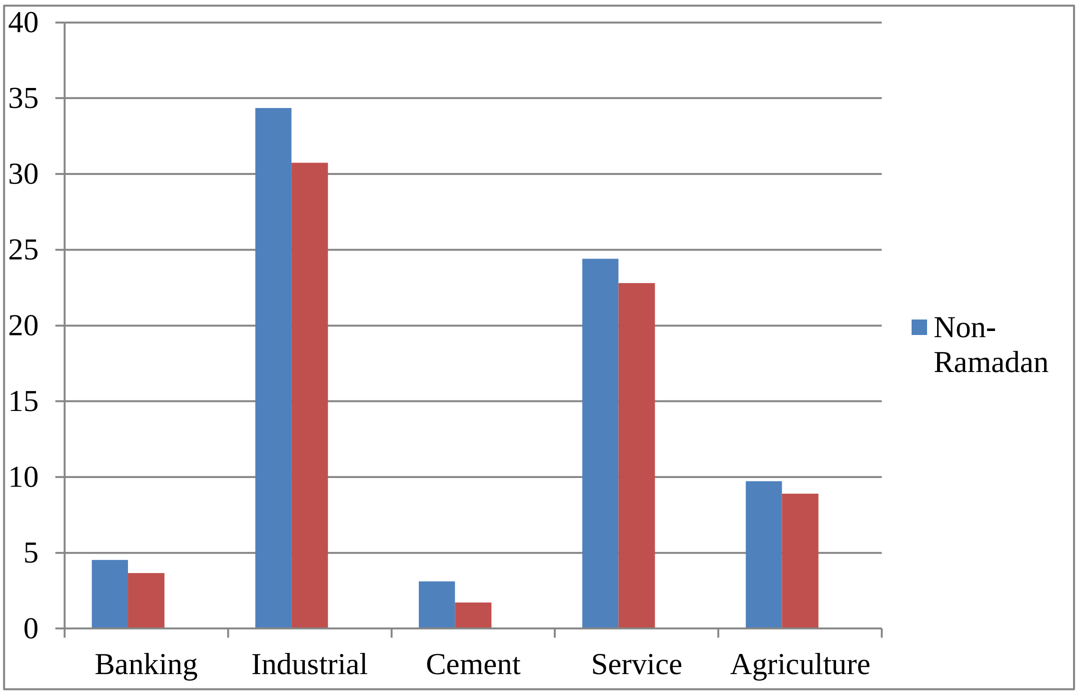


Figure 3.5 shows the average market value in Saudi Riyals (SR). It is clear that, during Ramadan, the level of market value is lower for all five sectors compared with non-Ramadan period. Furthermore, we notice that a fall in the Banking and Cement sectors is greater when compared with the rest of the market's sectors.

Figure 3.5. Average market value during Ramadan versus non-Ramadan, (2002–2008).



Empirical results:

Table 3.7 shows the estimated results of GARCH (1, 1) on both the mean and variance equations for 5 Saudi stock market sectors.

Table 3.7. Estimated return and conditional variance with Ramadan dummy variable.

	Mean		Conditional Variance			
	Cons.	$D_{ramadan}$	Cons.	$D_{ramadan}$	$\gamma(\varepsilon^2_{t-i})$	$\delta(\sigma^2_{t-j})$
Bank	0.0021*** (0.0001)	-0.0009 (0.0006)	3.6E-05*** (3.3E-06)	-1.63E-05*** (4.9E-06)	4.106661*** (0.0659)	0.0915*** (0.0088)
Industrial	0.0063 (0.0052)	2.9E-05 (0.0011)	6 E-06*** (8.7E-07)	5.7E-06* (2.9E-06)	0.1961*** (0.0148)	0.8173*** (0.01137)
Cement	0.0006*** (0.0002)	0.0008 (0.0009)	6E-06*** (4.2E-07)	3 E-06*** (1.2E-06)	0.2609*** (0.0169)	0.0127*** (58.903)
Service	0.0014*** (0.0004)	-0.0015 (0.0017)	7.3E-06*** (1E-06)	1.6E-07 (2.8E-06)	0.1672*** (0.0139)	0.8306*** (0.0102)
Agriculture	0.0018*** (0.0005)	-0.0039* (0.0013)	2.8E-05*** (2.86E-06)	4.5E-06 (6.7E-06)	0.2629*** (0.0217)	0.7256*** (0.0155)

Asterisks indicate significance at *10%, ** 5%, and *** 1% level. Standard errors are given in the parenthesis.

Several results become apparent from Table 3.7:

i. Despite the fall in stock activity and trading volume during Ramadan, the effect on mean return was limited and insignificant in four of the five Saudi market sectors. The mean returns for the Agricultural sector was, however, affected by Ramadan. This effect may be attributed to heavy speculation behaviour in this sector, which tends to diminish during Ramadan.

ii. The effect of Ramadan on the volatility is significant for the Bank, Cement, and Industrial sectors, whereas the Agricultural and Service sectors observe insignificant Ramadan effects on their returns' volatility. This finding supports a hypothesis that investors in the Saudi market prefer to invest in *halal* sectors, regardless of any additional benefits that could be accrued from the *haram* sectors. Furthermore, the results confirm that investors avoid investing in or speculation concerning *haram* sectors during Ramadan. *Haram* activities during this holy month are particularly despicable according to *Sharia'a*.

iii. The dummy variable is statistically significant for both the Banking and Cement sectors. For the Industrial sector, the *p*-value was 0.0493 (not reported), meaning the level of statistical significance becomes smaller as one moves from the *haram* sector to *mixed* sectors. On the other hand, no significant effect of Ramadan was found in the pure *halal* sectors (Agriculture and Service). However, the magnitude of the estimated coefficients reported in Table 3.7 is during the market boom, and one would not expect any strong Ramadan effect.

iv. Comparing the coefficients of the three sectors affected by Ramadan, the coefficient for Banking has a value greater than the Cement sector. Furthermore, the latter is greater than the Industrial coefficient in terms of absolute value. This finding supports the earlier observation that the Saudi investors prefer to invest in the *halal* sectors, irrespective of the higher profits one could earn from the *haram* sectors.

v. Comparing our result with Seyyed *et al*. (2005), we were not able to find a significant Ramadan effect in the Agriculture and Service sectors; this may be explained by the large number of market participants and many mutual funds, all of which have made the Saudi market more active and more crowded compared with the period examined in the study of Seyyed *et al*. (2005).

3.6 Conclusion

Islamic religion is deeply embedded within Saudi Arabia social, political and economic activities; however, the effects of these characteristics have not been taken into account in previous studies. Hence, in this chapter, the effect of Islamic *Sharia'a* law on the Saudi stock market has been investigated, with each sector in the market treated separately according to its relationship with Islamic *Sharia'a*.

The results of univariate GARCH models reveal that the Ramadan effect on volatility is significant for the Banking, Cement, and Industrial sectors, although its impact on mean returns is minor except in the case of the Agriculture sector. The results of the BEKK-MGARCH (1, 1) indicate that all sectors reported significant autoregressive return volatilities. Furthermore, in all five sectors, the own-mean spill-over effects are found to be positive, thus reflecting the market run-up during the period under consideration. As far as volatility spill-over is concerned, however, only two sectors—namely Cement and Agriculture—are affected by lagged returns of other sectors. In particular, the Bank sector is isolated from all other *mixed* and *Sharia'a*-complaint sectors in terms of cross mean spill-overs, thus highlighting the limited influence of the sector on the entire equity market.

Regarding the variance equations of the multivariate GARCH model, the lagged own-volatility persistence is found to be the highest in the Agriculture sector, whereas the smallest volatility is established for Cement firms and Bank sectors. This volatility persistence may reflect Islamic *Sharia'a*, which provides more market participants with favourable trading and investment environment opportunities for *halal* than *haram* sectors. Overall, these results confirm the hypothesis that the *haram* and close to *haram* sectors are more likely to be sluggish in the month of Ramadan compared with *halal* and *mixed* sectors.

Finally, based upon the evidence of GARCH models discussed in Section 3.4, it appears that it is necessary to extend the univariate GARCH model to the multivariate, as the former does not account for covariances amongst different sectors. Often, in the case of major market structural reforms, such as those that took place in the market under consideration, volatility persistence can be caused by structural changes in the variance process (see, for example, Lamoureux and Lastrapes (1990), amongst others; that is, volatility can remain constant, homoskedastic and persistent until a structural breaks take place. In the case of structural breaks, a Markov Regime Switching model, where each regime is characterised by its specific unconditional variance, is often favoured in the literature. In such types of model, the conditional probability of switching amongst all regimes is modelled as a function of the joint conditional probability of the current state, and the transition probabilities across all states. Modelling the time series of the Saudi stock market with the implementation of a Markov switching framework will be considered in the next chapter.

Chapter 4

Volatility and Bubble in the Saudi Stock Market: The Role of Noise Traders

4.1 Introduction

Since the beginning of 2002, the Saudi stock market (SSM) has been overflowing with a large number of first-time investors with no previous knowledge of stock investment. The large daily returns and huge capital gains of Initial Public Offering (IPOs)[28] during the years 2002–2005 attracted large numbers of participants, who entered the stock market. Many investors participated by purchasing new IPOs using the names of either themselves or families and friends in order to acquire a larger number of shares during the allocation process.

Statistics show that the number of market participants rose almost 30 times from roughly 53,000 in 2002 to 1.5 million in 2005. Meanwhile, the number of participants reached 4 million in some IPOs, and such oversubscriptions and the limited number of shares available pushed up stock prices to unreasonable and unprecedented levels. Indeed, the returns were observed at almost the maximum daily limit of 10% for 4 years. The IPO shares were offered to the public at a price of SR10, although capital gains were 10 to 20 times such figures when they were sold in the secondary market on their first trading day.

The huge returns attracted a large number of private investors who constituted approximately 99% of total market participants; however, owing to a lack of knowledge and experience, private investors' behaviours were influenced in different ways through market information cascade. For example, internet websites, SMS messages, and advice played a significant role in the inflated prices, subsequently making the market fragile and prone to collapse at any time.

[28] A private company offering its shares to public for purchase for the first time and the external capital can be used to finance its existing and future projects.

As is often the case with over-inflated stock prices yielding large returns, there is the tendency for the market to correct itself. Such a correction took place in the form of stock market collapse in late February 2006, at which time the bubble burst. Following the market crash in February, stock prices continued to fall throughout the rest of the year, albeit at a much slower rate. More specifically, the general index collapsed from its peak of 21,000 points, closing the year at 8,000 points. In other words, it lost 13,000 points in only ten months.

It is of interest to note that the stock market collapse could not be attributed to economic reasons when considering the Saudi economy was growing at 4.5% yearly during the same period. In addition, oil prices were increasing for the entire period during which the bubble lasted. The government also declared a national plan to invest SR 400 billion in major infrastructure during 2004–2010. Hence, external factors, such as the micro and macroeconomy, were unlikely to have played a significant role at the time at which the bubble burst. Such details help the researcher to isolate economic factors, and to instead focus more keenly on the role of atomistic behaviour as possible causes of the financial bubble in the Saudi market.

As discussed in previous chapters, market inefficiencies can have implications for both investors and the market itself; that is, on the one hand, investors may respond to cascaded market information; on the other hand, market information can be interpreted and transmitted differently amongst Islamic and non-Islamic sectors. Such mispricing anomalies can be seen as the failure of the efficient market hypothesis.

This chapter considers two issues. First, we investigate whether herd behaviour was a possible cause of the stock market crash in 2006. For this purpose, the return dispersion model (RDM) proposed by Chang *et al.* (2000) is used. Second, regime shifts in volatility and returns are examined during the period under investigation by estimating the Markov regime switching model (MRS) suggested by Hamilton (1989).

The remainder of the chapter is organised as follows: Section 4.2 introduces the role of noise traders in the Saudi stock market; Section 4.3 focuses on the methodologies used for the empirical investigation, and reviews relevant studies concerning both herd behaviour and the Markov switching model; empirical results are reported in Section 4.4; and finally, Section 4.5 offers a conclusion.

4.2 The role of noise traders in the Saudi stock market

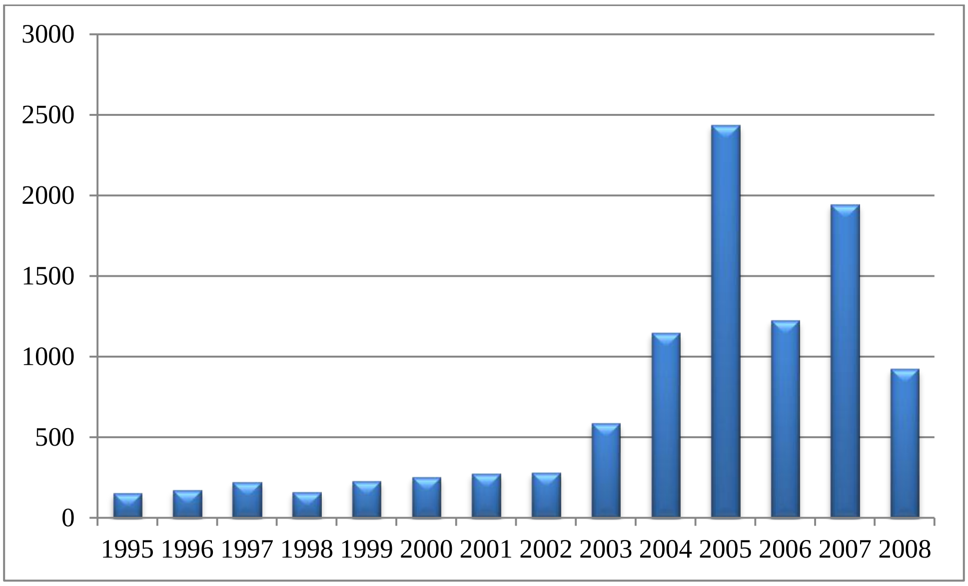
The Saudi stock market boom began in 2002. During this period, the market was flooded by individual investors[29] who had little or no knowledge relating to stock investment. In particular, the period 2002–2005 witnessed a huge increase of market participants. According to the Al-Riyadh newspaper reports, the number of market participants increased from 52,598 in 2001 to 79,800 by the end of 2002. Moreover, in 2003, the number of investors reached 428,074—an increase of 436% compared with the previous year. The number of market participants continued to increase, reaching 800,000 investors by the end of 2004 (Al-Riyadh newspaper, Issue no. 13278, October 28, 2004). Furthermore, by the end of 2005, the numbers of market participants reached 1.5 million investors in the market.

On the other hand, the Initial Public Offering (IPOs)[30] that the market witnessed during the period of study attracted an additional 2–2.5 million first-time investors/traders to buy in these new IPOs. The overflow of investors associated with the limited number of shares offered in the market deeply changed the market structure in terms of market capitalisation, share value, and the number of transactions.

As shown in Figure 4.1, the share capitalisation increased by 110.14% from SR 280 billion by the end of 2002 to 589.93 billion in 2003. By the end of 2004, the number further increased to 1,148.60 trillion, representing an increase of 94.70%, before jumping sharply to a historically high level at approximately SR 2.5 trillion in 2005 (112.28%).

[29] “Note that individual investors are often referred to as noise traders in the literature”.
[30] 1,4,5, 9,26, 13,number of IPOs in SSM in 03,04,05,06,07,08.

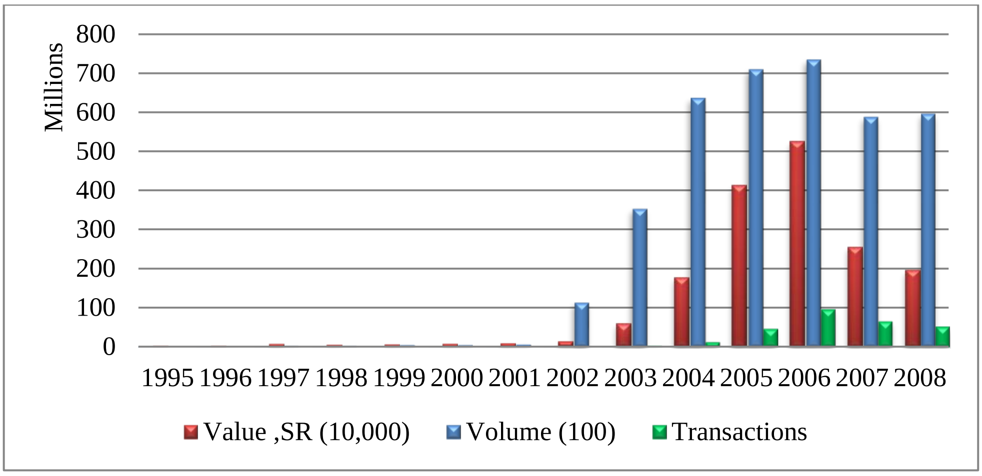
Figure 4.1. Saudi stock market capitalisation, (SR, Billion).



Source: Tadawul annual reports ,02,03,04,05,06,07,and 08.

Figure 4.2 shows the huge increase in the value of shares, volume, and number of transactions executed. The rate of growth in the value of shares traded, for example, was 345.87%, 197.37% and 133.32% in 2003, 2004 and 2005, respectively. The number of shares traded and number of transactions executed experienced large increases during the same period.

Figure 4.2. Saudi stock market value, volume, and transactions.

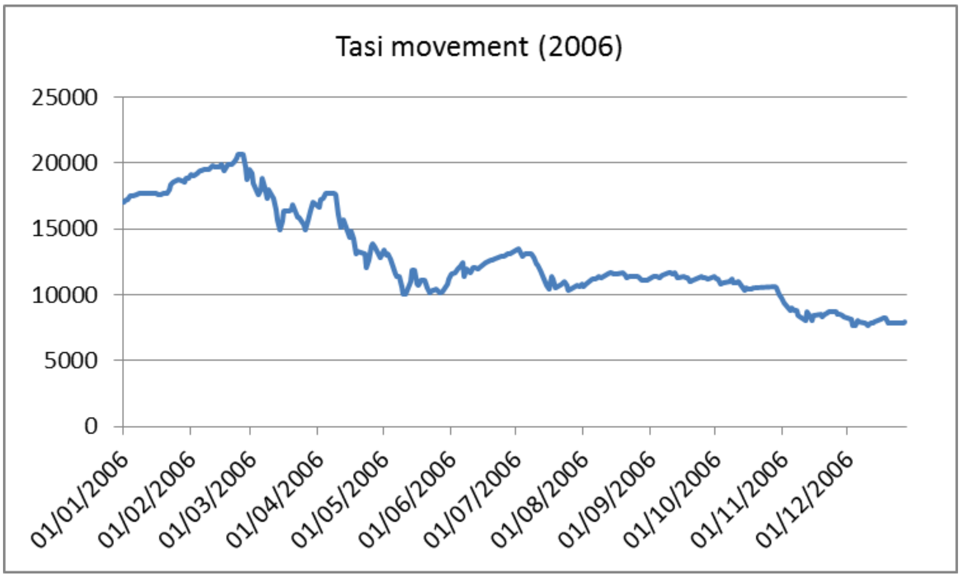


Source: Tadawul annual reports ,02,03,04,05,06,07 and 08.

