The Profitability of Trading Rules in Stock Markets: Evidence from GCC Countries

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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

Nassar Al Nassar

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SUMMARY

The thesis provides empirical evidence on weak-form efficiency in the Gulf Cooperation Council (GCC) stock markets. To communicate the academic concepts to the practitioners' intuition, we utilise several trading rules to test weak-form efficiency in these markets. The trading rules are formulated on the basis of widely used technical indicators, namely moving average oscillator and trading-range break. Furthermore, we use several econometric estimation techniques to investigate the presence of seasonal effects in these markets (specifically the weekend, the holiday, the turn-of-the-month, and the month-of-the-year effects). Once a seasonal effect is found to be statistically significant, trading rules designed on the basis of these seasonal effects are evaluated. In addition, the role played by fundamentalists and technicians in the price-formation process is also examined. The empirical results reveal that trading rules generally outperform the passive buy-and-hold trading strategy. However, the performance of the trading rules appears to be highly temporal and largely diminishes when transaction costs are taken into consideration. Both fundamentalists and technicians have a role to play in price determination, although the technicians appear to be the more influential.

CHAPTER 1

INTRODUCTORY BACKGROUND

1.1 Introduction

In his seminal review of the efficient-market hypothesis (EMH), Fama (1970, p. 383) contends that "a market in which prices always 'fully reflect' available information is called 'efficient'". Thus, any attempt to predict future prices using technical or even fundamental analysis is fruitless and will not fare any better than the passive buy-and-hold strategy. Following the work of Fama (1970), the EMH enjoyed intellectual dominance among financial economists. However, by the turn of the twenty-first century, the mushrooming literature on the predictability of stock returns, as well as the failure of the EMH to predict bubbles in asset prices have cast serious doubts on its validity (Brown, 2011; Malkiel, 2003).

A major part of the literature on stock-return predictability is devoted to providing empirical evidence on the deviation of stock prices from the predictions of the EMH. This strand of literature includes empirical studies that document persistent cross-sectional and time-series patterns in stock returns. Evidence on time-series predictability includes the statistical measures used to gauge how closely stock returns follow the random walk (RW) process. The most widely used statistical techniques to test the RW hypothesis include unit root tests (for example Alimov *et al.*, 2004; Chaudhuri and Wu, 2003; Cooray, 2004); autocorrelation-based measures (for example Claessens *et al.*, 1995; Errunza and Losq, 1985; Mookerjee and Yu, 1999; Solnik, 1973); and a battery of variance ratio tests (for example Chow and Denning, 1993; Lo and MacKinlay, 1988; Wright, 2000).

Yet another subset of the time series return predictability literature focuses on the profitability of trading strategies. On the other hand, the evidence on cross-sectional anomalies includes momentum in stock returns (for example Chan *et al.*, 2000; Hameed and Kusnadi, 2002; Jegadeesh and Titman, 1993, 1999; Rouwenhorst, 1998); abnormal returns that emerge from the implementation of contrarian trading strategies (for example Bildik and Gülay, 2007; Conrad *et al.*, 1997; Jegadeesh, 1990; Lehmann, 1990; Levis and Liodakis, 2001); value and growth strategies (for example Chan *et al.*, 1991; Chan and Lakonishok, 2004; Fama and French, 1992, 1998); and relative-value arbitrage trading strategies such as pairs trading (for example Do and Faff, 2010; Gatev *et al.*, 2006).

Notwithstanding its limitations, Brown (2011) argues that the EMH remains a useful benchmark that carries important practical implications. Thus, answering questions about the state of market efficiency in a certain stock market is of great interest to investors, portfolio managers, policy makers, and other market participants. This interest in informational efficiency stems from the fact that the prices of securities determine the allocation of capital. This implies that more informationally efficient markets enjoy a better allocation of capital which, in turn, contributes to economic growth (Wurgler, 2000).

1.2 Objectives

In this thesis we aim to examine the profitability of trading strategies with the ultimate goal being testing the EMH in the context of the Gulf Cooperation Council (GCC) regional stock markets. Our motivation stems from the following considerations:

1 Despite the abundance of empirical studies that assess the EMH in developed and emerging markets, only a few studies examine efficiency in GCC markets. Even large cross-country studies of market efficiency do not usually include GCC markets in their sample. This may be explained by the relatively short history of these markets, and the difficulty in finding reliable data.

2 The GCC economies have unique characteristics that highlight the worthiness of their investigation. Four of the six GCC members are major oil-exporting countries, which are important decision makers in the Organization of Petroleum Exporting Countries (OPEC).

3 The GCC markets are weakly correlated with the world markets and have varying restrictions on ownership by foreigners. The empirical evidence shows that the GCC stock markets are segmented from developed markets with a negative correlation. The segmentation of the GCC markets highlights the merits of international diversification.

4 The GCC markets are classified as "long-only" markets without derivatives trading. Thus, trading strategies in these markets are restricted to buying stocks when the market is expected to rise and liquidating them when it is expected to fall.

5 Prior GCC studies evaluate market efficiency mainly using statistical tests such as autocorrelation and variance ratio, in addition to the analysis of a subset of seasonal anomalies. However, to the best of our knowledge, analysis of the profitability of trading strategies remains largely untapped.

6 The scarcity of research on GCC markets and their unique characteristics mitigates the data-snooping bias that occurs when the same data or positively correlated data are examined frequently (Lo and MacKinlay, 1990). This offers valuable settings in which to confirm, reject, or expand upon the conclusions of existing studies of the EMH.

We take a step in this thesis toward filling these gaps in the EMH literature. We examine the efficiency of the GCC stock markets using trading strategies designed on the basis of technical analysis and seasonal effects. The objective is to answer the following research questions: (i) Do technical trading strategies outperform the passive buy-and-hold strategy in the GCC stock markets? (ii) Are seasonal anomalies present in the GCC stock markets and, if so, do trading strategies designed to exploit these anomalies outperform the passive buy-and-hold strategy? and (iii) we conduct an econometric examination of the role played by fundamental analysts and technical traders in stock-price formation to find out whether technicians or fundamentalists play the dominant role in the stock-price-formation process in the GCC markets.

1.3 Structure of the Thesis

The thesis is organised as follows. Chapter 2 presents a survey of the literature on seasonality in stock returns, wherein we focus on daily seasonal effects (the turn-of-the-month, the holiday, and the weekend effects), and the monthly seasonal effects (the month-of-the-year and the Halloween effects). In order to identify the gaps in this literature, we conduct a systematic review of numerous studies through which—for each of the reviewed studies—we focus on the following aspects: the sample and research design.

Chapter 3 examines the presence of daily as well as monthly seasonality in stock returns in the GCC stock markets. The daily seasonal effects under investigation are the turn-of-the-month, the holiday, and the weekend effects; the monthly seasonal effects are the month-of-the-year and the Halloween effects. The existence of the aforementioned seasonal effects is tested using several econometric techniques in order to examine the sensitivity of results to alternative model specifications. Furthermore, an econometric specification that allows testing the hypothesis of time-varying seasonality is employed to ascertain whether the detected seasonal effects persist throughout the selected sample period and are not confined to a certain time period.

In Chapter 4 we explore the profitability of trading rules formulated on the basis of the documented seasonal effects. We construct these trading rules using the forecasts generated from returns time series regressions, namely autoregressive (AR) models that are augmented with daily seasonal dummies. A recursive-window estimation approach is employed in which the forecast equations are estimated using an in-sample period of one trading year. Then, a sequence of one-step-ahead forecasts are computed, rolling the sample forwards one observation after each forecast until the end of the entire sample is reached. To evaluate the performance of the trading rules, we test the hypothesis that the returns generated by the trading rules designed on the basis of the forecasts from the regression models are equal to those offered by a passive buy-and-hold trading strategy. Furthermore, a number of forecast-evaluation criteria are utilised.

In Chapter 5 we investigate the profitability of widely used technical trading rules. To guard against data-snooping bias, we apply the same set of trading rules examined by Brock *et al.* (1992) and by several later studies. These trading rules are constructed on the basis of moving average oscillators and trading-range breaks with variable and fixed holding-periods. In order to judge the performance of the technical trading rules under investigation, we test the hypothesis that the returns generated by technical trading rules are equal to those that can be obtained from a passive buy-and-hold trading strategy. We employ several robustness checks that include Jensen's alpha and the Sharpe ratio, in addition to the market-timing test of Henriksson and Merton (1981).

The role of technicians and fundamentalists in price formation is explored in Chapter 6. This is achieved by using the model put forward by Moosa and Korczak (2000), which enables us to determine which group of traders (technicians or fundamentalists) exerts the largest influence on stock prices. To ensure that the model is well specified, we conduct standard residuals diagnostics tests, including serial correlation (SC), functional form (FF), and heteroscedasticity (HS). To determine which group of traders is the most influential in price formation, a battery of non-nested model-selection tests is utilised. Chapter 7 concludes the thesis by reviewing the main research objectives, discussing the limitations of our research, and presenting several potential pathways for future work.

1.4 The GCC Stock Markets

The GCC consists of six member countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates. Indeed, all GCC member countries have one stock exchange, apart from the United Arab Emirates that has two stock exchanges: in the capital city of Abu Dhabi and in Dubai. In spite of the short history of organised stock trading in GCC markets, they have received mounting attention.[1] This interest stems from the fact that the majority of the GCC markets were relatively sheltered from the drastic declines in the main stock markets in the Middle East and North Africa (MENA) region, particularly the Egyptian market, which was the hardest hit by the Arab Spring. The flight of capital out of unstable MENA countries, in addition to the availability of petro-dollars, boosted liquidity in the GCC markets.

GCC markets are often classified as frontier markets by major index providers. Recently, Morgan Stanley Capital International (MSCI) upgraded the markets of Qatar and the United Arab Emirates to emerging status.[2] Before the upgrade, the markets of Kuwait, Qatar, and the United Arab Emirates dominated the MSCI frontier markets index—which captures large and mid-cap representation across 26 frontier markets—despite the fact that the market of Saudi Arabia (the largest of the GCC markets) is not included in that index. In fact, the collective

1 Al-Ajmi and Kim (2012) offer a comprehensive discussion of the early history of stock trading in the GCC markets.

2 http://online.wsj.com/news/articles/SB10001424052702304572204579501910298257436

weight of the three markets in the MSCI frontier markets index amounts to 53.1 percent (17.9 percent for Kuwait, 16.3 percent for Qatar, and 18.9 percent for the United Arab Emirates). Although foreign-ownership restrictions vary across GCC countries, foreign investors are allowed to participate in these markets via mutual funds. Therefore, international investors are able to gain diversification benefits from investing in the GCC markets.

Table 1.1 contains basic information about the broad market indices of the GCC stock markets in terms of the country to which they belong, weight factors, the sample period for the present study, the number of listed companies, market capitalisation, value traded, and turnover. A close look at Table 1.1 reveals that the market capitalisation of GCC countries amounted to US$718.36 billion in 2011, representing slightly more than 81 percent of the total market capitalisation of the broader MENA region, compared to only 38 percent in 2000 (AMF, 2011). The Saudi market is the largest in terms of market capitalisation, alone constituting more than 47 percent of the total market capitalisation of the GCC markets. The market capitalisation of the remaining markets ranges from US$128.44 billion for Qatar to US$16.51billion for Bahrain.

Due to IPOs, total market capitalisation of the GCC markets almost doubled over the period 2003 to 2011, increasing from US$365.85 billion to US$718.36 billion. The market of Qatar enjoyed the highest growth, trebling its market value from US$40.44 billion to US$128.44 billion over eight years. The remaining markets grew substantially, with growth rates ranging from as high as 198 percent for Oman to as low as 16 percent for Abu Dhabi.

The number of listed companies in the GCC markets has conspicuously risen over the period from 2003 to 2011. The growth was from 434 in 2003 to 716 listed companies by the end of the sample period. Half of these companies are listed in the Kuwaiti and Saudi stock markets.

Interestingly, the data show that the increase in market capitalisation is not necessarily attributable to IPO activity, as the number of companies listed in the Omani market slightly declined from 141 to 130. In contrast, the number of listed companies has risen considerably, particularly in the markets of Abu Dhabi, Dubai, Saudi Arabia, and Kuwait.

With regard to liquidity, the turnover ratio indicates that the Saudi market is by far the most liquid and actively traded, followed by the Kuwaiti market. Bahrain is the least liquid with only 1.49 percent of its market capitalisation traded in 2011. Indeed, the turnover ratio declined significantly between the 2003 and 2011 in the majority of the GCC markets (Bahrain, Dubai, Kuwait, and Saudi Arabia). This pattern is attributed to the uncertainty created by the Arab Spring and the European sovereign debt crisis.

Table 1.1: GCC stock market characteristics

Country	Index	Weight factor of index	Sample start date	No. of Comp		Market Cap		Value traded		Turnover	
				2003	2011	2003	2011	2003	2011	2003	2011
Bahrain	Bahrain All Share	Market value	1/02/2003	44	49	9.70	16.51	0.26	0.25	2.63	1.51
Kuwait	Market IXP	Price	12/31/2001	108	216	61.31	100.93	53.30	20.84	86.93	20.65
Oman	Muscat Securities Market (MSM 30)	Market value	12/30/2001	141	130	6.62	19.70	1.22	2.54	18.50	12.89
Qatar	Doha Securities Market (DSM 20)	Market value	12/31/2001	28	42	40.44	128.44	1.65	21.59	4.07	16.81
Saudi Arabia	Tadawul All Share (TASI)	Market value	12/31/2001	70	150	157.16	338.79	158.57	287	100.89	84.70
UAE	ADX General	Market value	12/31/2001	30	67	55.52	64.44	3.34	6.64	6.01	10.30
UAE	Dubai Financial Market (DFM)	Market value	12/31/2003	13	62	35.11	49.55	11.63	8.69	33.12	17.54

Sources: Arab Monetary Fund, Gulfbase.com and the official stock exchanges' websites.