However, the rapid expansion of the stock market, caused by a sharp increase in the number of individual investors, subsequently resulted in unprecedented increases in market volatility, which eventually led to the crash in 2006. Indeed, the difference between the offer price or share per-value in the IPOs processes and the market price when shares were sold in the secondary market was huge. For example, Bank Albilad offered to the public at SR 50; however, during the first day of trade, shares reached SR 950. This extraordinary gain encouraged people to invest using their family members' names, i.e. their wife's and children's names, for instance, in order to get more and more shares in circumstances where the IPO shares were divided equally amongst the number of participants. The huge net gains and the frequency of this process attracted more and more people to enter the market, leading the number of market participant to reach beyond 4 million.

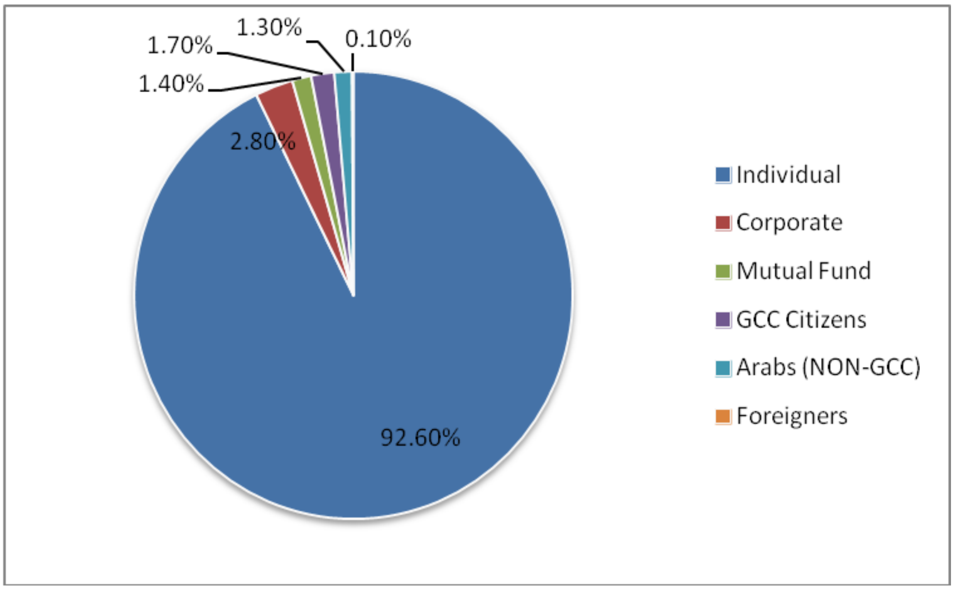
Unfortunately, however, the bonanza time did not last long: the huge and continuous growth of the Saudi market, since 2002, associated with the dominance of newcomers or first-time investors, finally led to havoc market correction at the beginning of 2006. On February 26, 2006, the bubble burst. Figure 4.3 shows the Tasi index performance during the year of bubble. As can be seen when considering the figure, the market dropped from its peak of 21,000 points, ending the year with less than 8,000 points in just a period of ten months.

Figure 4.3. Tasi movement during the year of bubble (2006).



A key reason for the market collapse was the huge amount of over-speculation and dominance of first-time and inexperienced investors on the market, which inflated prices. In this respect, the market crash was not surprising if one realises that individual investors constituted approximately 99% of the total market participants according to various unofficial sources. Officially, Tadawul started to publish the share of agents in the market since January 2008. Figure 4.4 shows the percentage share of different agents in Saudi market. It is of interest to note that corporate and mutual funds constitute only 4.2%, whereas 95.8% are individual investor shares.

Figure 4.4. Agencies' share in the Saudi stock market.



Source: Tadawul monthly report, January08.

In summary, as the Saudi stock market witnessed many evolvement and reforms following 2001, many negative factors were also experienced. The dominance of individual participants on stock market activities was one of the most negative factors resulting in the market's collapse in early 2006. This negative impact should be taken into consideration when studying the Saudi stock market.

4.3 Methodology and related literature review

The weak form of EMH was not accepted within the Saudi stock market. Two possible explanations for this failure are investors' herd behaviour, or shifts in market regimes. On the one hand, herd behaviour can impede the transmission of market information, subsequently reducing market efficiency; on the other hand, if there are fundamental changes in the market structure, the cascading process of market information can be segmented, and therefore should be studied separately. Accordingly, this section proposes two approaches for modelling the behaviour of the Saudi stock market during the bubble period: one refers to the herd behaviour, and the other to shift in market regimes.

4.3.1 Related studies in herd behaviour modelling

Various empirical models have been employed with the objective to detect herd behaviour in the matured and emerging stock markets. In an attempt to reflect the return dispersion as a result of herd behaviour, a common approach used in literature is to calculate either cross-sectional standard or absolute deviations of returns.

Herd behaviour was first examined in various emerged stock markets. For example, Caparrelli *et al.* (2004) examined herd behaviour in the Italian market for a period of thirteen years (September 1988– January 2001). Using a number of non-linearity tests, they were able to detect herd behaviour during extreme market conditions.

Caporale *et al.* (2008) further calculated cross-sectional absolute deviation on daily, weekly, and monthly data for the Athens stock exchange. The result supported evidence of herd behaviour, with such evidence becoming specifically stronger over the daily frequency. Furthermore, under asymmetric market conditions they indicated that herding was much keener during periods of a rising market compared with a falling market.

Economou *et al.* (2010) utilised daily data for the years 1998–2008 with the aim of testing for herd behaviour in four Mediterranean stock markets (Greek, Italian, Portuguese, and Spanish). Their results showed the presence of herd behaviour in the Italian and Greek stock markets; however, no evidence of herding was shown in the Portuguese and Spanish markets. Under asymmetric conditions, herding was found in the Portuguese stock market during periods of a falling market, whereas herding during periods of a rising market was detected in Italy and Greece.

Herd behaviour was also tested in developing markets. For example, Tan *et al.* (2008) examined herd behaviour in 87 dual-listed firms in the Chinese A-share and B-share stocks. Each of the two market participants belonged to a different group of investors; that is, the A-share market was dominated by domestic individual investors; in contrast, the B-share market was dominated by foreign institutional investors. The result based on the daily data suggested that the existence of herding in both A and B share markets in Shanghai and Shenzhen markets. However, when weekly data were considered, the herd behaviour was less significant when compared with the one when daily data were used. Under asymmetric market conditions, the results indicated the presence of a herding phenomenon in both rising and falling markets.

Demirer *et al.* (2009) tested for the presence of a herd effect in the Taiwanese market using the daily data of 18 sectors for the period 1995–2006. The results for the non-linear cross-sectional absolute deviation showed herding existence in 16 of the 18 sectors. When the data were restricted to up and down markets, the herding effect was found, although it appeared to be stronger during the falling market times.

Overall, there is a wide consensus in the literature that supports the belief that statistically significant herd behaviour can be easily identified in emerging markets rather than matured ones. For example, Zheng (2010), amongst others, investigated herd investors in a number of global stock markets (five developed, four Latin American, and nine Asian markets). Using daily data from the years 1989–2009, his findings supported the belief that herd behaviour are apparent in advanced countries, with the exception of the US. All 9 Asian markets support the herd phenomena, whereas no such phenomena is believed to exist in Latin American markets.

The Saudi stock market is still emerging and therefore still inefficient in terms of the transmission of information. For this reason, it is of interest that the existence of herd behaviour amongst individual investors in market be examined.

4.3.2 Modelling herd behaviour

During recent years, many different approaches for measuring herd behaviour in security markets have been proposed. The return dispersion model proposed by Christie and Huang (1995) is a commonly used method in empirical studies with the aim of detecting herd behaviour on stock returns; however, simply considering the return dispersion is not very informative; rather, more sophisticated methods of investigating herd behaviour have been proposed in the recent literature. In this section, we briefly review some of the procedures used in empirical works.

The Basic Model

Christie and Huang (1995) employed cross-sectional standard deviation (CSSD) with the objective to measure dispersion return. The authors argued that, in the presence of herd behaviour, individual investors suppress their own information and beliefs in favour of the market consensus, subsequently resulting in a more uniform change between individual security and total market return. Christie and Huang further calculated the cross-sectional standard deviations as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t} - R_{m,t}\right)^2}{N-1}}, \qquad (4.1)$$

where $R_{i,t}$ is the observed stock return on sector/firm i at time t and $R_{m,t}$ is the cross-sectional average/mean return of the N returns on all individual firms in the market portfolio at time t, and N is the number of stocks in the market.

A possible shortcoming of the cross-sectional standard deviation is that this measure of dispersion could be significantly affected by the existence of outliers (see Economou *et al.*, 2010). Chang, Cheng and Khorana (2000) instead proposed the use of a cross-sectional absolute deviation (CSAD). The calculation of CSAD is as follows:

$$CSAD_t = \frac{\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|}{N} \; . \qquad (4.2)$$

Chang, Cheng and Khorana (2000) investigated in their model whether or not equity return dispersions were significantly lower than average during periods of extreme market fluctuation. The CSAD of returns, as can be seen in Equation 4.2, was regressed against a constant and two dummies in order to identify the extreme market phases, as following:

$$CSAD_t = \alpha + b_1 D_t^L + b_2 D_t^U + \varepsilon_t \tag{4.3}$$

where $D_t^L = 1$, if the return on the aggregate market on day t lies in the *lower* tail of the return distribution; 0 otherwise, and $D_t^U = 1$, if the return on the aggregate market on day t lies in the *upper* tail of the return distribution; 0 otherwise.

The coefficient α indicates the average dispersion of the sample with the exclusion of the regions corresponding to the two dummy variables. A negative and statistically significant value of b_1 and b_2 suggests the presence of herd behaviour. If herding occurs, the CSAD will then be smaller during periods of market stress, i.e. returns on the individual sector would converge to the returns on the total market.

Model extensions: The model with non-linearity

There is wide consensus amongst the empirical literature that herd behaviour detected in financial markets exhibit certain non-linearity. Chang, Cheng and Khorana (2000) also proposed the following specification with the aim of detecting herd behaviour over the entire market return distribution:

$$CSAD_t = \alpha + \gamma_1 |R_{m.t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t\ , \tag{4.4}$$

where $CSAD_t$ is the cross-sectional absolute deviation of returns; $R_{m.t}$ is the average market/sector return.

The market return dispersion—markedly measured by cross-sectional absolute deviation from the market in Equation 4.4—usually has a positive, linear relationship with overall market returns, therefore implying that individual stock returns are dispersed when there is a large movement of the market return. Hence, γ_1 is expected to be significantly positive and linear in the context of normal market conditions.

However, in the presence of irrational market behaviour, such dispersions can be weakened as a result of increased correlations between individual stocks and the market index. Hence, if herd behaviour is not present, i.e. if γ_2 is not significant but is positive, this means that the dispersion between $CSAD_t$ and $R_{m.t}$ increases linearly. In the presence of herd behaviour, i.e. if γ_2 is statistically significant and negative, the relationship between $CSAD_t$ and $R_{m.t}$ is non-linear. Importantly, this means that the dispersion amongst asset returns will either increase at a decreasing rate or decrease in the case of severe herding (see Economou *et al.*, 2010 for further details).

Model Extensions: The model with asymmetry

Finally, Chang, Cheng and Khorana (2000) specified a model that enables one to control for an asymmetric relationship between CSAD and market returns, differentiating between the bull and bear markets. This is achieved through the use of two different models, as follows:

$$CSAD_t^{up} = \alpha + \gamma_t^{up} \mid R_{m,t}^{up} \mid + \gamma_2^{up} (R_{m,t}^{up})^2 + \varepsilon_t \ , \ R_{m,t} \geq 0 . \qquad (4.5)$$

$$CSAD_t^{down} = \alpha + \gamma_1^{down} \left| R_{m,t}^{down} \right| + \gamma_2^{down} \left(R_{m,t}^{down} \right)^2 + \varepsilon_t \ , R_{m,t} < 0 . \qquad (4.6)$$

In Equation 4.5 and Equation 4.6, the coefficients γ_2^{up} and γ_2^{down} are expected to be significantly different from zero and negative if herding is present in the market or sector. Moreover, $CSAD_t^{up}$ or $CSAD_t^{down}$ increases at decreasing rate, as mentioned earlier.

4.3.3 Related studies in structural break modelling

Aside from the herd behaviour of investors, market efficiency can be affected by poor or improper market structure; that is, if the entire system of a capital market itself is not functioning smoothly, it will then be difficult for market information to be transmitted efficiently amongst investors, firms, and the regulator. Therefore, it is of interest to test for structural breaks in the stock market. In order to do so in regard to the structural breaks of conditional volatility, the Markov switching model, proposed in Hamilton (1989), is commonly implemented.

The advantage of the Hamilton's approach is that the model is built in such way that it can capture discrete changes in a time series, and hence speculative behaviour in a stock market. The model can be used to investigate an asset return process by using different latent states or regimes[31].

In the literature, the Markov switching model has often been used to investigate switching in the mean equation; however, in some instances, the model was extended to investigate a shift in volatility, or both shifts in the mean and conditional variance equation.

For instance, Moore and Wang (2007) tested for regime-switching in five new EU member states, namely Czech Republic, Hungary, Poland, Slovenia, and Slovakia. Using weekly Monday closing prices from 1994 to 2006, the authors found two regimes for Czech Republic, Hungary, and Slovakia, whereas three regimes were found for Poland and Slovenia.

Chkili and Nguyen (2011) investigated the volatility behaviour of six Mediterranean stock markets (Spain, France, Greece, Egypt, Turkey, and Tunisia) through the implementation of Hamilton's (1989) model. The authors used weekly data for the period 1995–mid-2010. The result showed strong evidence of regime shifts in each of these markets. The volatility reported in the case of the high volatility regime was twice as much when compared with the volatility in the low regime in Greece, France, Spain, and Turkey; the same number is three times in Tunisia and four times in Egypt. The findings suggest that developed markets are less affected by international market events, such as the Asian and Russian financial crisis, than emerging markets (Tunisia and Egypt).

Wang and Theobald (2008) investigated the regime-switching volatility of six East Asian emerging markets in the period 1970–2004. The findings confirmed that Malaysia, Philippines, and Taiwan were all characterised by two regimes, whilst the markets in Indonesia, Korea, and Thailand were characterised by three regimes over the sample period.

[31] As an extension, bubbles can be investigated by a regime-switching model. For example, Brooks and Katsaris (2005), amongst others, define a regime-switching model with three states for dormant, explosive, and collapsed markets, respectively, for detecting speculative behaviour.

Similarly, Ismail and Isa (2008) employed a univariate two-regime Markov switching autoregressive model (MS-AR) with the objective to capture regime shift behaviour in both the mean and variance in four indices in the Malaysian stock market. Using monthly data between 1974 and 2003, it was found that the MS model was suitable for capturing the timing of regime shifts during the economic and financial crises, such the 1974 oil price shock, the 1987 stock market crash, and the 1997 Asian financial crisis.

In the next section, the Markov switching model, as suggested by Hamilton (1989), is introduced briefly, and subsequently used to investigate non-rational bubbles in the Saudi stock market. The reader is referred to the original article by Hamilton for further details.

4.3.4 Modelling of market structural changes

Consider a time series y_t, generated as an autoregression of order p with regime switching in mean and variance depending on the state variable, $S_t \in \{0,1,\ldots,K\}$, e.g :

$$y_t - \mu(S_t) = \sum_{i=1}^{p} \phi_i (y_{t-i} - \mu(S_{t-i})) + \sigma(S_t)\varepsilon_t\,,\ \varepsilon_t \sim \text{i.i.d.N}(0,1)\,. \quad (4.7)$$

The mean $\mu(S_t)$ and standard deviation $\sigma(S_t)$ depend on the regime at time t. and K is the number of states. The change from $S_{t-1} = i$ to $S_t = j$, e.g. the probability of moving from state i to state j at time t is only governed by a first-order Markov chain. Accordingly, the transition probability is only dependent on the state one period ago:

$$P(S_t = j \mid S_{t-1} = i) = p_{ij}\,,\ i, j \in \{0,1,\ldots,K\}$$

If we assume only two regimes, $S_t \in \{0,1\}$ for the simplest specification of the Markov regime switching model, then:

$$\mu(S_t) = \mu(S_t = 0) + \mu(S_t = 1), \quad (4.8)$$

$$\sigma^2(S_t) = \sigma^2(S_t = 0) + \sigma^2(S_t = 1). \quad (4.9)$$

The state S_t is unobserved and is assumed to follow a first order Markov process taking the values of 1 or 2, implying that the current state S_t ,, depends solely on the previous state, so that:

$$P(S_t = 0 \mid S_{t-1} = 0) = p_{00}, \tag{4.10}$$

$$P(S_t = 0 \mid S_{t-1} = 1) = p_{10} = 1 - p_{11}, \tag{4.11}$$

$$P(S_t = 1 \mid S_{t-1} = 0) = p_{01} = 1 - p_{00}, \tag{4.12}$$

$$P(S_t = 1 \mid S_{t-1} = 1) = p_{11}, \tag{4.13}$$

where $p_{00} + p_{10} + p_{01} + p_{11} = 1$.

The transition probability p_{10} gives the probability that state 1 will be followed by state 0. The transition probabilities p_{00} and p_{11} denote no change in a given state. In equation (4.10) – (4.13) the current state depends only on the state before.

Estimation of the transition probabilities p_{ij} can be obtained, together with other parameters μ, σ, ϕ of equation (4.7) using maximum likelihood method. This involves maximising the log likelihood function

$$\max Ln(\mu, \sigma, p, \phi \mid y_T) = \max \sum_{t=1}^{T} Ln\left(\sum_{j=1}^{s} \sum_{i}^{s} g(y_t | S_t = j, S_{t-1} = i, y_{t-1}) \times P(S_{t-1} = i \mid y_{t-1}) \right),$$

for the observations y_t, $t = 1...T$, where

$$g(y_t | S_t = j, S_{t-1} = i, y_{t-1}) = \frac{1}{\sqrt{2\pi}\sigma(S_t)} \times \exp\left(- \frac{\left(y_t - \mu(S_t) - \sum_{i=1}^{p} \phi_i (y_{t-i} - \mu(S_{t-i}))\right)^2}{2\sigma^2(S_t)} \right)$$

and $y_t - \mu(S_t) - \sum_{i=1}^{p} \phi_i (y_{t-i} - \mu(S_{t-i}))$ comes from the conditional information on residuals of equation (4.7).

In order to estimate a Markov regime-switching model, it is first important to define the proper number of states within which the time series under investigation can switch. Subsequently, one should test the null hypothesis of no shift against several states; however, such tests are not straightforward, and can be problematic owing to the presence of *nuisance parameters*, which are unspecified under the null. For example, the transition probabilities of a two-state Markov regime-switching model, p_{00} and p_{11}, are not identified under the null hypothesis of one state (no switching). As a result, the usual tests for constraint and unconstraint models, such as the likelihood ratio and Lagrange multiplier tests, do not have a standard asymptotic χ^2 distribution[32].