Note: The market capitalisation and the value traded are expressed in US$ billions, while the turnover is expressed in percentage terms.

1.5 Data Description

The primary data required for this analysis are (i) daily closing prices of the broad stock market indices of the seven GCC stock markets: Abu Dhabi, Bahrain, Dubai, Kuwait, Oman, Qatar, and Saudi Arabia, and (ii) interest rates. As shown in Table 1.1, all the indices included in the study have at least eight years of data for each market. The sample spanned the period 31 December 2001 to the last trading day in December 2011. The data on the indices of the Bahrain All Share, Market IXP, Muscat Securities Market (MSM 30), Doha Securities Market (DSM 20), Tadawul All Share (TASI), and Abu Dhabi General Index (ADX) were sourced from the relevant exchanges. The Dubai Financial Market index (DFM) and the interest rates of all of the GCC countries were obtained from DataStream. We calculate the continuously compounded return of each market index at time t, r_t in the conventional fashion as:

$$r_t = ln\left(\frac{p_t}{p_{t-1}}\right) \times 100 \tag{1.1}$$

where p_t is the close price of the market index on day t. We calculate several descriptive statistics for the daily and monthly returns on each index. In addition, we conduct the Jarque and Bera (1987) test for normality; the Ljung-Box Q-statistic (Ljung and Box, 1978) for the null of no autocorrelation for 6 lags is also performed. The results are reported in Table 1.2.

Panel A of Table 1.2 shows the descriptive statistics and test results for daily and monthly returns. We can see that the mean daily return is positive across the board, ranging from 0.065 percent for Qatar to 0.004 percent for Bahrain. In line with the mean results, the median daily return is also found to be positive across all of the GCC markets. However, sorting the GCC markets on the basis of the median daily return paints a slightly different picture. The Saudi market is highest with 0.123 percent median daily return, while the market of Bahrain remains the lowest. These findings highlight the possibility of the presence of outliers in the returns series.

Table 1.2: Summary statistics

Market	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A: Daily return							
Mean	0.024	0.004	0.014	0.050	0.053	0.065	0.036
Median	0.035	0.006	0.050	0.110	0.066	0.080	0.123
Maximum	7.630	3.613	10.220	5.047	8.039	9.422	9.391
Minimum	-8.679	-4.920	-12.157	-3.875	-8.699	-9.359	-10.329
Std. Dev.	1.195	0.627	1.903	0.864	1.080	1.532	1.689
Skewness	-0.10	-0.44	-0.03	-0.59	-0.98	-0.36	-0.86
Kurtosis	10.92	8.75	7.99	6.52	18.84	9.15	10.87
Jarque-Bera	6921.33	3128.99	2202.65	1410.44	26360.36	4026.56	7330.00
N	2645	2220	2124	2455	2482	2520	2713
Serial correlations							
$\rho(1)$	0.268	0.176	0.04	0.241	0.251	0.253	0.065
$\rho(2)$	-0.011	0.044	0.041	0.07	0.023	0.041	-0.038
$\rho(3)$	-0.014	0.037	0.02	0.043	-0.015	-0.014	0.041
$\rho(4)$	0.008	0.002	0.038	0.075	-0.081	-0.032	0.031
$\rho(5)$	0.021	0.033	0.065	0.086	-0.032	-0.001	0.043
$\rho(6)$	0.031	0.051	0.026	0.074	0.025	0.003	-0.023
$Q(6)$	194.37	84.83	21.23	205.70	178.88	168.48	29.11
Panel B: Monthly return							
Mean	0.529	0.087	0.315	1.020	1.100	1.372	0.809
Median	0.345	0.502	-0.293	1.917	1.439	1.423	1.599
Maximum	35.907	9.248	34.770	18.444	16.238	25.960	17.895
Minimum	-19.105	-13.016	-40.378	-27.122	-31.315	-29.600	-29.775
Std. Dev.	7.560	4.006	11.428	6.098	5.906	9.218	8.543
Skewness	0.585	-0.479	-0.094	-0.938	-1.437	-0.497	-0.819
Kurtosis	6.998	3.874	4.995	6.562	9.952	4.217	4.258
Jarque-Bera	86.770	7.572	16.059	81.016	282.932	12.348	21.318
N	120	108	96	120	120	120	120
Serial correlations							
$\rho(1)$	0.334	0.459	0.34	0.51	0.33	0.148	0.206
$\rho(2)$	0.194	0.357	0.38	0.237	0.376	-0.014	0.133
$\rho(3)$	0.074	0.226	0.12	0.171	0.23	0.122	0.119
$\rho(4)$	0.074	0.16	0.195	0.126	0.069	0.077	0.153
$\rho(5)$	0.122	0.104	0.167	0.024	0.011	0.041	0.079
$\rho(6)$	0.064	0.13	0.098	-0.053	-0.146	-0.067	0.082
$Q(6)$	22.19	49.63	35.14	45.11	40.94	6.09	13.75

With respect to the volatility dimension, the market of Dubai displays the highest variability with a standard deviation of 1.903 percent, whereas the market of Bahrain is the least volatile with a standard deviation of 0.627 percent. Furthermore, the daily return is shown to be negatively skewed and leptokurtic, while the normality assumption is strongly rejected for every market. Autocorrelation is evident in daily returns, with first order autocorrelation coefficients being positive across the board, ranging 0.268 percent for the market of Abu Dhabi to 0.04 percent for the market of Dubai. The null of no autocorrelation for 6 lags is rejected for all markets.

The results in Panel B of Table 1.2 tell a similar story. The mean monthly returns are positive across the GCC market with the market of Qatar generating the highest mean monthly returns (1.372 percent), while the lowest mean monthly returns pertain to the market of Bahrain (0.087 percent). The median monthly return is found to be negative in the market of Dubai and positive in the remaining markets. The results pertaining to volatility of monthly returns are largely in accordance with those for daily returns, with the markets of Dubai (Bahrain) being the most (least) volatile. The monthly returns are also found to be negatively skewed and leptokurtic, while the normality assumption is strongly rejected for all markets. The autocorrelation analysis for monthly data produces largely similar results to those of the daily returns. The exception is the market of Qatar, where there is insufficient evidence to reject the null of no autocorrelation for 6 lags.

CHAPTER 2

SEASONALITY IN STOCK RETURNS: A REVIEW OF THE LITERATURE

2.1 Introduction

Seasonality in stock returns is well-established in the asset-pricing literature in developed and emerging markets. This strand of literature has documented a wide range of seasonal effects in stock returns. These include the January effect, where the returns of small firms in January are higher than in any other month (for example Keim, 1983; Reinganum, 1983; Rozeff and Kinney, 1976); the holiday effect where stock returns on pre-holidays are higher than in other days of the year (for example Ariel, 1990; Cadsby and Ratner, 1992); the weekend effect where stock returns are lower on Monday compared to other trading days of the week (for example French, 1980; Jaffe and Westerfield, 1985; Lakonishok and Levi, 1982; Lakonishok and Maberly, 1990); the turn-of-the-month effect where stock returns are higher around the turn of the month than on other days of the months (for example Ariel, 1987; Lakonishok and Smidt, 1988; Ogden, 1990); and the Halloween effect where stock returns are significantly higher in the period from November to April than for the rest of the year (for example Bouman and Jacobsen, 2002; Jacobsen and Visaltanachoti, 2009).

In addition to the aforementioned extensively studied seasonal effects, recently documented effects include the-week-of-the-year effect at which the return of the 44th week of the year is found to be positive and statistically significant, while the return of the 43rd week is negative and statistically significant across several stock markets (Levy and Yagil, 2012). The daylight-saving anomaly is documented by Kamstra *et al.* (2000), who argue that sleep deprivation is associated with the negative return during the daylight-saving change period.

Studies of weather-related effects reveal links between weather and stock returns (Dowling and Lucey, 2005; Goetzmann and Zhu, 2005; Hirshleifer and Shumway, 2003; Jacobsen and Marquering, 2008; Kamstra *et al.,* 2003, 2012; Kelly and Meschke, 2010; Saunders, 1993). The effect of lunar phases on stock returns has been unveiled by Dichev and Janes (2003) and Yuan *et al.* (2006) who show that the mean return during the full moon period is significantly lower than the mean return during the new moon period. There is also the Ramadan effect, where a distinctive pattern in mean return and volatility is detected during the Muslim fasting month in several stock markets in predominantly Muslim countries (Al-Hajieh *et al.*, 2011; Białkowski *et al.*, 2013; Białkowski *et al.*, 2012; Seyyed *et al.*, 2005).

While systematic seasonal patterns in stock returns, *prima facie*, pose a challenge for the Efficient Market Hypothesis (EMH), Sullivan *et al.* (2001) rightly argue that since these seasonal effects are based on purely empirical evidence, with no theoretical grounding, one cannot confidently conclude as to whether the documented regularities in stock returns are genuine or are a consequence of elaborate data mining.[3] Furthermore, the explanations proposed for the above-mentioned seasonal effects are diverse and range from market micro-structural to behavioural explanations. Despite their diversity, these explanations have long been criticised for being *ad hoc* in nature. Therefore, it is suggested that these explanations may be sample-specific, leaving a question on whether these seasonal effects will remain significant in the future (Siegel, 1998).

[3] This EMH paradigm holds that all available information is fully incorporated in security prices or, in other words, security prices follow a random walk (RW) (Fama, 1970). This implies that historical prices are useless for the purpose of predicting future returns. In an early paper on the subject, Rozeff and Kinney (1976) mathematically describe the behaviour of stock returns in the absence of seasonal effects using the RW model. They propose an alternative model that allows for seasonal effects, from which they derive a testable hypothesis for the existence of seasonal patterns in stock returns.

The majority of empirical studies utilise US data, which casts doubts *vis-à-vis* the out-of-sample validity of these studies. Thus, it is maintained that in order to support the proposition that these anomalies represent a worldwide phenomenon and are not simply a manifestation of institutional (and cultural) settings in the US, the presence of these anomalies should be investigated in other stock markets (Jaffe and Westerfield, 1985; Lakonishok and Smidt, 1988). This argument motivated a considerable increase in the number of studies conducted on developed markets, other than the US, as well as on emerging markets (for example Agrawal and Tandon, 1994; Gultekin and Gultekin, 1983; McConnell and Wei, 2008).

In addition to the differences in seasonal effects across markets, these effects are shown to vary over time. Several researchers suggest that seasonal effects gradually fade away once traders become aware of their existence (Chong *et al.*, 2005; Kohers *et al.*, 2004; Marquering *et al.*, 2006). Others, however, argue that seasonality in stock returns has not disappeared *per se*, but instead has moved from one period to another (Doyle and Chen, 2009). While the former view is consistent with the EMH, the latter is rather more in line with the adaptive market hypothesis (AMH).[4]

Most of the early empirical work on seasonal anomalies rests on a foundation of simple econometric models with strong statistical assumptions. The consequences of the violation of these assumptions are rarely examined systematically. We believe that Connolly (1989) was the first to highlight the econometric problems raised by the use of such models—namely the ordinary least square (OLS) estimation technique—to detect seasonality in daily data. This is because daily stock returns are characterised by non-normality, which implies the existence of significant outliers and high-leverage data points (for example Brown and Warner, 1985). Furthermore, early research points out that the distribution of daily stock returns exhibits

[4] A brief discussion of the AMH is offered in Chapter 5.

“fatter tails” compared to a normal distribution (for example Fama, 1965). These stylised facts on daily stock returns violate the assumptions of the OLS regression model. Connolly (1989) investigated the problem of interpreting classical test statistics with very large samples.

Connolly (1989) advocates the use of several estimation techniques when testing for the presence of seasonal effects. This approach has the advantage of being robust against such statistical validity threats. Numerous recent studies take this issue into consideration by exploiting the power of modern econometric techniques and research designs. For example Keef and Khaled (2011) and Kamstra *et al.* (2012) use panel data estimation techniques, while Białkowski *et al.* (2012) and Kaplanski and Levy (2012) employ an event-study methodology.

In spite of the abundance of studies conducted using emerging-market data, calendar-time anomalies in the GCC region have received minimal attention. The sparse empirical work on this region is based on evidence from a subset of the markets in this region, and it covers a rather narrow range of the seasonal effects. GCC-based studies focus on the day-of-the-week effect, the January effect and, to a lesser extent, the holiday and the Ramadan effects. However, the turn-of-the-month and the Halloween effects, to the best of our knowledge, have not been investigated. Moreover, the bulk of these studies assume that seasonality is fixed in time. Furthermore, the majority of these studies employ one econometric technique, especially OLS, whose assumptions are usually violated in practice. These gaps in the literature offer a valuable setting in which to confirm, reject, or expand upon the conclusions of existing studies in the calendar-time anomalies literature in the following three ways. These are first, expanding the range of calendar-time anomalies examined in GCC studies to include the turn-of-the-month and the Halloween effects that are investigated in the US market and a wide range of international stock markets, but which remain untapped in the GCC region; second, employing econometric techniques that allow the testing of the hypothesis of the time-varying seasonality; third, utilising a number of econometric techniques to examine the sensitivity of the results to alternative model specifications.

2.2 The-Turn-of-the-month Effect

In his influential paper, Ariel (1987) says that a seasonal pattern in stock returns around the turn of the month was initially detected by a number of financial planners, such as Merrill (1966) and Fosback (1976). Furthermore, these investment advisors encouraged their clients to exploit this anomaly by taking it into account in their investment strategy. To test for the presence of this seasonal regularity, Ariel (1987, p. 162) proposed an operational definition for the trading month. This definition states that the trading month extends from "the last trading day (inclusive) of each calendar month to the last trading day (exclusive) of the following calendar month". The data set that Ariel (1987) utilised comprises the CRSP value-weighted and equally weighted stock index over the period 1963 to 1981. In his empirical analysis, he split the trading month into two halves and compared their mean returns. The results reveal that the mean returns over the first part of the month are significantly higher than the mean returns in the second part for both weighting schemes. He termed this phenomenon "the monthly effect".