In literature, testing for this type of the null hypothesis in the presence of *nuisance parameters* concentrates on establishing an upper bound of the distribution of the test under the null hypothesis. This type of approach was first suggested by Davies (1977, 1987).

The Davies' test provides upper bound *p*-values, and thus the test itself is more conservative; however, the weakness associated with this approach is that it does not provide the asymptotic distribution of the test statistic. For this reason, other tests have been developed based on simulations. For example, Hansen (1992, 1996) proposes a method for calculating the Supremum of the likelihood ratio test through examining and approximating an empirical distribution of the standardised likelihood-ratio statistic, where the likelihood function is a function of the unknown parameters. Although the Hansen's approach (1992, 1996) is powerful, it is nevertheless recognised as time-consuming, and can be impractical in the application of large datasets. In particular, it is difficult to run sequential tests for Hansen's LR statistic as the number of hypotheses on different regime-switching can be explosive for multiple, unconstrained structural changes. Furthermore, it does not provide critical values[33]. Accordingly, we therefore apply the Davies approach for testing the number of appropriate regimes.

[32] See Davies (1977, 1987), Garcia (1998), Hansen (1992, 1996), and Gong and Mariano (1997) for more details.
[33] See Charfeddine and Guegan (2006) for more details.

4.4 Empirical results

The data set used in this study is collected directly from Saudi market company (Tadawul), and covers the period from January 1, 2002–April 4, 2008. The data set contains the daily closing prices of Saudi stock index (Tasi) and the daily closing prices of five sectors indices, namely Banks, Industrial, Cement, Service, and Agriculture. These five sector indices are chosen amongst eight indices in the Saudi market owing to data availability considerations. The total number of observations amounts to 1,781 per index.

4.4.1 Results of herd behaviour

In order to investigate the phenomenon of herd behaviour at an individual company level, daily closing prices of individual companies were considered. All individual banks were regressed against the Bank sector indices. The eight Cement companies and eight Agriculture companies were analysed in a similar way. The 13 largest companies from the Industrial sector were selected in this study where 17 individual companies were chosen in Service sector.

In this study, daily data are preferred to lower frequency data since, as suggested by Christie and Huang (1995), herding is a very short-lived phenomenon, and lower frequency data may not be able to capture the occurrence this behaviour. In a related study, Caporale *et al.* (2008) utilised daily and monthly data, subsequently establishing that the evidence of herding over daily time intervals was much stronger than at lower frequency data.

Table 4.1 reports the summary statistics of calculated $CSAD_t$ and equally weighted market return $R_{m.t}$ for all six indices. The first two columns (shaded area) show the descriptive statistics of the market at the aggregate level. The CSAD, as reported in the first column, is calculated for the general index on the basis of weighted average of the five sector indices. The rest of the table's columns report the statistics at an individual level, where CSAD calculated for each sector depends on the cross-sectional data for individual companies belonging to the sector.

Table 4.1. Descriptive statistics of cross-sectional absolute deviations.

	Tasi		Bank		Industrial		Cement		Service		Agriculture	
	CSAD	Index	CSAD	Index	CSAD	Index	CSAD	Index	CSAD	Index	CSAD	Index
Mean	0.0173	0.0004	0.0167	0.0006	0.0258	0.0012	0.0182	0.0004	0.0191	0.0006	0.0368	0.0011
Median	0.0116	0.0014	0.0123	0.0003	0.0199	0.0014	0.0120	0.0004	0.0127	0.0016	0.0293	0.0009
Max.	0.1385	0.9390	0.1114	0.0946	0.2245	0.0951	0.1704	0.0946	0.1173	0.0936	0.1472	0.0946
Mini.	0.0009	-0.1032	0.0019	-0.1004	0.0024	-0.1047	0.0019	-0.1044	0.0018	-0.1042	0.0033	-0.1048
S.D	0.0178	0.0182	0.0136	0.0152	0.0206	0.0215	0.0179	0.0186	0.0185	0.0244	0.0251	0.0313
Obs.	1780	2050	1665	1781	1598	1781	1712	1781	1683	1781	1606	1781

Note: CSADs for Tasi were calculated based on the weighted average of five sectors, and for individual index were calculated based on weighted average of its components.

From Table 4.1, the mean value of CSAD in the Agriculture sector is 0.0368, and appears to be the largest compared to those of the other four sectors as well as the general index. The Agriculture sector also reports the highest standard deviation of 0.025, followed by the Industrial and Services sectors; this can be explained by the large number of participants and high speculation in these sectors' companies during the study period owing to their compliance with Islamic *Sharia'a*.

The Banking and Cement sectors have the lowest CSAD mean values, as well as their standard deviations, which have resulted from their conflict with *Sharia'a*. On an aggregate level, CSAD of Tasi's mean and standard deviation, located in the middle between high and low sectors, indicate that the Tasi index is calculated as the weighted average of sectors' mean and standard deviations.

It should be noted that the standard deviations are roughly the same, and keep their values and ranks when calculated directly from the sector returns and when the sectors' CSAD are calculated.

Table 4.2 reports the regression results of the non-linear herd behaviour model for the general index (Tasi) and the five sectors' indices. From Table 4.2 it appears that: the coefficient of the absolute return, γ_1 in each regression is positive and statistically significant for all the sectors, even at the 1% level. These findings confirm the results highlighted in the related literature, which support that CSAD has a strong positive relationship with the absolute market/sector return, i.e. an increase in the absolute market returns results in an increase of CSADs.

Table 4. 2. Regression result for daily data (1st January, 2002 to 4th April, 2008).

$$CSAD_t = \alpha + \gamma_1 \left| R_{m.t} \right| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

	α	γ_1	γ_2	$\bar{R}^2$
Tasi	0.0074 (14.6)***	1.0016 (17.9)***	-2.1720 (-2.5)***	41%
Bank	0.0089 (26.6)***	0.9003 (21.2)***	-0.4349 (-0.61)	55%
Industrial	0.0144 (23.4)***	0.8164 (14.4)***	0.3644 (0.48)	45%
Cement	0.0075 (20.2)***	1.0444 (25.7)***	-1.4593 (-2.6)**	66%
Service	0.0063 (27.2)***	0.7459 (35.4)***	2.2332 (8.4)***	89%
Agriculture	0.019113 (31.4)***	0.8479 (18.2)***	-0.1229 (-0.23)	66%

***, **, and * indicate the significance levels at 1%, 5% and 10%, respectively.
(t-ratios in parentheses).

The coefficient of the squared market/sector return γ_2 is negative and significant for Tasi, indicating the presence of herd behaviour in the Saudi stock market at the aggregate level. A significant negative coefficient of squared returns leads to a smaller CSAD, implying that the underlying cross-sectional stocks move towards the same direction; that is, there is a higher correlation amongst individual sectors in Saudi market, resulting in the occurrence of herd behaviour. The resultant co-movement caused by such behaviours subsequently decrease—or even entirely eliminate—dispersion amongst five individual sector indices.

At a sector level, the coefficient γ_2—which represents the degree of return dispersion—is negative and statistically significant for the Cement sector only. In the Bank and Agriculture sectors, the coefficient it is negative, and not statistically significant. Moreover, the coefficient is neither negative nor statistically significant in the Industrial and Service sectors, thereby indicating the absence of herd behaviour in these sectors. The absence of herd behaviour in Industrial and Service sectors can be attributed to additional numbers of joint companies in these sectors during of the period under consideration. For example, in 2002, the number of joint companies in Industrial sector was just 24, whereas the number in the Service sector was 17. In 2006, the number of joint companies rose sharply to 32 for Industrial, and to

24 for Service. These numbers increased to 37 and 29 in 2008 for Industrial and Service respectively. Consequently, herd behaviour in these sectors are more difficult to detect.

In the case of the Agricultural sector, the number of joint companies did not change between 2002 and 2008. The number of companies in the Bank sector increased slightly from 9 to 10 during the same period; hence, this sector is considered to be one of the most stable sectors in the Saudi stock market.

The absence of herd behaviour in the Bank sector can be explained by contradiction with Islamic *Sharia'a* and less investors in this sector. Consequently, the relationship between market returns and stock return dispersion is difficult to detect. In the case of the Agricultural sector, the γ_2 coefficient is of the right sign, although it is statistically not significant. The lack of herd behaviour in the Agriculture can be attributed to two factors. Firstly, Agriculture is the most volatile sector in the Saudi market, and thus there can still be some outliers in the calculated return dispersions; hence, even during the high price movements, perceiving any changes in return tendencies remains difficult. Secondly, this sector attracts a huge number of market participants, providing better degree of diversification and lowering the relationship between returns and dispersion.

In order to better understand herd behaviour, we move to models that incorporate the asymmetric feature, where the herd behaviour is more likely to exist in different market conditions, i.e. bull and bear markets.

Table 4.3 reports the herding regression results under asymmetric market conditions with the use of CSAD as the dependent variable. Panel A refers to the herd behaviour during periods of a rising market, whereas Panel B is intended to capture the behaviour when the market is declining.

As noted previously, if the regression coefficients yield negative and statistically significant γ_2 estimates, herd behaviour is confirmed.

Table 4.3. Regression results of the daily cross-sectional absolute deviation during the market stress.

A. $CSAD_t^{up} = \alpha + \gamma_1^{up}\left|R_{m,t}^{up}\right| + \gamma_2^{up}\left(R_{m,t}^{up}\right)^2 + \varepsilon_t \,, R_{m,t} \geq 0$

	α	γ_1^{up}	γ_2^{up}	$\bar{R}^2$
Tasi	0.0029 (9.5)***	1.3216 (27.7)***	-8.6247 (-9.2)***	46%
Bank	0.0026 (11.7)***	1.5096 (28)***	-9.6113 (-10)***	66%
Industrial	0.0046 (11.1)***	1.5443 (28.3)***	-8.2964 (-9.3)***	55%
Cement	0.0024 (11)***	1.4405 (41.9)***	-6.6429 (-12)***	73%
Service	0.0019 (12.6)***	1.0833 (56)***	-1.7591 (-5.7)***	88%
Agriculture	0.0057 (13.9)***	1.6018 (34.8)***	-7.2564 (-11.9)***	73%

B. $CSAD_t^{down} = \alpha + \gamma_1^{down}\left|R_{m,t}^{down}\right| + \gamma_2^{down}\left(R_{m,t}^{down}\right)^2 + \varepsilon_t \,, R_{m,t} \prec 0$

	α	γ_1^{down}	γ_2^{down}	$\bar{R}^2$
Tasi	0.0015 (5.7)***	1.6099 (36.4)***	-8.2529 (-12)***	65%
Bank	0.0028 (13.6)***	1.4734 (38.6)***	-7.1200 (-11.3)***	69%
Industrial	0.0034 (10.9)***	1.5327 (35.4)***	-6.5189 (-10.7)***	69%
Cement	0.0023 (9.9)***	1.4766 (39)***	-5.4786 (-10.7)***	73%
Service	0.0016 (12)***	1.0357 (54.9)***	-0.5176 (-2.1)**	93%
Agriculture	0.0044 (12.8)***	1.7035 (42.2)***	-8.1622 (-16.4)***	79%

***, **, and * indicate the significance levels at 1%, 5% and 10%, respectively.
(t-ratios in parentheses).

It can be seen from Table 4.3 that the coefficient γ_2 is statistically significant in all estimated models, showing negative signs for all indices. This provides evidence of the existence of herd behaviour in the Saudi market at aggregate and sector levels. In other words, the returns on the sectors converge to the general returns of the Tasi index. This pattern of trading supports the herd behavioural phenomenon in the Saudi market. The same results are also found in the models for individual sectors. Table 4.3 also shows that, with the exception of Agriculture, the dispersion increases: the absolute values of γ_2 during periods of stress in an up-market condition are greater than those during circumstances of extreme down market.

The Wald test, as shown in Table 4.4, suggests that such coefficient differentials are significant as the null hypothesis $H_0 : \gamma_2^{up} - \gamma_2^{down} = 0$ can be rejected. It is interesting to note that, according to the Wald test, herd behaviour in the Agriculture sector is not present in up and down markets, which is consistent with the results for the Tasi. This is not surprising when considering that investors of the Agriculture sector are well diversified.

Table 4.4. Wald Test for asymmetry of herd behaviour.

$H_0 : \gamma_2^{up} - \gamma_2^{down} = 0$

	$\gamma_2^{up} - \gamma_2^{down}$	F-Stat.
Tasi	-0.37178	-0.399760 0.6894
Bank	-2.4913	7.848899 (0.0051)***
Industrial	-1.777544	4.006680 (0.0455)**
Cement	-1.164332	4.428712 (0.0355)**
Service	-1.241475	16.45043 0.0001
Agriculture	0.905744	2.238952 0.1348

4.4.2 Results of Markov switching model

In order to test for regime changes in the Saudi market, weekly data of the Tasi and five sector indices were used considering the fact that the weekly data is preferred owing to the presence of more noise at higher frequencies. The data comprises 356 observations for each index over the period spanning January 1, 2002–April 2, 2008.

Table 4.5 provides various descriptive statistics for the data under review. The weekly returns are small when compared with the standard deviation. All return series exhibit the pattern of left fat tails given the evidence of negative skewness and positive excess kurtosis. In addition, normal distribution for each index is strongly rejected by the Jarque-Bera test.

Table 4.5. Descriptive statistics of Saudi market six indices.

	Tasi	Bank	Industrial	Cement	Service	Agriculture
Mean	0.0037	0.0029	0.0057	0.0022	0.0030	0.0052
Maxi.	0.1414	0.1224	0.1615	0.1419	0.2148	0.3399
Mini.	-0.2356	-0.1519	-0.2246	-0.2898	-0.4561	-0.4644
Std.Dev.	0.0439	0.0357	0.0512	0.0418	0.0594	0.0814
Skewness	-1.7476	-0.6127	-0.9970	-1.5053	-2.1318	-1.2262
Kurtosis	10.1309	6.4949	6.6776	13.3343	15.8047	10.0924
J.Bera	932.878	202.895	258.865	1713.796	2694.122	833.028
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

With respect to individual sectors, the Agricultural sector exhibits the greatest volatility, followed by the Service and Industrial sectors. From Table 4.5, it appears that, on average, weekly means are rather small for all sectors, ranging from 0.29% to 0.57%; however, the Industrial sector has the largest mean followed by the Agricultural sector. For all series, Skewness is negative, which is consistent with the typical stock return distributions, which are fat tailed and left skewed.

In order to investigate any potential non-linearity in each of the indexes. the Markov switching process was assumed to be driven by shifts either in the mean, variance, or a combination of both. The number of regime shifts was decided on the basis of the ratio $LR = 2(\log(L_{ms}) - \log(L_{linear}))$ with the critical values calculated by Davies (1987).[34] For an estimated regime switching model, the structural changes were further investigated by testing the regime-switch in the mean and/or the variance using the Wald's test.

[34] For details, see Wang and Theobald (2008).

In an attempt to determine the correct lag specification of the model, the usual diagnostic tests on the estimated residuals, such as the normality (J-B), ARCH and Portmanteau (Autocorrelation) tests, were carried out.

Table 4.6 reports the estimates generated from a two-state Markov switching variance model (S=2) for all six Saudi stock market indices. The ϕ_p terms indicate the number of lags selected on the basis of serial correlation tests. From this test, it appears that the appropriate number of lags differs amongst stock indices considered: the Cement sector and Tasi show no autocorrelation, whereas the Industrial and Agriculture sectors have one lag. Finally, two lags are used for the regime-switch model for both the Bank and Service sectors.

Table 4.6. Two-states model estimates for Saudi market six indices.

	Tasi	Bank	Industrial	Cement	Service	Agriculture
ϕ_0	—	0.1539	0.1077	—	0.1607	0.1373
		(0.010)	(0.053)		(0.001)	(0.011)
ϕ_1	—	0.0924	—	—	0.1165	—
		(0.055)			(0.032)	
μ_0	-0.0233	0.0000	0.0040	-0.0005	-0.0284	-0.0045
	(0.066)	(0.994)	(0.507)	(0.948)	(0.095)	(0.769)
μ_1	0.0097	0.0035	0.0060	0.0033	0.0085	0.0077
	(0.000)	(0.006)	(0.005)	(0.011)	(0.000)	(0.002)
σ_0	0.0844	0.0529	0.0725	0.0719	0.1237	0.1437
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ_1	0.0241	0.0163	0.0233	0.0180	0.0299	0.0367
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p_{0|0}	0.8507	0.9175	0.9226	0.8816	0.8489	0.9104
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p_{0|1}	0.0334	0.0535	0.0621	0.0488	0.0308	0.0318
	(0.035)	(0.007)	(0.021)	(0.011)	(0.017)	(0.014)
L-L(2)	703.8	754.1	611	733.7	615.9	503.2
LR-test	195.92	142.06	122.62	220.31	238.38	226.28
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

L-L(2) is the log likelihood value from the two-state model. LR is the likelihood ratio test of one-state against two-state. The number in the square bracket is the Davies (1987) upper bound *p*-value.

In Table 4.6, the second and third rows report the constant term μ_s, followed by σ_s. The probability of being in regime 0 or 1 is given in the seventh and eighth rows, followed by log likelihood value for the two-state model. The likelihood ratio test statistics in the last row compares a one-state model against a two-state model, with all recognised as significant, therefore suggesting that a two-regime model is preferred. Of the two states, *St* = 0 indicates a low-mean and high-variance regime (bear market), whereas the state *St* =1 suggests high-mean, low-variance state (bull market).

Furthermore, Table 4.7 reports the estimated results of the three-state Markov switching-variance model (S=3). Markedly, it should be noted the last two rows of the table respectively show both the log likelihood value from the four-state model and the corresponding *p*-value of the Davies (1987) test statistic of four regimes against the null hypothesis of three states.

Table 4.7. Three-states model estimates for Saudi market six indices.