In subsequent studies, the definition and the name of this effect were slightly changed. Lakonishok and Smidt (1988) named it "the-turn-of-the-month effect" after narrowing its definition to the last day of the prior month plus the following three days of the subsequent month. They utilise 90 years of data on the DJIA over the period 1897 to 1976 .They indicate that the mean returns of this four-day interval around the turn of the month is significantly greater than the mean return during the rest of the month. In both studies (Ariel, 1987;

Lakonishok and Smidt, 1988), this regularity in stock returns remains strong, even when the turn-of-the-year returns are deleted.

The findings of these two papers are confirmed in numerous subsequent studies conducted using data from the US market and from other countries. The US-based studies include the work of Ogden (1987, 1990), Gerlach (2007), and Sharma and Narayan (2014). Studies that focus on one developed market include Ziemba (1991), who provides evidence from the Japanese market, as well as Booth *et al.* (2001) and Nikkinen *et al.* (2009) who investigate the Finnish market. Moreover, there exist a number of salient multi-country studies such as Cadsby and Ratner (1992), who focus on developed markets, and Kunkel *et al.* (2003) and McConnell and Wei (2008) where a wider range of stock markets are investigated. In other papers, more attention is paid to emerging markets—for example Freund *et al.* (2007), Maher and Parikh (2013), Oğuzsoy and Güven (2006), Compton *et al.* (2013), and McGuinness and Harris (2011). Stock markets investigated are India, Turkey, Russia, China, and Hong Kong.

Despite the robustness of this anomaly, a widely accepted explanation among financial economists for this phenomenon is yet to be found. Nonetheless, one plausible explanation is the elevated liquidity levels around the turn of the month due to salaries and other payments (for example Ogden (1990) for evidence from the US market; Ziemba (1991) for evidence from the Japanese market; and Booth *et al.* (2001) for evidence from the Finnish market). An alternative explanation attributes the abnormal pattern to the clustering of US macroeconomic announcements at the turn of the month. Gerlach (2007) provides evidence on US markets and Nikkinen *et al.* (2009) use a data set on Finland's stock market. Ogden (1990), Ziemba (1991), Booth *et al.* (2001), Gerlach (2007), and Nikkinen *et al.* (2009) use broad market indices in their empirical analyses, thus implicitly assuming that the turn-of-the-month seasonality has the same strength across firm size and across different market-sector portfolios. Using US data, Sharma and Narayan (2014) provide evidence against this assumption, as they show that the strength and volatility of the turn-of-the-month returns vary across firm size and market sector. Using data from the Indian market, Maher and Parikh (2013) find that the turn-of-the-month effect is confined to up-market periods.

The definition and the methodology employed to test for the presence of the turn-of-the-month effect varies across studies. With respect to definition, the majority of studies either employ the definition proposed by Ariel (1987) (Ogden, 1990; Booth *et al.*, 2001; Gerlach, 2007; Floros, 2008), or the definition put forward by Lakonishok and Smidt (1988) (Cadsby and Ratner, 1992; Kunkel *et al.*, 2003; McConnell and Wei, 2008; McGuinness and Harris, 2011; Sharma and Narayan, 2014). However, a few studies employ alternative definitions. Ziemba (1991) adjusts the turn-of-the-month period to run from the last five trading days of the prior month to the first two trading days of the following month; Maher and Parikh (2013) include the last trading day of the month along with only the first and second days of the following month. Likewise, several econometric techniques can be used to test for the presence of the turn-of-the-month effect. The majority of studies employ OLS regression (for example Ariel, 1987; Lakonishok and Smidt, 1988; Ogden, 1990; McGuinness and Harris, 2011. Some studies utilise the GARCH-type models (McConnell and Wei, 2008; Maher and Parikh, 2013; and Sharma and Narayan, 2014).

Because the literature on the turn-of-the-month effect is vast, an in-depth review of all of the relevant studies is beyond our scope. However, a detailed review of salient studies in this literature is warranted. We start with Ogden (1990), who finds empirical evidence in support of the liquidity-based explanation. The data set used in his study, which is obtained from the CRSP database, comprises the value-weighted and equally weighted stock index over the period 1969 to 1986. He put forward and tested the “the payday” hypothesis, which postulates that the turn-of-the-month period is characterised by elevated liquidity due to the standardisation of payments in the US. He posits that the cash infusion from salaries, and from dividend and interest payments is invested is the stock market, thus leading to an anomalous pattern in stock returns around the turn of the month. He shows that this effect is amplified during periods of expansionary monetary policy.

Another study is Ziemba (1991), who investigates the presence of the turn-of-the-month effect in the Japanese market using data on the NSA and TOPIX market indices over the period 1949 to 1988. He detects significant returns around the turn of the month in Japan when the definition of the turn of the month is adjusted to coincide with salaries and other payments in the Japanese economy.[5] Indeed, this finding is not confined to the largest two economies at that time. Booth *et al.* (2001) provide evidence in support of the payday hypothesis from the small but developed Finnish market. They utilise a rich data set of bid, ask, and closing prices as well as trading volumes for 148 stocks over the period 1991 to 1997. Their empirical results show that the documented higher returns during the turn-of-the-month period are linked to increased liquidity, as gauged by several metrics such as FIM volume, share volume, and the number of trades. In addition, the number of bid quotes increases around the end of the month.

On the other hand, Gerlach (2007) investigates the effect of macroeconomic announcements on the strength of six well-documented seasonal effects. His sample includes the S&P 500 and the CRSP equally weighted indices spanning the period from 1980 to 2003 and, in addition, he has data for 6058 macroeconomic announcements. He maintains that the market response to macroeconomic announcements is the main factor behind the high returns around

[5] The turn of the month is adjusted to run over the last five trading days of the prior month and the first two trading days of the following month.

the turn of the month, rather than the institutional factors argued in Ogden (1990), Booth *et al.* (2001), and Ziemba (1991). This is because these announcements are clustered around the turn of the month. The author shows that when controlling for the days on which macroeconomic announcements are released, the turn-of-the-month effect disappears. However, the data set used in this study is relatively short, and the findings are specific to the US market.

A number of international studies have been conducted, motivated by concerns about the external validity of the studies that use US data (Lakonishok and Smidt, 1988; Lo and MacKinlay, 1988). These concerns pertain particularly to data-mining biases and the institutional settings that are unique to the US. Indeed, the findings of the international studies are consistent, overall, with their American counterparts. In fact, instead of focusing on providing an explanation for the turn-of-the-month effect, the following studies are concerned with its presence in international markets, and whether it is persistent over time.

Cadsby and Ratner (1992) investigate the turn-of-the-month effect in 10 major markets and find a significant effect in six of them. Using a broader sample that comprises data from 18 developed markets, Agrawal and Tandon (1994) provide stronger evidence in support of the persistence of the turn-of-the-month effect internationally. Their results indicate that the turn-of-the-month effect is significant in 14 of the 18 markets examined. Kunkel *et al.* (2003) test for the turn-of-the-month effect over the period 1988 to 2000 in the stock returns of 19 developed and emerging markets. They implement both parametric and nonparametric measures in response to the concerns raised by Connolly (1989) about the statistical validity of the findings of previous studies that use parametric measures whose assumptions are violated in practice. They show that stock returns in the majority of these markets are significantly higher around the turn of the month.

In a comprehensive study that confirms the prevalence of this effect internationally, McConnell and Wei (2008) utilise a comprehensive data set of 35 developed and emerging markets. They report that the effect is present in 31 of the 35 markets under examination. Their findings dismiss the notion that this effect is confined to the US and to certain time periods, or to small stocks. Despite the empirical evidence provided by the previous studies, McConnell and Wei (2008) claim that this anomaly cannot be explained, as their empirical results do not constitute sufficient evidence to accept or reject the previously proposed hypothesis in the literature as a satisfactory explanation for the turn-of-the-month effect. However, they do not cite or refer to the analysis undertaken by Gerlach (2007).

A summary of the studies that examine the turn-of-the-month effect is presented in Table 1A.1 in the appendix to this chapter. In this summary, a number of aspects are considered: the markets under examination, the sample period, the days considered (that is, the definition of the turn-of-the-month period employed in the study), the econometric technique used to measure the effect of the turn-of-the-month effect, and whether the study controls for other seasonal effects. The main conclusions are stated.

2.3 The Weekend Effect

The formal documentation of this anomaly dates back to the 1930s when Fields (1931) empirically examined the Wall Street wisdom of the time. He stated that traders tend to liquidate their long positions before the weekend because they do not want to be exposed to uncertainties over the weekend. If this wisdom holds, stock returns on Saturday (the last trading day of the week at the time) should be significantly lower than on other trading days. His results (based on data on the DJIA over the period 1915 to 1930) show that market up-movements are more prevalent on Saturday compared to Friday and Monday. In a similar vein, Cross (1973) examined the S&P 500 over the period 1953 to 1970. He found that the average returns on Monday are negative and lower than Friday's returns. These two studies lack statistical sophistication. A formal and more comprehensive study was undertaken by French (1980) who updated the data set utilised by Cross (1973) to cover the period 1953 to 1977 and used a rigorous methodology. He tested two hypotheses: the calendar-time hypothesis and the trading-time hypothesis. Under the calendar-time hypothesis, returns on Monday should be three times higher than returns on the other trading days; returns are expected to be equally distributed among the trading days of the week according to the trading-time hypothesis. However, the empirical results reject both hypotheses and indicate that returns on Monday are significantly lower than returns on the other trading days of the week. Furthermore, French (1980) investigated this phenomenon by examining stock returns after holidays to decide whether market closure is responsible for the low returns on Monday. Surprisingly, stock returns after holidays were significantly higher than for normal trading days. Thus, the market-closure explanation is not supported by the data.

These findings motivated Rogalski (1984) to investigate this anomaly by altering the return metric from the difference between Friday's closing price and Monday's closing price to be the difference between Friday's close and Monday's opening. This analysis disentangles the effect by revealing whether the price decline on Monday takes place during trading hours on Monday, or between Friday's close and Monday's opening. The study utilises data from the DJIA and the S&P 500 for the periods 1974 to 1984 and 1979 to 1984, respectively. He found that the price increased during Monday's trading and that negative returns were generated between Friday's close and Monday's opening. This effect, consequently, has been termed the weekend effect rather than the Monday effect. In addition, Rogalski (1984) shows that the Monday returns are positive in January.

Numerous studies—the majority of which use US data—support the documented negative returns over the weekend. Salient US studies include Keim and Stambaugh (1984), who use S&P 500 data over the period 1928 to 1982, and Lakonishok and Smidt (1988), who examine a long time series for the DJIA spanning the period 1897 to 1986, thus adding to the work of Damodaran (1989) and Lakonishok and Maberly (1990). Moreover, a noticeable multi-country study confirms the negative weekend returns in developed markets except Japan and Australia where the lowest returns are generated on Tuesdays (Jaffe and Westerfield, 1985). Weaker support for the weekend effect is provided by Agrawal and Tandon (1994), who show that Monday's returns are the lowest in nine out of the 18 markets examined, while Tuesday's returns are the lowest in eight markets. Gibbons and Hess (1981) affirm that weekend seasonality is not confined to stock markets, as the same pattern is found in treasury-bill returns.

Recent studies provide evidence for the diminishing and (or) reversal of the weekend effect in recent times. Using US data spanning the period 1962 to 1993, Kamara (1997) shows that while the weekend effect has diminished for large firms, it remains robust for small firms. Hiraki *et al.* (1998) examine the Japanese market, and Faff and McKenzie (2002) study the markets of Australia, Germany, Japan, Spain, the UK, and the US—their results confirm that the pattern documented by Kamara (1997) transcends international boundaries. In addition, Kohers *et al.* (2004) analyse the aggregated broad market indices for a wider range of markets over the period 1990 to 2002. Consistent with the findings of Kamara (1997), Hiraki *et al.* (1998) and Faff and McKenzie (2002) show that the weekend effect has weakened in recent years which, in turn, implies that markets are becoming more efficient. A number of studies document a reversal in the weekend effect—that is, the mean returns generated over the weekend became positive and significantly higher than the mean returns for the other days of the week over recent periods, particularly for large firms (Brusa *et al.*, 2005; Galai *et al.*, 2008; Mehdian and Perry, 2001). Mehdian and Perry (2001) utilise a data set consisting of four US broad market indices over the period 1964 to 1998. Using the Chow (1960) test for structural breaks for the identification of break points, they partition the data on the basis of the documented break points into three subsamples. The results that emerge from the refined analysis indicate that during recent periods, the weekend mean return is found to be positive and uncorrelated with the preceding week's return. This conclusion only pertains to large firms, as the weekend effect remains unchanged for small firms. Using a different research design, Brusa *et al.* (2005) corroborate the findings of Mehdian and Perry (2001). Galai *et al.* (2008) investigate the weekend effect using S&P 500 data over the period 1980 to 2000. They find that the significantly negative returns on Monday, that are well documented in the literature, are driven by outliers. Therefore, they show that after controlling for the outliers, Monday returns become positive and significant.

An alternative view of seasonality is encapsulated by Hiraki *et al.* (1998, p. 505), who argue that "return seasonality in itself is a dynamic process and that previously documented returns patterns are likely to change whenever there is a major structural change in financial markets". Moreover, the focus of studies has recently shifted towards dynamic analyses that allow for tracking the evolution of seasonal patterns over time, (for example Doyle and Chen, 2009; Marquering *et al.*, 2006). In their noteworthy paper, Doyle and Chen (2009) investigate 13 broad market indices from five developed markets (US, Japan, UK, Germany, and France) and three emerging markets (Hong Kong, China, and India) over the period 1993 to 2007. The thrust of their argument is that the weekend effect is not fixed but, rather, it is time-varying. Moreover, they highlight the continuity of this pattern although it is not entirely predictable. They propose a formulation that facilitates the testing of the aforementioned hypotheses.[6] The empirical results indicate that anomalous returns are not confined to Monday. Instead, the seasonal patterns in stock returns move through the days of the week. They call this phenomenon the "wandering weekday effect". In addition, they show that the seasonal pattern they document is not wandering to a halt but, rather, remains strong although appearing in a different way.