	Tasi	Bank	Industrial	Cement	Service	Agriculture
ϕ_0	—	0.0725	0.0430	—	0.1011	0.0951
		(0.266)	(0.456)		(0.055)	(0.088)
ϕ_1	—	0.0589	—	—	0.1388	—
		(0.186)			(0.010)	
μ_0	-0.0337	-0.0027	-0.0234	-0.0069	-0.0410	-0.0096
	(0.020)	(0.609)	(0.084)	(0.484)	(0.052)	(0.602)
μ_1	0.0138	-0.0022	-0.0009	-7.3e-005	0.0035	-0.0014
	(0.000)	(0.241)	(0.765)	(0.955)	(0.090)	(0.674)
μ_2	0.0028	0.0153	0.0178	0.0094	0.0139	0.0145
	(0.106)	(0.045)	(0.000)	(0.008)	(0.001)	(0.009)
σ_0	0.0884	0.0548	0.0901	0.0791	0.1327	0.1487
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ_1	0.0291	0.0113	0.0153	0.0111	0.0211	0.0153
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)
σ_2	0.0126	0.0192	0.0361	0.0281	0.0377	0.0452
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p_{0|0}	0.8167	0.9074	0.8271	0.8913	0.7962	0.9019
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p_{1|0}	—	0.0545	—	—	—	—
		(0.200)				
p_{0|1}	0.0479	—	—	—	—	—
	(0.035)					
p_{1|1}	0.917753	0.7654	0.9048	0.8716	0.9738	0.6841
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)
p_{0|2}	—	0.1200	0.0580	0.0594	0.0591	0.0461
		(0.059)	(0.036)	(0.034)	(0.018)	(0.027)
p_{1|2}	0.0762612	0.2434	0.0364	0.1248	0.0169	0.1522
	(0.035)	(0.122)	(0.307)	(0.049)	(0.242)	(0.160)
L_L(3)	726.1	762	629	751.8	633.4	515.3
LR-test(3 against2)	44.6	15.8	36	36.2	35	24.2
	[0.000]	[0.137]	[0.000]	[0.000]	[0.000]	[0.002]
*L_L(4)	729.5	—	629.49	756.2	637.9	525.9
LR-test(4 against3)	6.8	—	0.98	8.8	9	21.2
	[1.000]	—	[1.000]	[0.944]	[0.241]	[0.006]

L_L(3),is the log likelihood value from the three-state model.. LR is the likelihood ratio test of the two-state against three-state. The number in the square bracket is the Davies (1987) upper bound *p*-value. *L_L(4), is the log likelihood value from the four-state model.*LR is the likelihood ratio test of three-state against four-state. The number in the square bracket is the Davies (1987) upper bound *p*-value.

The diagnostic test statistics of the derived two-regime switching models are reported in tables 4.8 and 4.9, highlighting that both the two and three-state Markov switching variances satisfy the common diagnostic criteria for models, indicating the adequacy of the model specification. The ARCH (1, 1) test statistics show that there is no one-lag autoregressive conditional heteroscedasticity for residuals in both tables. Results from the Portmanteau test statistics for serial correlation in residuals suggest that there is no significant serial correlation in residuals at the 5% level. Importantly, tests for normality based on residuals are satisfied at the 5% level, with the exception of the Agricultural sector. In the case of the Agricultural sector, where three volatility regimes are found, the normality assumption does not hold; this may be attributed by either abnormal returns in this sector or the existence of outliers. Moreover, the failure of normality test may indicate that this sector is potentially more volatile and affected by other exogenous variables not captured in the model.

Table 4.8. Two regimes diagnostic test.

	Tasi	Bank	Industrial	Cement	Service	Agriculture
Normality	1.6614	0.47103	2.1719	4.7061	0.84503	0.96339
	[0.4357]	[0.7902]	[0.3376]	[0.0951]	[0.6554]	[0.6177]
ARCH test	1.1198	0.14322	1.5767	0.99949	0.14745	0.11805
	[0.2907]	[0.7053]	[0.2101]	[0.3181]	[0.7012]	[0.7314]
Portmanteau	14.003	17.556	15.045	18.864	16.513	13.988
	[0.7289]	[0.3505]	[0.5922]	[0.4002]	[0.4178]	[0.6680]

Marginal significance levels are in square brackets.

Table 4.9. Three regimes diagnostic test.

	Tasi	Bank	Industrial	Cement	Service	Agriculture
Normality	2.6955	5.3554	2.8419	4.1761	4.1211	13.679
	[0.259]	[0.068]	[0.241]	[0.123]	[0.127]	[0.001]**
ARCH test	0.1170	0.3652	0.1278	3.2870	1.3364	1.3562
	[0.732]	[0.546]	[0.720]	[0.070]	[0.248]	[0.245]
Portmanteau	12.335	18.911	13.865	17.801	15.580	14.344
	[0.829]	[0.273]	[0.676]	[0.468]	[0.482]	[0.642]

Marginal significance levels are in square brackets.

The diagnostic tests suggest that the two- or three-state Markov switching models provide a reasonable approximation of the heteroscedasticity in weekly stock returns for all six indices. Overall, all of the regime-switching models are not mis-specified. Table 4.6 also shows that a single state model (S=1) is always rejected in favour of multiple regimes for all six indices. All LR-test results are highly statistically significant for levels of 1% significance. Thus, there is no need to estimate S=1. The choice for all indices will be between *S* = 2 and higher specifications.

Combing the LR test statistics in Table 4.6 and Table 4.7, and the diagnostic tests of Tables 4.8 and 4.9, it becomes apparent that the bank sector should be modelled as a two-regime model as the LR test is unable to reject the null of two states. In addition, it appears that a four-state model is favoured by Davies LR test for the Agriculture sector; however, a four-state model will result in more complicated structural breaks for this sector. Furthermore, two of the four regimes are almost the same in terms of drifts and variances, and the non-normality in the residuals of the three-state model proves that this sector is more volatile. Hence, the most appropriate number of regimes for the Agriculture sector is three.

Finally, shifts of structural breaks in the mean and/or variance are tested by the general Wald's statistic for the best Markov switching model of each index. The results are reported in Table 4.10.

Table 4.10. Wald test for regime switching in mean and variance.

		Tasi	Bank	Industrial	Cement	Service	Agriculture
No. of regimes		3	2	3	3	3	3
Mean switching	μ_d^{01}	10.3871 [0.0013] **	0.483775 [0.4867]	2.75173 [0.0971]	0.453064 [0.5009]	4.42758 [0.0354] *	0.088449 [0.7662]
	μ_d^{02}	6.19639 [0.0128] *	-----	7.71031 [0.0055] **	2.09181 [0.1481]	6.42954 [0.0112] *	1.40002 [0.2367]
	μ_d^{12}	12.1895 [0.0005] **	-----	17.7087 [0.0000] **	5.96266 [0.0146] *	5.19023 [0.0227] *	10.5392 [0.0012] **
Variance switching	σ_d^{01}	35.6324 [0.0000] **	95.7733 [0.0000] **	61.8714 [0.0000] **	83.9467 [0.0000] **	42.1802 [0.0000] **	103.351 [0.0000] **
	σ_d^{02}	54.5464 [0.0000] **	-----	32.4671 [0.0000] **	46.1803 [0.0000] **	33.0506 [0.0000] **	66.8316 [0.0000] **
	σ_d^{12}	51.3555 [0.0000] **	-----	45.6912 [0.0000] **	28.3945 [0.0000] **	24.0548 [0.0000] **	57.0253 [0.0000] **

Note: μ_d^{XY} and σ_d^{XY} are mean and variance differential between the state X and Y, respectively. *P*-values are given in brackets. The asterisks ** and * denote statistically significant at the levels of 1% and 5%, respectively.

It is obvious that, within the Bank sector, although the high (5.29%) and low (1.63%) volatile states are significantly different, the corresponding means—low (0.0%) and high (0.35%)—are not statistically distinct, implying that no switching in the mean exists. Further, there are some interesting finding based on this table: first, it is not suspiring that all pair-wise variance are statistically significant different, even at the 1% level, therefore suggesting that the variance switching is the main driver of structural breaks and volatility of each regime is not the same as that of the other; secondly, only the general stock index and the Service sector exhibit strong mean switching across all three regimes, which are statistically significant at the 5% level. The Wald test suggests that there are distinct drifts in each of three dynamic regimes—bull, bear and flatted markets—and the corresponding weekly drifts are 1.38%, 0.28%, -3.37% and 1.39%, 0.35%, –4.10%, respectively for both Tasi and Service. Overall, these figures are quite similar in relation to the two indices. With this in mind, it should be noted that the Service sector is the largest sector in the Saudi market, constituting approximately 50% of the general index (Tasi). As discussed by Brooks and Katsaris (2005), if a return series exhibits any bubble behaviour, then three distinct regimes must be detected; therefore, it can be stated that these two sectors in the Saudi market have possibly experienced a bubble effect.

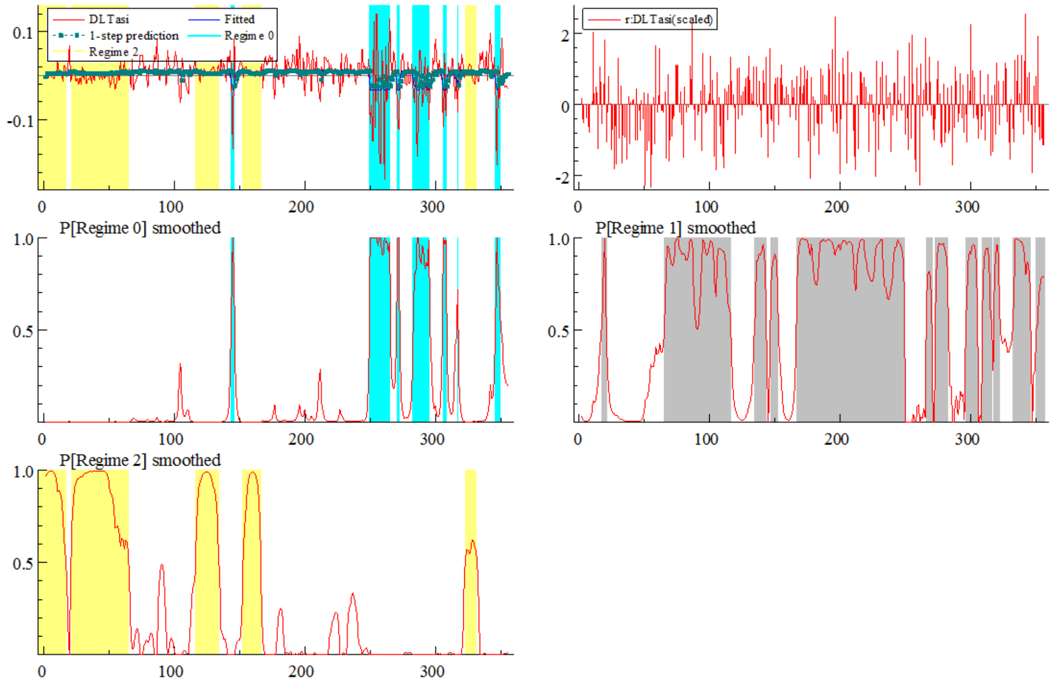
Thirdly, Cement and Agriculture sectors share the same mean switching pattern owing to the fact that there are only significant positive drifts (0.94% and 1.45%, respectively) under the market condition of moderate volatility (2.81% and 4.52%, respectively).

Lastly, there are only two significant constants amongst three states in the Industrial sector—the low (-0.09%) and high (1.78%) means, respectively corresponding to the low (1.53%) and moderate (3.61%) variances.

The interpretation and implications of the estimation result for each index based on the optimal number of regimes are discussed below.

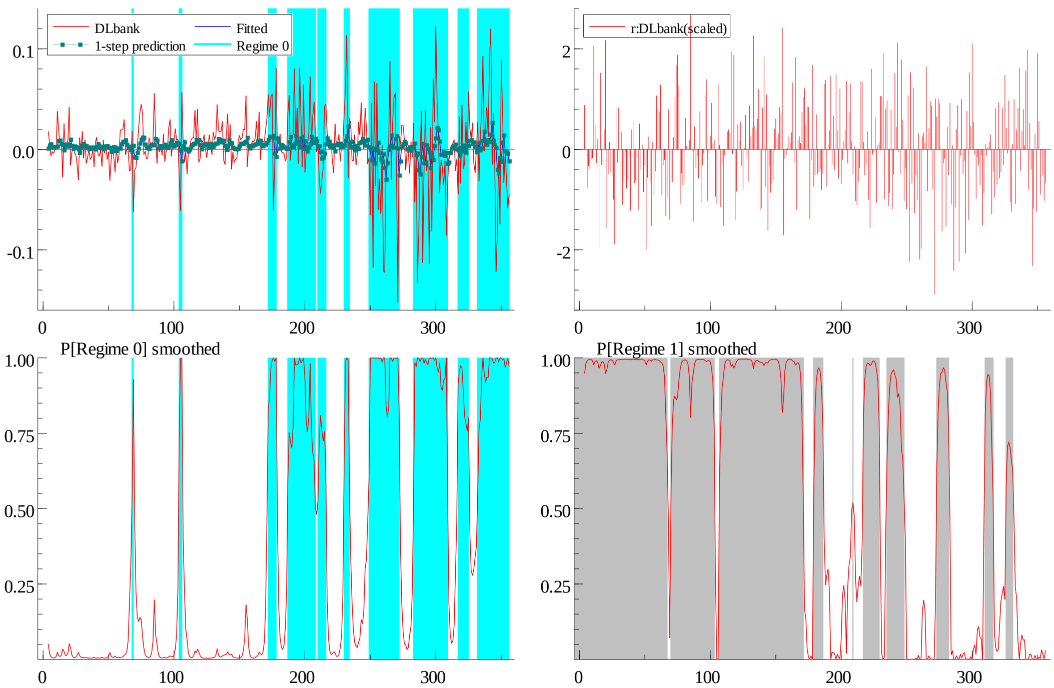
For the Tasi, a nonlinear switching model of three regimes with no lag term is chosen. The estimates show that there are strong changes in both the mean and the variance of each states, and if the entire period is classified as bear, bull and flat markets, the corresponding mean–volatility pair are then (-3.37%, 8.84%), (1.38%, 2.91%) and (0.28%, 1.26%), respectively. These indicate that the general market is more volatile in down trends, and less so when the sentiment is getting better, which is reasonable concerning the practice periods of high volatility being often linked to falling markets. In terms of risk persistence, the probability of the next step remaining in the current state is 81.67%, 91.78% and 92.37%, for the high, medium and low volatile states respectively, although a flatted market is more likely to move to the bear state compared with the bull market when considering the transitory probability of 4.80% vs. 3.43%. This assertion is supported by Figure 4.5, where the high volatility of return is clearly seen during the period 2005–February 2006, when the bubble burst. The medium volatility of return dominates most of this period, particularly from mid-2003 onwards. In addition, the low volatility can be seen from the beginning of this study period in 2002 until mid-2003. Markedly, it appears that the low volatility regime of Saudi market did not return, and indeed the overall volatility has increased.

Figure 4.5. Tasi regime-switching.



The nonlinearity characteristic in the Bank sector is quite straightforward as it favours a two-regime model with two lags in the autoregressive terms. Combined with Wald test in Table 4.10, a two-regime-switching model with no mean changes suggests that this sector can be either volatile (5.29%) or tranquil (1.63%). Moreover, the probabilities indicate that the transition from the tranquil to the volatile state is 5.35% and 8.25%. Figure 4.6 demonstrates that high volatility concentrates during the market boom period around observation 200 and thereafter; notably, this is where the low volatility is concentrated in the earlier period from the beginning of the period to mid-2004. This specification for the Banking sector is expected and reasonable when considering that Banking is the more stable sector in the Saudi market in terms of unconditional volatility. Moreover, this sector is considered unlawful from a *Sharia'a* perspective, which would make it less favourable for Saudi investors. Furthermore, when compared with the nonlinear model for the other five indices and the reported standard deviation in Table 4.5, both the variance figures and transition likelihoods provide evidence to support that the Bank sector is not only less risky but also less volatility persistency.

Figure 4.6. Bank regime-switching.



For both the Industrial and Cement sectors, a three-state model is selected for the non-linearity of the associated returns. From Figure 4.7 and Figure 4.8, it can be seen that such sectors demonstrate the dominance of medium volatility for most of the study period, and therefore are relatively riskier in comparison to the Bank sector. High volatility dominates the quarter before the bubble burst; on the other hand, low volatility in these sectors at the beginning of the study period data, i.e. prior to mid-2003, suggests that the appetite for risk in both sectors was between low to medium regimes initially, and then medium to high afterwards.

Specifically, the volatilities for the Industry sector were 9.01%, 3.61% and 1.53% for high, medium and low states, respectively. For the Cement sector, this was 7.91%, 2.81% and 1.11% for the same states, respectively. In terms of the probability of transition across the three regimes, slight differences exist. The probability of the Industry sector remaining in the high volatility state is 82.7%, whereas it is 89.1% for Cement. In comparison, the probability of Industry and Cement remaining in their low volatility state was 90.5% and 87.1%, respectively. Finally, the chance of moving from medium to low volatility is 10.5% for Cement and only 3.6% for the Industrial sector, therefore indicating that the Cement sector is less volatile when compared with the Industrial sector.

Figure 4.7. Industrial regime-switching.

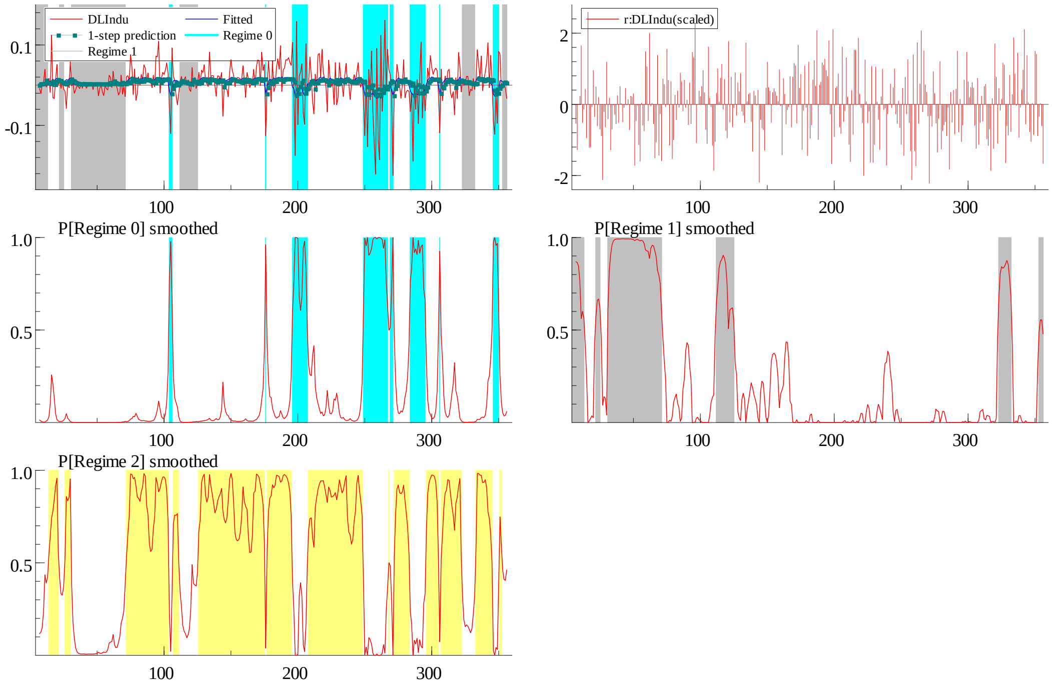
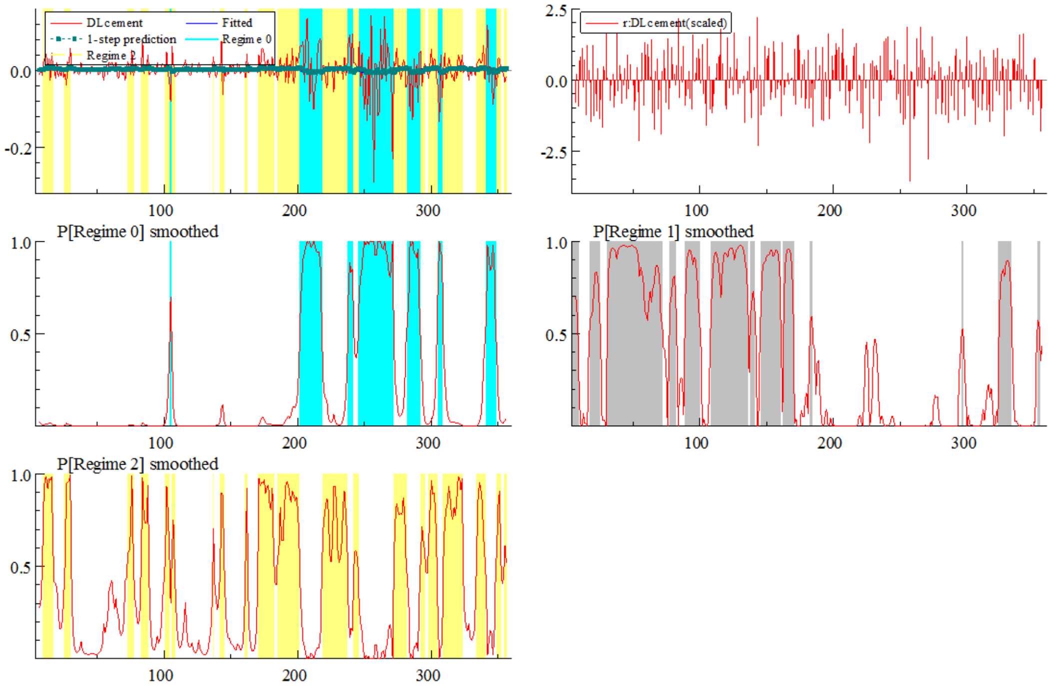


Figure 4.8. Cement regime-switching.



The Service and Agricultural sectors are the most volatile in terms of unconditional standard deviations. This finding can be confirmed when considering their three-regime-switching models.

In Table 4.7, these sectors also have the largest variances for all three regimes when contrasted alongside all other indices. The average volatility in the high regime are 13.27% and 14.87% for the high risk periods. It is noted that high volatility starts early in these sectors: for example, the high volatility starts in 2003 (observation 100), and arises again in 2004 (observation 150), then remained during the market run up to 2005 and early 2006. It is also noticeable that there has been volatility since the mid-2004 interchange between high and medium volatilities, without the low volatility state being touched since this period (from observation 200 onward).

The Agriculture sector is even more volatile than the Service sector. Indeed, the probability of remaining highly volatile regime is 90.2% for Agriculture and 79.6% for the Service sector, which keenly indicates that the former is more likely than the latter to stay in the risky state. This is also consistent with the probability of staying in the low volatility state, where the probability of being low and staying low is found to be 97.4% in the Service sector, and 68.4% in the agricultural sector. Overall, both sectors fluctuate between high and medium volatilities for most of the period, which confirms our findings in the previous paper where the Agriculture index was found to be the most volatile sector in the Saudi stock market, followed by Service sector.

The main difference between the two indices can be that there is no obvious drift change in regimes of the Agriculture sector, where no significant negative return means are observed during the high-volatility regimes. For the Service sector, as would be expected, the higher the regime volatility, the more likely the negative regime mean.

Figure 4.9. Service regime-switching.

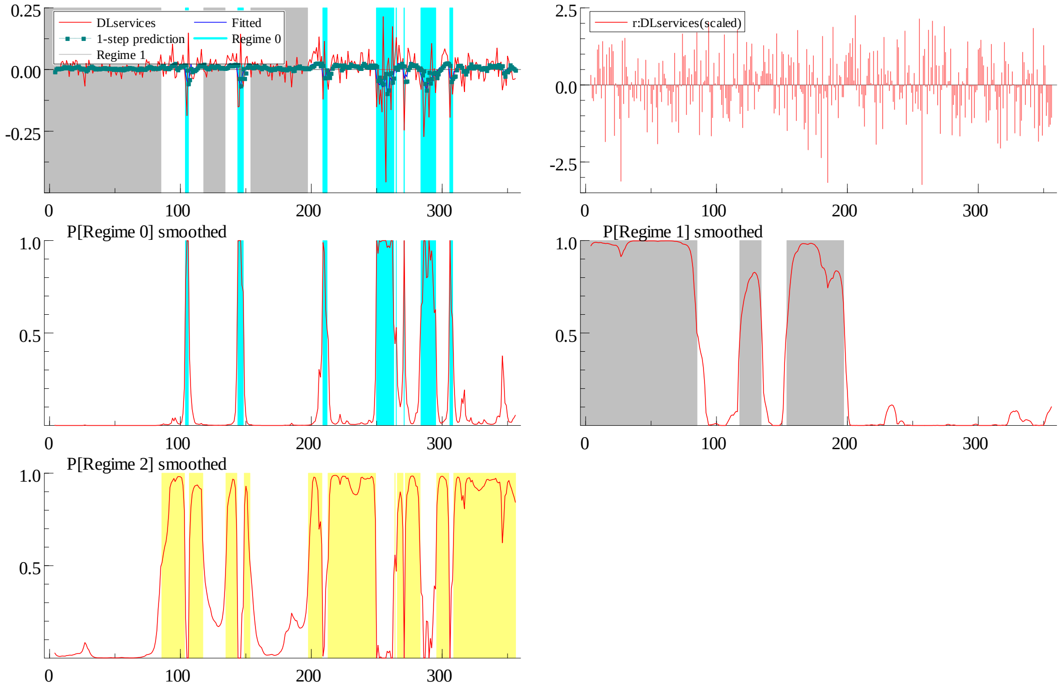
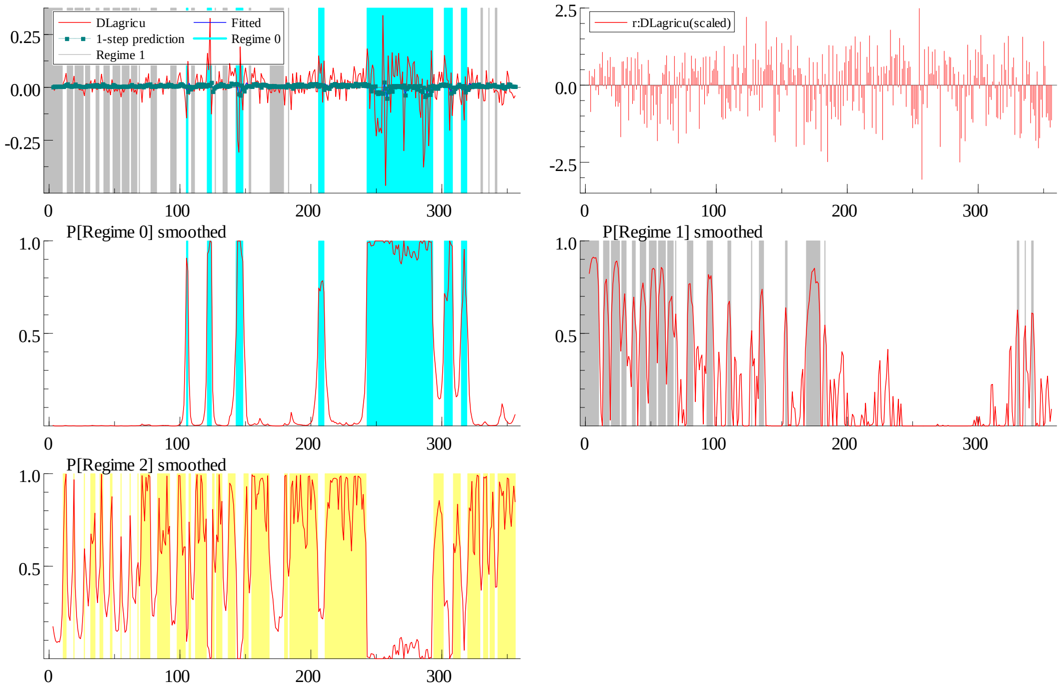


Figure 4.10. Agriculture regime-switching.



4.5 Conclusion

Herd behaviour is a well-known phenomenon in emerging markets, and can be used to explain the failure of efficient market hypothesis. Herd behaviour emerges from a lack of experience of the market participants or an altogether absence of institutional investment, as well as a lack of supervision and unequal information in such markets, all of which play an important role. The structure of emerging markets is often immature and unstable, and is therefore expected to shift over time. Hence, if EMH is rejected, an investigation of the potential structural breaks can reveal better understanding into the ways in which the market structure has changed.

In this chapter, both herd behaviour and market regime-switching in the Saudi stock market have been examined with the use of the closing prices of five individual indices, along with a general index. The result shows the existence of herd behaviour at an aggregate for the Tasi. A similar result is found for the Cement sector. However, no clear results are reported for the remaining individual sectors.

Under asymmetric market conditions, our results confirm the existence of herd behaviour in both market stresses up or down. Furthermore, the dispersion (calculated by absolute values of the coefficient of the squared return) increases during periods of stress in an up-market condition, with this level of dispersion recognised as being greater than that found during extreme down-market conditions. This result may be explained by the tendency of investors to take any opportunity to make gains during rising market conditions, in addition to their resistance to escape from the market during falls. However, this was not the case for the Agricultural sector, which was flooded by investors during all market conditions.

The regime switching model results show that three regimes are preferred to two regimes in the general index, as well as Industrial, Cement, and Service sectors. In most cases, the volatility began at relatively low levels at the beginning of the study period, subsequently fluctuating between high and medium volatilities without returning to low volatility. In the Bank sector, two regimes are preferred over three regimes.

The finding is supported by the *haram* and *halal* norms that affect investors' behaviour in the Saudi stock market. Finally, as indicated earlier, the Agriculture sector is the most volatile amongst six Saudi market indices, where the probability of remaining in a highly volatile regime in this sector is 90.2%. This finding is also supported by the *halal* norm, which makes the Agriculture sector the most preferred sector in the Saudi market in which to invest or speculate.

Chapter 5

Summary and Conclusions

5.1 Final remarks

The traditional efficient market hypothesis (EMH) was widely accepted in the literature after the publication of influential survey articles by Fama (1965, 1970). If the market efficiency holds, then any new information able to influence stock prices to rise or fall will be reflected immediately in the prices of those stocks. Since new information is unpredictable, stock market prices must be unpredictable under EMH, thus leading to stock returns following a random walk model.

In this context, this thesis examines the stock market efficiency in Saudi Arabia, which has recently undergone a series of market reforms and regulations. Such transformations were intended to improve market efficiency, and their impacts should be tested. Furthermore, it is not surprising that Islamic stock markets—such as that of Saudi—are inevitably influenced by their unique characteristics, i.e. *riba*-prohibition, Ramadan seasonality, and the immaturity of individual investors. Hence, the main objective of the thesis was to undertake a thorough investigation of the Saudi equity market in connection with Efficient Market Hypothesis and, in particular, the market efficiency related to various unique Islamic characteristics that may explain the failure of the market efficiency.

In order to understand the impact of regulation on the market efficiency of the Saudi stock market over time, we use the post-boom data after-market regulations. Traditional EMH tests, such as tests for serial correlation, variance ratio, runs test and filter rule, and other econometric models, i.e. co-integration tests, are first deployed. An empirical evaluation of the impact of regulation in the post-2001 period on the efficiency of the Saudi market was presented. Data from a total of 50 individual joint companies and five sector indices, trading over a seven-year period, were used in this study to determine the efficiency of the Saudi stock market. The sample was further divided into two sub-samples in order to detect the effect of the regulation that took place during this period.

Several important findings can be summarised from these tests. Comparing the findings of the existing literature, i.e. pre-2001, prior to regulations taking place, shows that, in the post-2001 period, there is a significant improvement in the efficiency of the Saudi stock market. Furthermore, evidence of market efficiency was also observed in the first sub-period (2002–2005) of the new era (post-2001), where most regulator activities were taking shape. Consequently, the Saudi market performance was more stable during this first sub-period compared with the second sub-period of post-2005. This is not surprising if one takes into account what the Saudi market experienced at the beginning of 2006; the instability during this second period may be attributed to the 'bubble' effect observed in the second sub-period. However, overall, the results reject the EMH in the Saudi capital market.

The invalidity of EMH in the Saudi stock market leads us to investigate the role of Islamic laws, which have been largely neglected by previous literature. First, we take into account the Islamic *Sharia'a* effect on sector volatility. Saudi Arabia's social, political and economic activities are rooted firmly in Islamic principles. For example, trading in *halal* (allowed) and *mixed* sectors are more active than the *haram* (forbidden), such as Banking. In order to assess the impact of Islamic rules in each of the business sectors, a parsimonious Multivariate Generalised AutoRegressive Conditional Heteroscedastic (MGARCH) (1, 1) model, a diagonal Baba-Engle-Kraft-Kroner (1990) (BEKK) is applied to study the innovation transmission degrees, as well as the persistence in conditional volatility transmission, or the GARCH effect. In addition, the Ramadan effect under post-boom data is modelled by the GARCH (1, 1) model, with Ramadan as a dummy variable.

The results of the BEKK-MGARCH indicate all sectors report significant autoregressive return volatilities. Furthermore, in all five sectors, the own-mean spill-overs are found to be positive reflecting the positive direction of the Saudi stock market during the time of the study under consideration. Notably, however, as far as conditional covariance of the five sectors are concerned, only two sectors—namely Cement and Agriculture—are affected by lagged returns of other sectors, whereas the Banking sector is independent and isolated from all other *mixed* and *Sharia'a*-complaint sectors in terms of cross- return spill-overs, thus indicating little influence of the sector on the entire equity market.

Regarding the variance equations of the multivariate GARCH model, the conditional variance persistence is found to be the most significant in the Agriculture sector, whereas the smallest volatility is in the Cement and Banking sectors. Overall, the volatility persistence ranges from *halal* to *mixed* to *haram* sectors, respectively. This can be attributed to the continuity of trading/investing in *halal* sectors in all market events or circumstance that prolong the persistency in these sectors. In contrast, the persistency in the *haram* sectors falls quickly due to less demand and less trading during the shock associated with such sectors. Importantly, the results of the univariate GARCH models reveal that the Ramadan effect in terms of volatility is significant for the Banking, Cement and Industrial sectors, although its impact on mean returns is little.

Evidence shows that noise traders have flooded into the Saudi stock market post-2001, and hence the herd behaviour of investors—which can be used to explain abnormalities of EMH—is tested for the Saudi market and its five underlying sectors. More specifically, the bubble effect—notably caused by herd behaviour—is investigated by two models: a cross-sectional absolute deviation model (CSAD) for both the bull and bear markets, and a Markov regime switching (MRS) model, where any stochastic bubbles can be assumed to display a particular kind of regime-switching. The CSAD model is straightforward for modelling asymmetric, irrational herd behaviour, whereas the MRS model is able to reveal not only whether a bubble is expected to either persistently grow or collapse within the same state, but also the degree of complexity of volatility persistence caused by any structural changes.

The empirical results of the CSAD model suggest the presence of symmetric herd behaviour for Tasi, whereas in the five major sectors, only Cement has such significant behaviour at the sector level. However, asymmetric return dispersions, particularly in the bull market, are more apparent for the general and sectoral indices, with the exception of Agriculture, which has greater herd behaviour in the bear market.

The complexity nature of high volatility in Saudi stock market is confirmed by the MRS model. This is owing to the fact that five out six indices—namely Tasi, Cement, Industrial, Service and Agriculture—prefer three volatility regimes, although only two volatility states are chosen by the Banking index. Furthermore, both the Tasi index and the Service sector can potentially exhibit some degree of speculative behaviour, where significant switching in both the means and variances of each three regimes are observed. Finally, the Agriculture sector is found to be the most volatile amongst the six Saudi market indices; its probability of remaining in a highly volatile regime is highest at 90.2%, consistent with our previous findings, i.e. the *halal* norm that makes the Agriculture sector the most preferred sector to invest or speculate in the Saudi stock market.

5.2 Contributions of the research

Taking into consideration the unique characteristic of Islamic law, this thesis examines the Saudi stock market against its market efficiency during the reforms period, where new regulations have been implemented. This is the first time such an approach has been implemented. More specifically, the contributions of this thesis to the literature are as follows.

Firstly, to the best of our knowledge, this is the first known full study carried out on this subject for the Saudi stock market in the context of Islamic rules. Specifically, since the weak form of Fama's Market Efficiency Hypothesis (EMH) is not generally accepted in Saudi, the thesis deploys various volatility models, namely GARCH and Markov regime switching models, as well as a herd behaviour model with the objective to predict stock returns for major indices, taking into account the role of Islamic religion.

Secondly, this study is useful for academics, policy makers, and investors—both at home and abroad. For example, researchers can compare this emerging stock market against other developing ones, and even matured markets. The government and regulatory bodies can empirically verify whether their market reforms have progressed as they would expect; market participants are likely to achieve a deeper understanding if the market is efficient, and may then understand which sector is better rewarded on the basis of risk-adjusted returns.

Finally, as the Saudi stock market has opened its equity market—partially, at least—to foreign investors, it may also be useful for international organisations and foreign investors who seek to invest in the emerging capital markets of Islamic countries.

5.3 Suggestions for further research

This thesis aims to test capital market efficiency in Saudi Arabia under the new regulations that have replaced the decades of old ones. In particular, unique Islamic characteristics and abnormal factors, such as religion, seasonality, and irrational investors' behaviour, are all taken into account in regard to modelling returns on major indices. Consequently, a number of interesting issues derived from the thesis can be addressed: for example, the data considered here are from the Saudi stock market only, and both Islamic laws and behaviour of irrational investors are known to affect the market volatility and hence the market efficiency;

therefore, a natural question is whether or not the conclusion can be supported by peripheral capital markets around Saudi, such as Dubai, Kuwait and Qatar, all of which notably share the same culture and religion.

One further issue concerns the influence from international capital markets. This research is conducted the international background of an influx of the oil capital and repatriation money, trigged by the 9/11 terrorism attack, as well as market regulation. If they contribute to market efficiency and volatility behaviour in Saudi, then it may be of interest to investigate whether or not there is a direct impact on the domestic market from foreign stock markets, such as European and the US equity markets. If such international markets are recognised as being explicit exogenous factors in the modelling, then foreign market influence can be directly addressed.

Lastly, as mentioned in Chapter 2, market efficiency can be tested on the basis of risk-adjusted returns, and for this purpose, either a single-factor model of the Capital Asset Pricing Model (CAPM) or the Fama-French's three-factor model may be useful in analysing the associated risk premia, e.g. the excess equity return over the risk-free rate. In Saudi, the bonds do not receive interest directly, and so it is difficult to calculate effective risk-free rates. Nevertheless, when calculating risk-adjusted returns, alternative methods have to be developed in order to approximate the representative compensation for the Saudi capital market.

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Appendix A

Table 1A. Descriptive statistics for the Saudi stock market (2002-2008).