Although the day-of-the-week effect varies, not only over time but also between markets, numerous studies provide potential explanations for this effect. However, most of these hypotheses do not hold for recent periods and across markets. In a comprehensive review paper, Pettengill (2003) classifies the explanations proposed for the weekend effect into three categories: statistical or econometric errors (for example Connolly, 1989 and Sullivan *et al.*, 2001), market microstructure effects, (for example Gibbons and Hess, 1981; Lakonishok and Levi, 1982; Keef and McGuinness, 2001), information-flow effects, (for example Dyl and Maberly, 1988; Damodaran, 1989), and order-flow explanations (for example Miller, 1988; Lakonishok and Maberly, 1990; Abraham and Ikenberry, 1994; Brooks and Kim, 1997).

The first plausible explanation for the presence of the weekend effect is on statistical grounds. While the weekend effect is confirmed by a number of well-established studies, Sullivan *et al.* (2001) argue that the seasonal effects, in general, are a manifestation of data mining. They employ a bootstrapping procedure to mitigate the data-mining bias. Using this approach, the researchers fail to find evidence for the weekend effect. Other studies focus on the sensitivity of the weekend effect to alternative model-specification and estimation techniques. Connolly (1989) emphasises the fragility of the results obtained by the simple OLS because this technique rests on strong statistical assumptions that are shown to be

[6] The model specifications used to test these hypotheses are discussed in detail in Section 3.1 of Chapter 3.

violated by daily-return data (Fama, 1965; Mandelbrot and Taylor, 1967).[7] He employs several econometric techniques with less-restrictive assumptions and finds the results to be sensitive to the estimation technique. Several studies take a similar approach when investigating the presence of the weekend effect and arrive at a similar conclusion. Easton and Faff (1994) examine the Australian market; Lucey (2004) seeks evidence from the Irish market; and Baker *et al.* (2008) investigate the Canadian market.

Market microstructure-based explanations include settlement procedures. Gibbons and Hess (1981) suggest that the settlement period (the time between the transaction and receiving the payment) partially explains the day-of-the-week effect. However, because the settlement period varies over time, and across markets, it only pertains to some markets in a specific historical time period. Likewise, Lakonishok and Levi (1982) investigate the impact of the time required for cheques to clear. However, they find limited evidence supporting this explanation. The findings in non-US studies, on the other hand, are mixed. The settlement procedure seems to explain the weekend effect in the stock markets of Greece (for example Condoyanni *et al.*, 1989), and Malaysia (for example Clare *et al.*, 1998). Keef and McGuinness (2001) show that the weekend effect in the New Zealand market is robust to changes in the settlement procedure.

The third explanation is based on the premise of market efficiency. If relevant market information releases follow a distinctive seasonal pattern, one would expect stock returns to reflect this pattern. Dyl and Maberly (1988) find that information releases cluster over the weekend, in particular those that carry unfavourable news. They suggest that this phenomenon constitutes a partial explanation for the negative returns that accrue over the weekend. Dyl and Maberly (1988) only group the announcements into favourable and

[7] A detailed discussion of this issue is presented in Section 3.1 of the following chapter.

unfavourable, but subsequent papers draw a fine distinction between micro-information releases, such as dividend and earning announcements (for example Damodaran, 1989; Choy and O'hanlon, 1989; Fishe *et al.*, 1993; DeFusco *et al.*, 1993), and macro-information releases such as economic indicators and monetary-policy announcements (for example Chang *et al.*, 1998; Steeley, 2001).

Damodaran (1989) argues that firms tend to release negative news in relation to earnings and dividends following the market closure on Friday, which leads to the negative returns on Monday. Nonetheless, negative returns on Monday persist even when the returns on the week following the bad news release are deleted. Choy and O'hanlon (1989) and Fishe *et al.* (1993) confirm the findings of Damodaran (1989). On the other hand, Schatzberg and Datta (1992) fail to find a relationship between the weekend effect and dividends announcement. Likewise, earnings announcements are shown to have no bearing on the weekend seasonal pattern (Peterson, 1990). Indeed, DeFusco *et al.* (1993) indicate that other firms' announcements and dividend and earnings announcements have some explanatory power. While the support for the firm-specific (micro) announcements explanation is weak, the macro-based explanation is more promising. Athanassakos and Robinson (1994) argue that while dividend announcements have no bearing on the weekend effect, macroeconomic announcements may explain the negative returns generated over the weekend. Chang *et al.* (1998) indicate that when the impact of macroeconomic news is controlled for, the weekend effect become less pronounced in small firms. Furthermore, Steeley (2001) shows that macroeconomic announcements explain the weekend effect, albeit only when negative returns are considered.

To understand the weekend effect, we consider the order flow that produces this pattern, as examined in several studies. The premise of order-flow-based explanations is that individual investors are net sellers on Mondays. Miller (1988) and Lakonishok and Maberly (1990) argue that individuals make their sell decision over the weekend, as the majority of these individuals are employed in full-time jobs, and so they tend to trade on Monday. In addition, Miller (1988) and Lakonishok and Maberly (1990) report that brokers produce significantly more buy recommendations than sell recommendations, but they are inactive over the weekend, which further enhances the tendency of individual investors to sell on Mondays. Rystrom and Benson (1989) claim that investors' lack of optimism on Mondays contributes to negative returns over the weekend. Foster and Viswanathan (1994) say that investors with discretionary liquidity are reluctant to buy on Mondays because of the possibility of losing by trading with informed traders who sell on the basis of unfavourable information. Brooks and Kim (1997) show that the unwillingness of institutional investors to trade on Mondays—in conjunction with the tendency of individual investors to trade—contributes to the negative weekend effect. The individual investors contribute to the seasonality through their trading. while institutional investors contribute through the withdrawal of liquidity. Wang and Walker (2000) posit that institutional investors are less likely to trade on Mondays because they engage in strategic planning. Chen and Singal (2003) subscribe to the argument that the reluctance of traders to hold short positions during market closures contributes to the weekend effect. They suggest that traders close their short positions by buying stocks on Fridays, and reopen their short positions on Mondays by borrowing stocks and selling them. This tends to boost returns on Fridays and to bring them down on Mondays.