	Code	No.of Obs.	Mean	Maximum	Minimum	Std.Dev	Skewness	Kurtosis	J - Bera
Bank sector	Ribl	1764	0.0003	0.0961	-0.2440	0.0207	-1.5055	22.9579	29887
	Bjaz	1752	0.0005	0.1619	-0.6344	0.0316	-5.3315	105.1797	770470
	Sibc	1756	-0.0001	0.0951	-0.4613	0.0261	-5.2961	83.61	483567
	Hollandi	1665	-0.0005	0.0953	-0.5376	0.0283	-6.2783	106	747209
	Fransi	1754	0.0001	0.0952	-0.5221	0.0256	-6.7945	125.4537	1109374
	Sabb	1740	0.0004	0.0951	-0.4481	0.0226	-5.1636	98.84	673684
	Arab bank	1742	4 e-07	0.0953	-0.4093	0.0253	-5.1783	75.39	388162
	Samba	1763	-8 e-05	0.0950	-0.4396	0.0215	-8.4245	174.3835	2178496
	Rajhi	1763	-0.0003	0.0953	-0.6263	0.0312	-9.6752	183.7546	2427553
	Bank.aver.	—	**0.0000**	**0.1027**	**-0.4803**	**0.0259**	**-5.9609**	**108.3983**	—
Industrial sector	Sabic	1763	0.0009	0.0953	-0.3290	0.0257	-2.4597	33.79	71450
	Safco	1763	0.0011	0.0953	-0.1967	0.0266	-0.1418	8.156	1959
	Savola group	1762	-0.0001	1.8638	-1.7742	0.0697	0.9355	532.4180	2057773
	Industrializ.	1763	0.0008	0.6018	-0.5991	0.0393	-2.1619	89.8981	556077
	Pharm.	1763	0.0005	0.0953	-0.1162	0.0309	-0.2701	6.292	817
	Gas	1763	0.0002	0.0953	-0.1896	0.0295	-0.5019	7.329	1450
	Food	1716	0.0006	0.1862	-0.2007	0.0415	-0.1969	4.5881	191
	Cables	1754	0.0011	0.1967	-0.1823	0.0357	-0.0986	5.6973	534
	Saudi indu.	1758	0.0009	0.1406	-0.2016	0.0398	-0.2505	4.5842	202
	Al ahsa	1760	0.0006	0.1716	-0.2056	0.0367	-0.2588	5.8351	609
	Amiantit	1732	-0.0001	0.8125	-0.7282	0.0484	1.2362	142.809	1411064
	Alujain	1763	0.0014	0.147920	-0.5411	0.0407	-1.4340	21.6640	26193
	Nama chemi-	1691	0.0009	0.11317	-0.5635	0.0419	-1.5507	23.0228	28925
	Indu. Aver.	—	**0.0007**	**0.3550**	**-0.4483**	**0.0389**	**-0.5502**	**68.1610**	—
Cement sector	Arab	1755	0.0004	0.0953	-0.2084	0.0229	-0.8241	14.9003	10554
	Yamama	1723	-0.0002	0.2336	-1.0511	0.0341	-16.8396	523.272	19514227
	Saudi	1761	0.0006	0.0953	-0.1551	0.0211	-0.5581	10.6648	4402
	Qassim	1710	0.0004	0.0953	-0.1754	0.0251	-0.2097	9.87689	3382
	Southernt	1745	0.0001	0.0953	-0.2885	0.0226	-1.4435	23.8491	32211
	Yanbu	1761	0.0005	0.0953	-0.1692	0.0217	-0.2986	11.3202	5105
	Eastern	1763	0.0002	0.0953	-0.3379	0.0230	-1.9957	34.9254	76041
	Tabuk	1761	0.0006	0.0953	-0.2039	0.0245	-0.3808	10.3818	4040
	Ceme.Aver.	—	**0.0003**	**0.1126**	**-0.3237**	**0.0244**	**-2.8188**	**79.8988**	—

Table 1A. Continue.

Services sector	Hotels	1698	0.0005	0.0953	-0.2058	0.0372	-0.2763	5.1790	357
	Real estate	1762	0.0005	0.0953	-0.5368	0.0344	-2.3713	38.368	93489
	Shipping	1760	0.0004	0.0953	-0.2184	0.0310	-0.5399	7.5370	1595
	Saptco	1762	0.0004	0.0953	-0.2201	0.0329	-0.5693	7.2547	1424
	Sasco	1763	0.0007	0.0953	-0.3612	0.0368	-0.8253	10.104	3907
	Tihama	1700	0.0006	0.0953	-0.2060	0.0402	-0.2455	4.5484	186
	Assir	1719	0.0009	0.0953	-0.3137	0.0358	-0.7702	9.8871	3567
	Taiba	1763	0.0007	0.2920	-0.3399	0.0338	-0.5698	14.950	10586
	Makkah	1763	-0.0002	0.0953	-0.7139	0.0337	-5.6059	117.66	975018
	Mubarrad	1763	0.0006	0.4890	-0.7138	0.0438	-1.8104	51.644	174788
	Saudi export	1721	0.0009	0.1896	-0.4913	0.0415	-0.9976	15.361	11243
	Arriyadh de	1763	0.0006	0.09517	-0.2015	0.0341	-0.3431	5.7283	581
	Serv. Aver.	**—**	**0.0006**	**0.1524**	**-0.3767**	**0.0363**	**-1.2437**	**24.018**	**—**
Agricultural sector	Nadec	1714	0.0011	0.0953	-0.2048	0.0343	-0.2382	6.0284	671
	Qassim	1742	0.0012	0.3803	-0.7071	0.0451	-1.9844	40.794	104824
	Hail	1751	0.0009	0.1178	-0.2074	0.0400	-0.2449	4.469	175
	Tabuk	1722	0.0009	0.0953	-0.2076	0.0405	-0.2046	4.7418	229
	fisheries	1606	0.0009	0.0953	-0.4596	0.0465	-0.6127	9.2958	2752
	Eastern	1691	0.0016	0.4678	-0.2093	0.0449	0.4977	10.525	4059
	Jouff agricul-	1677	0.0009	0.0953	-0.2082	0.0404	-0.2554	4.5628	188
	Jazan dev.	1757	0.0006	0.3564	-0.4831	0.0424	-1.5549	25.601	38104
	Agr. Aver.	**—**	**0.0011**	**0.2129**	**-0.3359**	**0.0417**	**-0.5747**	**13.252**	**—**
	Mar. Aver.	**—**	**0.0005**	**0.1994**	**-0.399**	**0.0341**	**-2.0575**	**57.902**	**—**

Table 2A. LB Autocorrelation statistics, first period (1st January, 2002 to 15th February, 2005).

	Code	Obs	Lag1	S.d at lag1	Lag2	Lag3	Lag10	Lag15	Q stat
Bank sector	Ribl	919	-0.003	0.033	-0.045	0.07	-0.036	0.023	23.19
	Bjaz	909	-0.086	0.033	-0.044	0.041	0.005	0.016	32.28
	Sibc	913	-0.14	0.033	-0.021	0.092	-0.004	0.013	34.20
	Hollandi	821	-0.019	0.034	-0.06	0.021	-0.009	0	9.129
	Fransi	909	0	0.033	0.018	0.025	-0.023	0.011	11.19
	Sabb	895	-0.127	0.033	-0.012	0.032	0.02	-0.048	30.09
	Arab bank	897	-0.153	0.033	0.017	0.007	0	0.026	32.36
	Samba	918	0.021	0.033	0.009	0.063	-0.017	-0.017	25.36
	Rajhi	918	-0.043	0.033	0.035	0.025	-0.008	0.035	23.82
	Bank. Aver.	**—**	**-0.061**	**0.033**	**-0.011**	**0.041**	**-0.008**	**0.006**	**24.62**
Industrial sector	Sabic	918	0.009	0.033	-0.045	0.025	-0.014	0.045	24.36
	Safco	918	-0.058	0.033	-0.064	0.037	-0.042	0.067	52.47
	Savola	917	-0.024	0.033	-0.059	0.073	-0.039	-0.003	25.17
	Indust.	918	0.032	0.033	-0.005	-0.021	-0.023	-0.014	12.40
	Pharm.	918	-0.079	0.033	-0.087	0.027	-0.113	-0.011	80.76
	Gas	918	-0.013	0.033	-0.168	0.023	-0.073	0.005	74.96
	Food	877	0.064	0.033	-0.043	-0.058	-0.024	-0.034	26.44
	Cables	910	0.058	0.033	-0.089	-0.049	0.025	-0.002	26.15
	S.Indu.	913	0.105	0.033	0.005	0.013	-0.01	0.001	27.99
	Ahsa	916	0.133	0.033	0.075	0.064	0.053	-0.023	55.83
	Amiantit	888	-0.044	0.033	-0.043	-0.001	-0.057	0.056	26.07
	Alujain	918	0.061	0.033	-0.042	0.012	0.005	-0.056	26.51
	Nama	846	0.015	0.034	0.063	0.016	0.004	0.038	18.30
	Indu.Aver.	**—**	**0.019**	**0.033**	**-0.038**	**0.012**	**-0.023**	**0.005**	**36.72**
Cement sector	Arab	910	-0.158	0.033	0.02	-0.01	0.012	-0.012	31.39
	Yamama	916	-0.082	0.033	-0.019	-0.013	-0.026	0.004	26.45
	Saudi	916	-0.142	0.033	-0.016	-0.021	-0.023	-0.044	43.55
	Qassim	857	-0.168	0.034	-0.066	-0.004	0.002	-0.008	37.18
	Southern	900	-0.073	0.033	-0.116	-0.065	0.017	-0.033	31.35
	Yanbu	916	-0.082	0.033	-0.019	-0.013	-0.026	0.004	26.45
	Eastern	918	-0.177	0.033	-0.076	0.052	-0.021	0.02	45.17
	Tabuk	918	0.001	0.033	-0.105	0.033	-0.025	-0.02	29.40
	Ceme. Aver.	**—**	**-0.110**	**0.033**	**-0.049**	**-0.005**	**-0.011**	**-0.011**	**33.87**

Table 2A. Continue.

Service sector	Hotels	853	-0.112	0.034	0.013	-0.047	-0.14	-0.057	55.88
	RealEstate	917	-0.085	0.033	-0.12	0.077	0	0.01	62.36
	Shipping	916	0.028	0.033	-0.055	-0.036	-0.079	0.033	26.79
	Saptco	917	0.015	0.033	-0.033	-0.037	-0.106	0.015	23.61
	Sasco	918	0.038	0.033	-0.016	0.022	-0.044	-0.001	31.58
	Tihama	855	0.064	0.034	0.067	-0.03	-0.006	-0.046	22.93
	Assir	874	0.033	0.033	-0.058	-0.033	-0.011	0.059	24.54
	Taiba	918	-0.012	0.033	-0.057	-0.029	-0.068	0.041	34.24
	Makkah	918	-0.016	0.033	-0.034	0.003	-0.027	-0.039	10.27
	Mubarrad	918	-0.01	0.033	-0.035	0.006	0.008	-0.01	9.11
	SaudiExport	876	-0.024	0.033	-0.001	-0.008	0.005	0.035	13.50
	ArriyadhDe	918	0.06	0.033	-0.014	0.015	-0.058	0.015	16.52
	Serv.Aver.	**—**	**-0.002**	**0.033**	**-0.028**	**-0.008**	**-0.043**	**0.004**	**27.61**
Agriculture sector	Nadec	869	-0.056	0.033	-0.050	-0.047	0.010	-0.021	19.59
	Qassim	897	0.065	0.033	-0.002	-0.027	-0.009	-0.008	13.69
	Hail	906	0.025	0.033	0.006	-0.003	0.072	-0.055	32.09
	Tabuk	877	0.013	0.033	-0.082	0.024	-0.071	-0.014	27.17
	Fisheries	745	-0.011	0.036	-0.092	-0.013	-0.066	-0.025	25
	Eastern	846	0.069	0.034	-0.053	-0.014	-0.029	-0.04	36.45
	Jouff	832	-0.019	0.034	0.001	-0.005	0.014	-0.01	8.37
	JazanDev	904	0.058	0.033	-0.052	-0.016	0.016	-0.036	35.33
	Agr.Aver.	**—**	**0.018**	**0.034**	**-0.040**	**-0.01263**	**-0.008**	**-0.026**	**24.73**
	Mar. Aver	**—**	**-0.021**	**0.033**	**-0.033**	**0.006**	**-0.021**	**-0.002**	**29.98**

Table 3A. LB AutoCorrelation statistics, second period (16th February, 2005 to 4th April, 2008).

Sector	Code	Obs.	Lag1	S.d at lag1	Lag2	Lag3	Lag10	Lag15	Q stat
Bank sector	Ribl	844	0.022	0.034	-0.015	0.020	-0.011	0.048	11.01
	Bjaz	842	0.099	0.034	-0.029	-0.018	0.017	0.058	34.89
	Sibc	842	0.052	0.034	-0.08	0.076	-0.029	0.036	35.50
	Hollandi	843	0.12	0.034	-0.052	-0.067	-0.004	0.073	47.33
	Fransi	844	-0.001	0.034	-0.028	-0.017	0.015	-0.042	11.89
	Sabb	844	0.035	0.034	-0.109	0.014	0.011	-0.02	35.95
	Arab bank	844	0.038	0.034	-0.04	0.028	0.029	0.052	26.39
	Samba	844	0.079	0.034	0.032	-0.054	-0.019	0	17.84
	Rajhi	844	0.05	0.034	0.018	0.043	-0.025	0.052	14.64
	Bank Aver.	**—**	**0.054**	**0.034**	**-0.033**	**0.0028**	**-0.001**	**0.028**	**26.16**
Industrial sector	Sabic	844	0.078	0.034	-0.006	-0.016	0.028	0.059	30.60
	Safco	844	0.032	0.034	-0.043	0.076	0.032	0.039	41.20
	Savola	844	0.032	0.034	-0.001	0.023	-0.004	-0.004	5.50
	Industrial.	844	0.052	0.034	-0.058	0.069	0.016	0.073	28.67
	Pharm.	844	0.11	0.034	0.034	0.117	0.02	0.101	52.37
	Gas	844	0.106	0.034	-0.007	0.091	-0.04	0.07	47.70
	Food	838	0.193	0.034	0.069	0.132	-0.073	0.062	72.02
	Cables	843	0.1	0.034	-0.023	0.103	0.003	0.069	30.27
	S.Indu.	844	0.131	0.034	0.039	0.123	-0.058	0.047	44.12
	Al Ahsa	843	0.12	0.034	-0.022	0.093	-0.001	0.029	38.75
	Amiantit	843	0.021	0.034	-0.049	0.013	0.028	0.016	8.84
	Alujain	844	0.102	0.034	-0.005	0.147	-0.053	0.055	38.87
	Nama	844	0.108	0.034	-0.004	0.114	-0.016	0.046	50.16
	Indu.Aver.	**—**	**0.091**	**0.034**	**-0.005**	**0.083**	**-0.009**	**0.050**	**37.62**
Cement sector	Arab	844	0.083	0.034	-0.055	0.035	0.045	0.07	38.52
	Yamama	829	0.063	0.034	-0.045	0.063	-0.001	0.016	38.56
	Saudi	844	0.036	0.034	-0.158	0.08	0.09	0.051	59.15
	Qasim	852	0.021	0.034	-0.019	0.14	0.011	0.066	43.14
	Southern	844	-0.009	0.034	-0.124	0.046	0.113	0.034	37.79
	Yanbu	844	0.058	0.034	-0.129	0.087	0.06	0.019	60.65
	Eastern	844	0.018	0.034	-0.106	0.063	0.024	0.102	43.45
	Tabuk	842	0.052	0.034	-0.06	0.112	0.02	0.043	50.26
	Ceme.Aver.	**—**	**0.040**	**0.034**	**-0.087**	**0.078**	**0.045**	**0.050**	**46.44**

Table 3A. Continue.

Service sector	Hotels	844	0.106	0.034	0.015	0.032	-0.012	0.074	23.25
	RealEstate	844	0.124	0.034	0.019	0.086	-0.008	0.048	30.44
	Shipping	843	0.102	0.034	-0.065	0.065	-0.038	0.13	58.80
	Saptco	844	0.045	0.034	-0.043	0.041	-0.011	0.041	24.79
	Sasco	844	0.034	0.034	0.01	0.067	0.038	0.085	36.89
	Tihama	844	0.18	0.034	0.076	0.094	-0.026	0.052	67.42
	Assir	844	0.114	0.034	0.024	0.096	-0.003	0.067	42.30
	Taiba	844	0.059	0.034	-0.014	0.037	-0.004	0.074	34.25
	Makkah	844	0.1	0.034	-0.03	0.037	0.022	0.051	36.56
	Mubarrad	844	0.145	0.034	0.01	0.045	-0.07	0.03	37.58
	S.Export	844	0.147	0.034	0.043	0.05	-0.038	0.058	46.90
	ArriyadhDe	844	0.082	0.034	-0.02	0.077	0.009	0.061	39.57
	Serv. Aver.	**—**	**0.103**	**0.034**	**0.002**	**0.060**	**-0.011**	**0.064**	**39.90**
Agriculture sector	Nadec	844	0.106	0.034	0.009	0.071	-0.023	0.017	33.91
	Qassim	844	0.099	0.034	0.053	0.126	-0.011	0.023	43.95
	Hail	844	0.112	0.034	0.068	0.101	-0.012	0.023	51.56
	Tabuk	844	0.12	0.034	0	0.052	-0.04	0.012	23.98
	Fisheries	860	0.207	0.034	0.078	0.085	-0.014	0.021	66.36
	Eastern	844	0.21	0.034	0.047	0.074	-0.049	0	68.23
	Jouff	844	0.133	0.034	0.025	0.085	-0.041	0.026	48.02
	JazanDev	852	0.061	0.034	0.086	-0.025	-0.026	0.048	29.36
	Agr. Aver.	**—**	**0.131**	**0.034**	**0.045**	**0.071125**	**-0.027**	**0.02125**	**45.67**
	Mar. Aver.	**—**	**0.08574**	**0.034**	**-0.013**	**0.060**	**-0.002**	**0.045**	**38.80**

Table 4A. LB Autocorrelation statistics of sectoral indecis.

First period	**Obs.**	Lag1	Lag2	Lag3	Lag10	Lag15	Q-stat.	*p*-value
Bank	919	-0.014	0.031	0.071	-0.013	0.001	24.049	0.064
Industrial	919	-0.007	-0.057	0.027	-0.025	0.031	27.751	0.023
Cement	919	-0.073	-0.057	-0.010	0.019	-0.019	22.636	0.092
Service	919	-0.008	-0.084	0.001	-0.119	0.015	85.219	0.000
Agriculture	919	0.079	-0.034	-0.058	0.012	-0.032	39.032	0.001
Second period	Obs.	Lag1	Lag2	Lag3	Lag10	Lag15	Q-stat.	*p*-value
Bank	844	0.152	-0.064	0.036	-0.011	0.035	56.390	0.000
Industrial	844	0.075	-0.035	0.057	-0.012	0.089	40.610	0.000
Cement	844	0.088	-0.124	0.077	0.006	0.073	56.698	0.000
Service	844	0.152	-0.020	0.064	-0.013	0.088	58.865	0.000
Agriculture	844	0.174	0.049	0.104	-0.010	0.046	62.948	0.000

Table 5A. Runs test, first period (1st January, 2002 to 15th February, 2005).

	Code	Obs.	n> median	n< median	Obs. No. Of runs	Exp. No. Of runs	R-std	Z- stat
Bank sector	Ribl	919	432	487	451	458.8	15	-0.5203
	Bjaz	909	399	510	481	448.7	14.8	2.1747**
	Sibc	913	450	463	492	457.4	15	2.2914**
	Hollandi	821	372	449	468	407.8	14.1	4.2356
	Fransi	909	446	463	482	455.3	15	1.7700*
	Sabb	895	429	466	465	447.7	14.9	1.1568
	Arab bank	897	446	451	496	449.4	14.9	3.1079***
	Samba	918	362	556	398	439.5	14.4	-2.8692***
	Rajhi	918	440	478	470	459.2	15.1	0.7136
	Bank Aver.	—	**419.5**	**480.3**	**467**	**447.1**	**14.8**	**1.3400**
Industrial sector	Sabic	918	459	459	431	460	15.1	-1.915*
	Safco	918	422	496	448	457	15	-0.599
	Savola	917	458	459	479	459.4	15.1	1.2886
	Industrial.	918	405	513	453	453.6	14.9	-0.043
	Pharm.	918	405	513	474	453.6	14.9	1.3631
	Gas	918	427	491	473	457.7	15	1.0108
	Food	877	336	541	377	415.5	13.9	-2.755***
	Cables	910	373	537	445	441.2	14.5	0.2590
	S.Indu.	913	366	547	398	439.5	14.5	-2.865***
	AlAhsa	916	387	529	434	447.9	14.7	-0.948
	Amiantit	888	393	495	462	439.1	14.6	1.5555
	Alujain	918	379	539	427	446	14.6	-1.298
	Nama	846	346	500	413	409.9	14	0.2146
	Indu.Aver.	—	**396.6**	**509**	**439.5**	**444.6**	**14.7**	**-0.364**
Cement sector	Arab	910	437	473	493	455.2	15	2.5055**
	Yamama	893	413	480	494	444.9	14.8	3.3007***
	Saudi	918	420	498	477	456.6	15	1.3514
	Qassim	861	397	464	476	428.8	14.5	3.2322***
	Southern	900	424	476	486	449.4	14.9	2.4430**
	Yanbu	916	426	490	486	456.7	15	1.9425*
	Eastern	918	425	493	496	457.4	15	2.5580
	Tabuk	918	407	511	447	454.1	14.9	-0.475
	Ceme.Aver	—	**418.6**	**485.6**	**481.8**	**450.4**	**14.9**	**2.1072**

Table 5A. Continue.

Service sector	Hotels	853	338	515	437	409.1	13.9	1.9952**
	RealEstate	917	426	491	459	457.1	15	0.1197
	Shipping	916	405	511	465	452.8	14.9	0.8131
	Saptco	917	388	529	452	448.6	14.7	0.2260
	Sasco	918	401	517	421	452.6	14.8	-2.125**
	Tihama	855	360	495	437	417.8	14.2	1.3447
	Assir	874	395	479	417	433.9	14.6	-1.158
	Taiba	918	384	534	444	447.7	14.7	-0.254
	Makkah	918	430	488	465	458.1	15	0.4530
	Mubarrad	918	371	547	445	443.1	14.5	0.1283
	SaudiExp.	876	374	502	441	429.6	14.4	0.7842
	ArriyadhDe	918	396	522	447	451.3	14.8	-0.293
	Serv.Aver.	—	**389**	**510.8**	**444.1**	**441.8**	**14.6**	**0.1693**
Agriculture sector	Nadec	869	334	535	436	412.2	13.9	1.7031*
	Qassim	897	330	567	386	418.1	13.9	-2.312**
	Hail	906	358	548	436	434	14.3	0.1337
	Tabuk	877	329	548	397	412.1	13.8	-1.092
	Fisheries	745	297	448	371	358.1	13	0.979
	Eastern	846	340	506	411	407.7	13.9	0.2351
	Jouff	832	332	500	410	400	13.8	0.7205
	JazanDev	904	360	544	409	434.2	14.4	-1.7549*
	Agr. Aver.	—	**335**	**524.5**	**407**	**409.6**	**13.9**	**-0.1735**
	Mar. Aver.	—	**392.58**	**503.06**	**447.16**	**439.7**	**14.6**	**0.4966**

***, ** and * indicate the significance levels at 1%, 5% and 10%, respectively.

Table 6A. Runs test, second period (16th February, 2005 to 4th April, 2008).

	Code	Obs	n> median	n< median	Obs. No. Of runs	Exp. No. Of runs	R-std	Z- stat
Bank sector	Ribl	844	384	460	417	419.5	14.3	-0.1790
	Bjaz	842	392	450	401	420	14.4	-1.3167
	Sibc	842	379	463	431	417.8	14.3	0.9188
	Hollandi	843	378	465	415	418	14.3	-0.2097
	Fransi	844	395	449	429	421.2	14.4	0.5344
	Sabb	844	397	447	438	421.5	14.4	1.1392
	Arab bank	844	386	458	428	419.9	14.4	0.5600
	Samba	844	422	422	401	423	14.5	-1.5154
	Rajhi	844	397	447	379	421.5	14.4	-2.9391***
	Bank Aver.	—	**392.2**	**451.2**	**415.4**	**420.2**	**14.4**	**-0.3341**
Industrial sector	Sabic	844	405	439	407	422.3	14.4	-1.0566
	Safco	844	422	422	438	423	14.5	1.0332
	Savola	844	387	457	410	420	14.4	-0.7003
	Industr.	844	411	433	397	422.7	14.5	-1.7724*
	Pharm.	844	412	432	415	422.7	14.5	-0.5350
	Gas	844	401	443	404	421.9	14.4	-1.2398
	Food	838	398	440	394	418.9	14.4	-1.7289
	Cables	843	406	437	408	421.9	14.4	-0.9614
	S.Indus.	844	395	449	394	421.2	14.4	-1.8863
	Al Ahsa	843	421	422	437	422.4	14.5	0.9994
	Amiantit	843	394	449	378	420.7	14.4	-2.956***
	Alujain	844	403	441	413	422.1	14.4	-0.6311
	Nama	844	412	432	418	422.7	14.5	-0.3282
	Indu. Aver.	—	**405.1**	**438.1**	**408.6**	**421.7**	**14.4**	**-0.9049**
Cement sector	Arab	844	390	454	404	420.5	14.4	-1.1482
	Yamama	844	392	452	439	420.8	14.4	1.2554
	Saudi	844	416	428	411	422.9	14.5	-0.8208
	Qasim	852	397	455	424	425	14.5	-0.0706
	Southern	844	389	455	429	420.4	14.4	0.5947
	Yanbu	844	392	452	439	420.8	14.4	1.2554
	Eastern	844	409	435	400	422.5	14.5	-1.5582
	Tabuk	844	360	484	412	413.8	14.2	-0.1331
	Ceme. Aver	—	**393.125**	**451.875**	**419.75**	**420.8**	**14.4**	**-0.0782**

Table 6A. Continue.

Service sector	Hotels	844	419	425	426	422.9	14.5	0.2081
	RealEstate	844	415	429	422	422.8	14.5	-0.0609
	Shipping	843	380	463	396	418.4	14.3	-1.5600
	SAPTCO	844	380	464	417	418.8	14.3	-0.1266
	SASCO	844	391	453	424	420.7	14.4	0.2269
	Tihama	844	414	430	427	422.8	14.5	0.2860
	Assir	844	415	429	415	422.8	14.5	-0.5432
	Taiba	844	401	443	430	421.9	14.4	0.5555
	Makkah	844	405	439	429	422.3	14.4	0.4612
	Mubarrad	844	411	433	415	422.7	14.5	-0.5316
	SaudiExport	844	410	434	417	422.6	14.5	-0.3901
	ArriyadhDe	844	388	456	422	420.2	14.4	0.1205
	Serv. Aver.	—	**402.4**	**441.5**	**420**	**421.6**	**14.4**	**-0.1128**
Agriculture sector	Nadec	844	422	422	436	423	14.5	0.8954
	Qassim	844	399	445	403	421.7	14.4	-1.2951
	Hail	844	406	438	412	422.3	14.4	-0.7169
	Tabuk	844	409	435	397	422.5	14.5	-1.7650
	Fisheries	860	404	456	397	429.4	14.6	-2.2209**
	Eastern	844	415	429	389	422.8	14.5	-2.3346**
	Jouff	844	413	431	409	422.8	14.5	-0.9515
	JazanDev	852	409	443	415	426.3	14.5	-0.7774
	Agr. Aver.	—	**409.6**	**437.3**	**407.2**	**423.8**	**14.5**	**-1.1458**
	Mar. Aver.	—	**400.9**	**443.3**	**414.1**	**421.6**	**14.4**	**-0.5183**

***, ** and * indicate the significance levels at 1%, 5% and 10%, respectively.

Table 7A. Runs test result for 5 Saudi sectors.

First period	Obs.	No.of runs	n1	n0	z-stat	*p*-value
Bank	919	784	862	918	-5.013	0.000
Industrial	919	849	901	879	-1.96	0.037
Cement	919	854	888	892	-1.730	0.064
Service	919	834	951	829	-2.492	0.007
Agriculture	919	831	875	905	=-2.810	0.002
Second period	**Obs.**	**No.of runs**	**n1**	**n0**	**z-stat**	***p*-value**
Bank	844	365	433	432	= -4.6267	0.000
Industrial	844	423	467	398	-0.496	0.671
Cement	844	418	446	419	-0.9929	0.304
Service	844	398	486	379	-1.961	0.041
Agriculture	844	395	462	403	-2.4601	0.025

Table 8A. Filter rule, first period (1st January, 2002 to 15th February, 2005).

	Code	B&H	0.001	strategy	0.005	strategy	0.01	strategy	0.05	strategy
Bank sector	RIBL	1.0429	1.1819	filter	1.3681	filter	1.4006	filter	0.8936	b&h
	BJAZ	1.3128	1.1143	b&h	0.9853	b&h	0.9048	b&h	0.7830	b&h
	SIBC	1.0003	0.5929	b&h	0.5779	b&h	0.8254	b&h	1.0061	filter
	Hollandi	0.2234	0.0472	b&h	-0.0319	b&h	-0.2367	b&h	-0.123	b&h
	Fransi	0.9321	0.7680	b&h	0.7061	b&h	0.4842	b&h	0.6293	b&h
	Sabb	0.9320	1.1155	filter	0.8505	b&h	0.9029	b&h	0.5780	b&h
	Arab bank	0.9563	0.9562	b&h	0.7258	b&h	0.7732	b&h	0.4983	b&h
	Samba	0.6447	1.0752	filter	1.0949	filter	0.9181	filter	0.6500	filter
	Rajhi	1.0287	1.8440	filter	1.5873	filter	1.4243	filter	1.3765	filter
	Bank. Aver.	**0.8970**	**0.9661**	—	**0.8738**	—	**0.8218**	—	**0.6991**	—
Industrial sector	Sabic	2.0234	4.8886	filter	4.4675	filter	4.6379	filter	3.8571	filter
	Safco	1.0665	1.4403	filter	1.7800	filter	1.5515	filter	0.8987	b&h
	Savola	1.3259	2.0057	filter	1.6735	filter	1.9368	filter	1.2195	b&h
	Industr.	2.0078	5.7752	filter	6.2505	filter	8.0018	filter	8.8530	filter
	Pharm.	0.7182	0.1618	b&h	0.1141	b&h	0.0486	b&h	0.2516	b&h
	Gas	0.6413	0.4826	b&h	0.4949	b&h	0.4423	b&h	0.2273	b&h
	Food	0.7674	0.9257	filter	0.9846	filter	0.9991	filter	1.5933	filter
	Cables	0.7435	1.7503	filter	1.5204	filter	1.4399	filter	1.3427	filter
	Industrial	1.9691	13.1733	filter	13.517	filter	12.730	filter	8.5156	filter
	Ahsa	1.2121	3.1016	filter	3.6539	filter	2.9099	filter	3.8924	filter
	Amiantit	0.3936	0.1800	b&h	0.1526	b&h	0.1586	b&h	0.0414	b&h
	Alujain	1.4434	4.2898	filter	4.8968	filter	4.4004	filter	7.8018	filter
	Nama	1.2848	4.4087	filter	5.5563	filter	5.0798	filter	8.2828	filter
	Indu.Aver.	**1.1998**	**3.2757**	—	**3.4663**	—	**3.4105**	—	**3.5982**	—
Cement sector	Arab	0.8078	0.4111	b&h	0.3337	b&h	0.4890	b&h	0.3251	b&h
	Yamamah	0.6484	0.5657	b&h	0.3462	b&h	0.2197	b&h	0.4255	b&h
	Saudi	0.7560	0.3300	b&h	0.1321	b&h	0.0315	b&h	0.5322	b&h
	Qassim	0.3358	0.1643	b&h	-0.0971	b&h	-0.1377	b&h	-0.0569	b&h
	Southern	0.5510	0.3212	b&h	0.0925	b&h	0.13863	b&h	0.1781	b&h
	Yanbu	0.9585	0.7416	b&h	0.6362	b&h	0.68231	b&h	1.0318	Filter
	Eastern	0.5104	0.1690	b&h	0.0314	b&h	0.0775	b&h	0.1884	b&h
	Tabuk	1.2927	2.7432	filter	2.5173	filter	2.3040	filter	1.5659	filter
	Ceme.Aver.	**0.73266**	**0.6807**	—	**0.4990**	—	**0.4756**	**---**	**0.5238**	—

Table 8A. Continue.

Service sector	Hotels	0.6276	-0.2573	b&h	-0.2612	b&h	-0.4383	b&h	0.0483	b&h
	RealEstate	0.9749	0.7035	b&h	0.7526	b&h	0.6846	b&h	0.7443	b&h
	Shipping	1.2463	1.5158	Filter	1.4596	filter	1.2575	filter	0.7183	b&h
	Saptco	1.2293	3.0822	Filter	3.8431	filter	3.0143	filter	1.7488	filter
	Sasco	1.3818	3.7267	filter	3.5162	filter	3.6330	filter	3.3790	filter
	Tihama	0.7787	1.0042	filter	1.2725	filter	1.1380	filter	2.0402	filter
	Assir	2.0967	7.7778	filter	7.6749	filter	5.5818	filter	4.6364	filter
	Taiba	1.2393	1.4787	filter	1.6772	filter	2.0006	filter	2.7428	filter
	Makkah	0.1895	-0.0779	b&h	0.0456	b&h	0.0541	b&h	-0.0409	b&h
	Mubarrad	1.0182	1.8733	filter	1.6235	filter	1.6562	filter	1.1482	filter
	SaudiExport	1.3077	0.5658	b&h	0.6137	b&h	0.5097	b&h	1.2839	b&h
	ArriyadhDe	1.1649	2.9773	filter	2.7691	filter	2.3323	filter	1.6923	filter
	Serv. Aver.	**1.1046**	**2.0308**	—	**2.0822**	—	**1.7853**	—	**1.6785**	—
Agriculture sector	Nadec	1.3659	1.8961	filter	2.0678	filter	1.7291	filter	1.1580	b&h
	Qassim	2.1542	5.9350	filter	7.0206	filter	7.7673	filter	5.3465	filter
	Hail	1.5602	5.5556	filter	5.8019	filter	8.3672	filter	4.9804	filter
	Tabuk	1.3267	2.8457	filter	2.9784	filter	3.1035	filter	3.4931	filter
	Fisheries	0.9622	0.5996	b&h	0.3492	b&h	0.3263	B&H	-0.224	b&h
	Eastern	2.0452	4.4690	filter	4.6011	filter	5.1628	filter	4.4217	filter
	Jouff	1.2178	1.5551	filter	1.6660	filter	1.6906	filter	2.7765	filter
	JazanDev	1.6233	5.1224	filter	5.5061	filter	5.8207	filter	4.8682	filter
	Agr. Aver.	**1.5319**	**3.4973**	—	**3.7489**	—	**4.2459**	—	**3.3524**	—
	Mar. Aver.	**1.1008**	**2.1815**	—	**2.2379**	—	**2.2186**	—	**2.0844**	—

Table 9A. Filter rule, second period (16th February, 2005 to 4th April, 2008).

	code	B&H	0.001	strategy	0.005	strategy	0.01	strategy	0.05	strategy
Bank sector	RIBL	-0.5583	-0.0181	filter	0.0404	filter	0.0132	filter	0.3123	filter
	BJAZ	-0.3707	0.6827	filter	0.4042	filter	0.4641	filter	-0.0824	filter
	SIBC	-1.2289	-0.4601	filter	-0.4055	filter	-0.4143	filter	0.0360	filter
	Hollandi	-0.9859	-0.4413	filter	-0.4226	filter	-0.4282	filter	-0.0590	filter
	Fransi	-0.7516	-0.6115	filter	-0.6691	filter	-0.7310	filter	-0.7042	filter
	Sabb	-0.2142	-0.3070	b&h	-0.3671	b&h	-0.2891	b&h	-0.5024	b&h
	Arab bank	-0.9909	-0.5795	filter	-0.5536	filter	-0.4575	filter	-0.2331	filter
	Samba	-0.8225	-0.1631	filter	-0.1767	filter	-0.0003	filter	-0.4694	filter
	Rajhi	-1.5433	-0.2954	filter	-0.1305	filter	-0.2495	filter	-0.1899	filter
	Bank.Aver.	**-0.8296**	**-0.2437**	—	**-0.2534**	—	**-0.2325**	—	**-0.2102**	—
Industrial sector	Sabic	-0.4649	0.5115	filter	0.4544	filter	0.1773	filter	0.2400	filter
	Safco	0.9390	2.3915	filter	2.1021	filter	1.6680	filter	1.7999	filter
	Savola	-1.5699	0.5251	filter	7.3171	filter	8.3211	filter	8.6117	filter
	Indust.	-0.4824	0.5264	filter	0.6228	filter	0.3939	filter	0.3335	filter
	Pharm.	0.1291	4.3203	filter	4.7342	filter	5.1046	filter	2.9541	filter
	Gas	-0.3364	1.1152	filter	1.4976	filter	1.4758	filter	0.6209	filter
	Food	0.2958	6.0475	filter	6.6376	filter	7.2245	filter	13.1863	filter
	Cables	1.2547	12.589	filter	11.3806	filter	9.1510	filter	3.9479	filter
	Industrial	-0.3326	6.5963	filter	6.8399	filter	7.3446	filter	4.4013	filter
	Ahsa	-0.2117	1.1669	filter	1.1060	filter	1.2663	filter	0.6922	filter
	Amiantit	-0.6335	0.3404	filter	0.4126	filter	0.1722	filter	-0.2914	filter
	Alujain	0.9856	13.548	filter	12.696	filter	12.368	filter	6.1046	filter
	Nama	0.2423	4.8733	filter	5.0012	filter	5.3011	filter	3.4699	filter
	Indu.Aver.	**-0.0142**	**4.1963**	—	**4.6771**	—	**4.6130**	—	**3.5439**	—
Cement sector	Arab	-0.1265	0.4885	filter	0.4149	filter	0.1879	filter	0.4294	filter
	Yamama	-0.9365	-0.1126	filter	-0.1286	filter	-0.2174	filter	-0.37843	filter
	Saudi	0.3353	0.3038	b&h	0.3906	filter	0.4743	filter	0.1514	filter
	Qassim	0.4067	0.8001	filter	0.8579	filter	1.0162	filter	1.0003	filter
	Southern	-0.3450	-0.1251	filter	-0.1426	filter	-0.0505	filter	-0.0115	filter
	Yanbu	-0.0778	-0.1427	b&h	0.0327	filter	0.0986	filter	-0.24275	b&h
	Eastern	-0.0608	0.9217	filter	0.6170	filter	0.2046	filter	0.61429	filter
	Tabuk	-0.4409	0.2833	filter	0.2681	filter	0.1195	filter	-0.0894	filter
	Ceme.Aver.	**-0.1557**	**0.3021**	—	**0.2887**	—	**0.2291**	—	**0.18416**	—

Table 9A. Continue.

Service sector	Hotels	0.2836	4.4579	filter	4.0061	filter	3.9797	filter	8.8863	filter
	RealEstate	-0.1133	1.7791	filter	1.7019	filter	1.2083	filter	3.1193	filter
	Shipping	-0.4897	0.4158	filter	0.2866	filter	0.2621	filter	0.3610	filter
	Saptco	-0.4420	0.5271	filter	0.5374	filter	0.6520	filter	0.6116	filter
	Sasco	-0.1778	3.8760	filter	3.6688	filter	3.5184	filter	1.5223	filter
	Tihama	0.3226	8.1435	filter	7.0497	filter	11.177	filter	12.759	filter
	Assir	-0.4418	0.5013	filter	0.7695	filter	0.8791	filter	1.0057	filter
	Taiba	0.1024	2.4389	filter	2.5106	filter	2.2461	filter	0.3380	filter
	Makkah	-0.5257	0.3310	filter	0.2001	filter	0.1401	filter	-0.3762	filter
	Mubarrad	0.1101	3.2443	filter	3.1062	filter	2.9112	filter	5.4974	filter
	SaudiExport	0.0770	4.2654	filter	4.6889	filter	3.6280	filter	8.1906	filter
	ArriyadhDe	-0.0630	5.102	filter	5.0918	filter	4.7727	filter	3.8545	filter
	Serv. Aver.	**-0.1131**	**2.9236**	—	**2.8015**	—	**2.9479**	—	**3.8141**	—
Agriculture sector	Nadec	0.5219	3.7286	filter	4.2408	filter	4.3491	filter	3.3908	filter
	Qassim	0.0127	9.8736	filter	9.3800	filter	9.1765	filter	8.6788	filter
	Hail	0.0935	4.6783	filter	4.3160	filter	4.3195	filter	5.2618	filter
	Tabuk	0.3860	2.9098	filter	3.5508	filter	4.9129	filter	3.8783	filter
	Fisheries	0.6167	30.2248	filter	29.979	filter	38.046	filter	42.759	filter
	Eastern	0.7688	12.0592	filter	10.720	filter	13.832	filter	31.367	filter
	Jouff	0.4723	5.2813	filter	5.7158	filter	7.1822	filter	6.4509	filter
	JazanDev	-0.4577	0.4227	filter	0.7588	filter	0.8530	filter	0.1468	filter
	Agr. Aver.	**0.3018**	**8.6473**	—	**8.5827**	—	**10.3340**	—	**12.741**	—
	Mar. Aver.	**-0.1568**	**3.1807**	—	**3.2622**	—	**3.5551**	—	**3.8671**	—

Table 10A. Filter rule results for 5 Saudi sectors.

First period	B&H	0.001	strategy	0.005	strategy	0.01	strategy	0.05	strategy
Bank	0.98982	1.250126	filter	1.481797	filter	1.426582	filter	0.880032	b&h
Industrial	1.83099	2.885531	filter	2.864596	filter	2.612286	filter	2.176963	filter
Cement	0.694539	0.493158	b&h	0.456871	b&h	0.604784	b&h	0.444462	b&h
Service	1.088198	2.043057	filter	1.955212	filter	1.531446	filter	1.833693	filter
Agriculture	1.465996	4.632	filter	5.214328	filter	4.871427	filter	3.075403	filter
Second period	B&H	0.001	strategy	0.005	strategy	0.01	strategy	0.05	strategy
Bank	0.147782	0.430794	filter	0.530981	filter	0.657057	filter	1.403423	Filter
Industrial	0.550794	1.150873	filter	1.289716	filter	1.331694	filter	1.016926	Filter
Cement	0.120617	0.602044	filter	0.852185	filter	0.920395	filter	0.348303	Filter
Service	-0.03221	3.756817	filter	3.714085	filter	4.25594	filter	2.300398	Filter
Agriculture	0.353297	8.558316	filter	7.995532	filter	9.617441	filter	11.60829	Filter

Table 11A. Variance ratio test, first period (1st January, 2002 to 15th February, 2005).

	Code	q =2	q =4	q =8	q =16
Bank sector	Ribl	0.9937	0.9820	0.9819	0.9944
	Bjaz	0.9120	0.8460	0.8815	0.8945
	Sibc	0.8615	0.8200	0.9189	1.0584
	Hollandi	0.9837	0.9291	0.9504	0.9976
	Fransi	1.0001	1.0260	1.1065	1.2180
	Sabb	0.8746	0.7913	0.8171	0.8454
	Arab bank	0.8491	0.7922	0.7806	0.7566
	Samba	1.0208	1.0635	1.1323	1.2772
	Rajhi	0.9593	0.9916	1.0797	1.1913
	Bank.Aver.	**0.9394**	**0.9157**	**0.9609**	**1.0259**
Industrial sector	Sabic	1.0105	0.9794	1.0529	1.1075
	Safco	0.9449	0.8749	0.9415	1.0013
	Savola	0.9759	0.9423	1.0686	1.208
	Indust.	1.0345	1.038	1.129	1.2445
	Pharm.	0.9218	0.8162	0.8427	0.8578
	Gas	0.9901	0.8305	0.7808	0.762
	Food	1.0665	1.0316	0.9979	1.1293
	Cables	1.0601	0.9796	0.9426	0.9066
	S.Indust.	1.1078	1.177	1.1632	1.1423
	Ahsa	1.1285	1.3259	1.6546	2.1814
	Amiantit	0.9571	0.8927	0.8495	0.7503
	Alujain	1.0637	1.0625	1.11	1.3627
	Nama	1.0172	1.0986	1.1666	1.2248
	Indu.Aver.	**1.0214**	**1.0037**	**1.0538**	**1.1445**
Cement sector	Arab	0.8419	0.7807	0.737	0.7658
	Yamama	0.8495	0.7582	0.6875	0.6888
	Saudi	0.8596	0.765	0.7496	0.7525
	Qassim	0.8516	0.6996	0.6279	0.5895
	Southern	0.9286	0.7463	0.6274	0.6461
	Yanbu	0.9199	0.8571	0.7946	0.8578
	Eastern	0.8239	0.6831	0.6306	0.6376
	Tabbuk	0.9923	0.9102	0.9613	1.134
	Ceme. Aver.	**0.8834**	**0.7750**	**0.7269**	**0.7590**

Table 11A. Continue.

Service sector	Hotels	0.8896	0.8258	0.8665	0.8314
	RealEstate	0.9165	0.7947	0.8053	0.8167
	Shipping	1.0306	0.9757	0.9218	0.8429
	Saptco	1.0164	0.9769	0.9648	0.9673
	Sasco	1.0402	1.0589	1.196	1.2458
	Tihama	1.0665	1.156	1.1651	1.1843
	Assir	1.0321	0.9758	0.93	0.9889
	Taiba	0.9895	0.9156	0.8758	0.9248
	Makkah	0.9857	0.9497	0.9734	0.9833
	Mubarrad	0.9925	0.9592	0.9984	1.1212
	SaudiExport	0.9777	0.9661	0.9042	0.8583
	ArriyadhDe	1.0571	1.0816	1.1303	1.0728
	Serv. Aver.	**0.9995**	**0.9696**	**0.9776**	**0.9864**
Agriculture sector	Nadec	0.945	0.8468	0.7915	0.71
	Qassim	1.0668	1.0901	1.1357	1.2677
	Hail	1.0264	1.0491	1.1965	1.305
	Tabuk	1.0148	0.9547	0.9641	0.8989
	Fisheries	0.9912	0.8893	0.7723	0.5886
	Eastern	1.0699	1.047	1.1615	1.2213
	Jouff	0.9834	0.9766	1.016	1.0855
	Jazan.Dev	1.0602	1.0313	1.1682	1.2359
	Agr. Aver.	**1.019713**	**0.985613**	**1.025725**	**1.039113**
	Mar.Aver.	**0.979056**	**0.94024**	**0.962042**	**1.006692**

Note: The critical value for Z(q) and Z*(q) at 5% level of significance is 2.49.
.Sampling intervals (q) are in days.
Z(q) - test statistic for null hypothesis of homoscedastic increments random walk.
Z* (q) - test statistic for null hypothesis of heteroscedastic increments random walk.

Table 12A. Variance ratio test, second period (16th February, 2005 to 4th April, 2008).

	Code	q =2	q =4	q =8	q =16
Bank sector	Ribl	1.0246	1.0348	0.9833	1.0563
	Bjaz	1.1017	1.118	1.0981	1.0757
	Sibc	1.0543	1.0438	1.1435	1.1582
	Hollandi	1.1222	1.1018	1.0947	1.3033
	Fransi	1.0012	0.9682	1.0149	1.071
	Sabb	1.038	0.9578	0.8616	0.8507
	Arab bank	1.0401	1.0378	0.9995	1.0581
	Samba	1.0818	1.1288	1.1505	0.8356
	Rajhi	1.0528	1.1219	1.2514	1.3043
	Bank Aver.	**1.0574**	**1.0569**	**1.0663**	**1.0792**
Industrial sector	sabic	1.0807	1.1127	1.1795	1.3278
	Safco	1.0344	1.0496	1.0938	1.028
	Savola	1.0347	1.0569	1.1356	1.1951
	Indust.	1.0545	1.0619	1.1534	1.1686
	Pharm	1.1131	1.2665	1.5079	1.6633
	Gas	1.1091	1.2049	1.4065	1.3444
	Food	1.1959	1.4345	1.6993	1.7708
	Cables	1.1026	1.1861	1.3764	1.5673
	S.Indust	1.134	1.3064	1.5252	1.5982
	Ahsa	1.1229	1.213	1.2852	1.3001
	Amiantit	1.0236	0.9966	1.045	1.0542
	Alujain	1.1046	1.228	1.4409	1.5293
	Nama	1.11	1.2226	1.4412	1.5665
	Indu. Aver.	**1.0938**	**1.1799**	**1.3299**	**1.3933**
Cement sector	Arab	1.0853	1.094	1.0779	0.9283
	Yamama	1.0656	1.0883	1.2131	1.4977
	Saudi	1.0378	0.9401	0.8968	0.8711
	Qassim	1.0236	1.09	1.2496	1.1852
	Southern	0.9926	0.8899	0.8823	0.9496
	Yanbu	1.0607	1.0077	0.9987	0.8976
	Eastern	1.0161	0.9597	1.0096	1.0327
	Tabuk	1.0831	1.1441	1.2878	1.2197
	Ceme. Aver.	**1.0456**	**1.0267**	**1.0769**	**1.0727**

Table 12A. Continue.

Service sector	Hotels	1.1088	1.1994	1.3327	1.4245
	RealEstate	1.1269	1.2578	1.3453	1.336
	Shipping	1.1046	1.1284	1.1753	1.1131
	Saptco	1.0473	1.0523	1.1291	1.1302
	Sasco	1.0362	1.1008	1.2613	1.5452
	Tihama	1.1826	1.4034	1.633	1.9155
	Assir	1.1166	1.2515	1.4101	1.4527
	Taiba	1.0617	1.0977	1.162	1.3319
	Makkah	1.103	1.147	1.3107	1.4232
	Mubarrad	1.1479	1.2594	1.3076	1.2272
	SaudiExport	1.1485	1.2962	1.4945	1.501
	ArriyadhDe	1.085	1.1495	1.3473	1.521
	Serv.Aver.	**1.1057**	**1.1952**	**1.3257**	**1.4101**
Agriculture sector	Nadec	1.1083	1.2117	1.3812	1.3414
	Qassim	1.1006	1.2766	1.5166	1.6268
	Hail	1.114	1.2948	1.5013	1.4479
	Tabuk	1.1226	1.2145	1.3171	1.3319
	Fisheries	1.2085	1.4432	1.742	1.8837
	Eastern	1.2131	1.41	1.699	1.8021
	Jouff	1.1357	1.2755	1.4971	1.4586
	JazanDev.	1.0634	1.1739	1.1705	1.1574
	Agr.Aver.	**1.1332**	**1.2875**	**1.4781**	**1.5062**
	Mar.Aver.	**1.0887**	**1.1542**	**1.2647**	**1.3076**

Note: The critical value for Z(q) and Z*(q) at 5% level of significance is 2.49.
Sampling intervals (q) are in days.
Z(q) - test statistic for null hypothesis of homoscedastic increments random walk.
Z* (q) - test statistic for null hypothesis of heteroscedastic increments random walk.

Table 13A. Variance ratio test result for 5 Saudi sectors.

First period	q =2	q =4	q =8	q =16
Bank	0.475***	0.247***	0.129***	0.061***
Industrial	0.525***	0.242***	0.130***	0.064***
Cement	0.493***	0.234***	0.125***	0.061***
Service	0.538***	0.230***	0.116***	0.061***
Agriculture	0.562***	0.253***	0.138***	0.065***
Second priod	**q =2**	**q =4**	**q =8**	**q =16**
Bank	0.628***	0.280***	0.134***	0.071***
Industrial	0.558***	0.251***	0.130***	0.066***
Cement	0.617***	0.256***	0.137***	0.069***
Service	0.603***	0.262***	0.146***	0.072***
Agriculture	0.577***	0.261***	0.153***	0.074***

The critical value for (Z_q) and (Z_q*) at 5% level of significance is 2.49.

Table 14A. First period results of ADF-PP for daily data, (log- Series level).

		Bank	Industrial	Cement	Service	Agriculture
ADF	Intercept(1)	2.8965*	2.0784	-0.0487	-0.6318	-0.3950
	Intercept and trend(2)	0.1488	-1.119	-2.5778*	-1.9427	-1.6656
PP	Intercept	2.6858*	2.3443	-0.0780	-0.7074	-0.4509
	Intercept and trend	0.0397	-0.993	-2.7290*	-2.6749*	-1.7759

***, ** and * denotes rejection of the null hypothesis at 1%, 5%, and 10% level respectively based on one side *p* values given by MacKinnon (1996).

Table 15A. First period results of ADF-PP for daily data, (series first differences).

		Δ (Bank)	Δ (Industrial)	Δ (Cement)	Δ (Service)	Δ (Agriculture)
ADF	Intercept	-31.3238	-32.2419	-25.8927	-24.2808	-28.275
	Intercept and trend	-31.6811	-32.4746	-25.8894	-24.2677	-28.2623
PP	Intercept	-31.5136	-32.2195	-38.2805	-53.7515	-28.2697
	Intercept and trend	-31.7219	-32.5234	-38.4062	-53.7189	-28.2562

***, ** and * denotes rejection of the hypothesis at 1%, 5% and 10% level, respectively based on one side *p* values given by MacKinnon (1996).

Table 16A. First period unrestricted co-integration rank test, (Trace).

No. of CE(s)	Eigenvalue	Trace Statistic(λ)	5% Critical Value	*p*-value
None *	0.0354	81.0700	76.9727	0.0235**
At most 1	0.0241	47.3855	54.0790	0.1725
At most 2	0.0154	24.5800	35.1927	0.426
At most 3	0.0061	10.0234	20.2618	0.6375
At most 4	0.0045	4.26567	9.16454	0.3740

p-values are given by MacKinnon-Haug-Michelis (1999).

Table 17A. First period unrestricted co-integration rank test, (Maximum Eigenvalue).

No. of CE(s)	Eigenvalue	Max-Eigen statistic	5%Critical Value	*p*-value
None	0.0354	33.6845	34.8058	0.0676*
At most 1	0.0241	22.8054	28.5880	0.2297
At most 2	0.0154	14.5565	22.2996	0.4124
At most 3	0.0061	5.75781	15.8921	0.8144
At most 4	0.0045	4.2656	9.1645	0.3740

p-values are given by MacKinnon-Haug-Michelis (1999).

Table 18A. Second period results of ADF-PP for daily data, (log- Series level).

		Bank	Industrial	Cement	Service	Agriculture
ADF	Intercept(1)	-1.3689	-1.3570	-1.7205	-1.2540	-2.1657
	Intercept and trend(2)	-2.2617	-2.0203	-2.4242	-2.3104	-2.1460
PP	Intercept	-1.3746	-1.4755	-1.6811	-1.2783	-2.2707
	Intercept and trend	-2.2992	-2.1241	-2.3751	-2.3017	-2.2314

***, ** and * denotes rejection of the hypothesis at 1%, 5% and 10% level, respectively based on one side *p*- values given by MacKinnon (1996).

Table 19A. Second period results of ADF-PP for daily data, (series first differences).

		Δ (Bank)	Δ (Industrial)	Δ (Cement)	Δ (Service)	Δ (Agriculture)
ADF	Intercept	-20.7077	-27.039	-15.9528	-24.7753	-24.2475
	Intercept and trend	-20.772	-27.0326	-15.9741	-24.8331	-24.3142
PP	Intercept	-24.8946	-27.1134	-26.4877	-24.9159	-24.8268
	Intercept and trend	-24.9516	-27.1051	-26.493	-24.9584	-24.8394

***, ** and * denotes rejection of the hypothesis at 1%, 5% and 10% level, respectively based on one side *p*- values given by MacKinnon (1996).

Table 20A. Second period unrestricted co-integration rank test, (Trace).

No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	*p*-value
None	0.026226	60.2047	76.9727	0.4671
At most 1	0.019764	37.8010	54.0790	0.5828
At most 2	0.010972	20.9732	35.1927	0.664
At most 3	0.008178	11.6728	20.2618	0.4786
At most 4	0.00562	4.75060	9.16454	0.3119

p-values are given by MacKinnon-Haug-Michelis (1999).

Table 21A. Second period unrestricted co-integration rank test, (Maximum Eigenvalue).

No. of CE(s)	Eigenvalue	Max-Eigen Stat	5% Critical Valu	*p*-value
None	0.0262	22.4036	34.8058	0.644
At most 1	0.0197	16.8278	28.5880	0.6752
At most 2	0.0109	9.3003	22.2996	0.8853
At most 3	0.0081	6.9222	15.8921	0.679
At most 4	0.00562	4.7506	9.16454	0.3119

p-values are given by MacKinnon-Haug-Michelis (1999).