A number of empirical studies operationalised and tested the contribution of individual traders to the weekend effect. In a pioneering paper, Lakonishok and Maberly (1990) use odd-lot trades as a proxy for the activity of individual traders. Using a detailed data set comprising trading volume and sell and buy transactions, they find that trading volume is significantly lower on a Monday compared to the remaining days of the week. Furthermore, the ratio of odd-lot trades to the NYSE trading volume is significantly higher on a Monday compared to the rest of the week. Moreover, sell odd-lot traders are relatively higher than buy odd-lot traders on a Monday compared to the other days of the week. On the basis of these distinctive patterns, Lakonishok and Maberly (1990) argue that the behaviour of individual traders on a Monday constitutes at least a partial explanation for the negative returns over the weekend. A subsequent study by Abraham and Ikenberry (1994)—who utilise odd-lot data as a proxy for individual-investor behaviour—confirms the finding that individual investors' selling activity is more evident on Mondays. In addition, they find that selling activity on a Monday increases if the preceding Friday's returns were negative, reflecting herd behaviour in response to negative market movements. Brooks and Kim (1997) provide supporting evidence for the role of individual investors in the weekend effect using intra-day data. Besides, they show that institutional investors amplify the weekend effect by withdrawing liquidity on Monday.

Indeed, Kamara (1997), Chan *et al.* (2004), Hiraki *et al.* (1998), Faff and McKenzie (2002), and Brusa *et al.* (2005), among others, subscribe to the argument that individual investors make the main contribution to the weekend effect. In general, these papers link the fading of the weekend seasonality during the past few decades to the shift in stock-ownership composition from individual to institutional investors, in addition to the introduction of index futures contracts. Using the S&P 500 data over the period 1962 to 1993, Kamara (1997) shows that the decline in weekend seasonality is associated with the increased activity of institutional investors, which he captures using the ratio of block to odd-lot trading volume. This relationship holds for large liquid stocks, while small stocks are not affected. In addition, he indicates that institutional investors utilise the less costly index futures contracts to arbitrage away the weekend effect. This is evident as the spread between futures and spot

S&P 500 returns displays a reversed seasonal pattern—Friday returns are negative and significantly lower than for the other days of the week, while Monday returns are positive and significantly higher than for the other days of the week.

Using Japanese data, Hiraki *et al.* (1998) confirm the findings of Kamara (1997). They document an alternation in the weekend seasonality pattern over the period at which the market index futures contracts are traded. Specifically, the Tuesday effect vanishes over the period following the introduction of the index futures, while the Monday effect becomes pronounced. To ascertain whether the disappearance of the weekend seasonal pattern pertains to non-US markets, Faff and McKenzie (2002) examine five stock markets in which index futures contracts are introduced in addition to the markets of the US and Japan. They employ a more sophisticated model that allows for testing the seasonal patterns not only in mean returns, but in autocorrelation and volatility. Their empirical results are consistent with those reported by Kamara (1997) and Hiraki *et al.* (1998) with respect to the weekend seasonality in mean returns. Furthermore, seasonal patterns are documented in both autocorrelation and volatility. While the introduction of index futures contracts has no impact on the autocorrelation seasonal pattern, a change in volatility seasonality is detected. In a more recent paper, Chan *et al.* (2004) rely on a detailed data set of institutional holdings to investigate the reason behind the weakening of the weekend effect. They form 10 portfolios on the basis of institutional ownership. The empirical results indicate that over the period 1990 to 1998, weekend seasonality is more pronounced for stocks with low institutional holdings, while the weekend mean returns are not different from mean returns over the other days of the week for stock with high institutional holdings.

Several studies in the extant literature show that the weekend effect is moderated by a number of factors, such as the prior four days' returns (Jaffe *et al.*, 1989); the prior day’s returns (for example Abraham and Ikenberry, 1994; Bessembinder and Hertzel, 1993; Högholm *et al.*, 2010; Tong, 2000); market conditions in terms of bull and bear market periods (for example Auer, 2014; Blose and Gondhalekar, 2013; Fishe *et al.*, 1993; Ma, 1986; Steeley, 2001); business-cycle phases (for example Liano and Gup, 1989; Liano *et al.*, 1993); and other seasonal effects (for example Ariss *et al.*, 2011; Liano and Lindley, 1995; Pettengill and Jordan, 1988; Swinkels and Van Vliet, 2012; Wang *et al.*, 1997).

Jaffe *et al.* (1989) show that the negative returns generated over the weekend are strongly correlated with the prior four days' returns. They point out that once the Monday mean return is conditioned on the prior week's up market-movement, the statistical significance of the negative returns generated over the weekend is greatly weakened for the US and UK markets; the weekend returns cease to be negative in the remaining markets. Bessembinder and Hertzel (1993) document a persistent seasonal pattern of autocorrelation using a wide range of securities. They find that the correlation between the returns of the day that directly precedes a market closure and the day that immediately follows a market closure are significantly higher than the autocorrelations of other days. Abraham and Ikenberry (1994) confirm the presence of this pattern by showing that the correlation between Friday's and Monday's returns is the highest among the other days of the week. Moreover, they show that when the mean return on a Monday is conditioned on the direction of market movement on the previous trading day (Friday), the mean return for Monday is found to be positive for 56 percent of the time if the preceding Friday's returns are positive. If, however, the preceding Friday's returns are negative, thenfor 77 percent of the time Monday's returns are found to be negative. They find that this pattern is more pronounced for small and medium-sized companies. Högholm *et al.* (2010) demonstrate that ignoring the autocorrelation structure in daily stock returns when testing for the weekend effect leads to erroneous conclusions with respect to the presence of weekend seasonality.

While market conditions are key in determining the presence and strength of weekend seasonality, there is no clear agreement as to their definition. Ma (1986) segmented the sample of gold spot daily returns into a number of bull and bear market phases on the basis of the sign of the realised annual returns. Blose and Gondhalekar (2013) identified bull and bear market regimes in a more arbitrary fashion, relying on a visual inspection of the price of gold over the sample period. Fishe *et al.* (1993) define market conditions differently, as they partition the sample into good and bad-news periods on the basis of the sign of realised daily returns; Steeley (2001) uses the sign of realised daily returns of the prior day instead. The main conclusion that emerges from these papers is that the weekend effect is more pronounced over down market-periods.

The association between the business-cycle phases and the weekend effect has been investigated empirically in a small number of studies in the extant literature. By dividing the sample into contractionary and expansionary periods, Liano and Gup (1989) show that negative weekend returns are more evident during contractionary periods. However, Liano *et al.* (1993) show that the impact of the correlation pattern between Monday’s returns and the prior week's returns on weekend seasonality is persistent across business-cycle phases.

The influence of the other well-established seasonal effects on the strength of the weekend effect has been addressed in numerous studies. Rogalski (1984) shows that weekend returns are positive during January. Several papers investigate the contribution of the monthly seasonal effect to the weekend’s returns (Liano and Lindley, 1995; Pettengill and Jordan, 1988; Wang *et al.*, 1997). The thrust of these studies is that although the weekend effect is persistent across the month, its strength is clearly affected by other seasonal effects. Ariss *et al.* (2011) indicate that the day-of-the-week seasonal pattern is undermined during the month of Ramadan.

As with other seasonal effects, the weekend effect is widely investigated internationally. The main conclusion that can be derived from these studies is that although the weekend effect is largely present in a number of markets, it varies across markets as to the days on which this seasonal pattern is observed. An early study is Jaffe and Westerfield (1985), who tested for the presence of this effect outside the US. Their selected sample comprises four developed markets (Canada, Japan, Australia, and the UK). The results are consistent with the US-based studies in terms of rejecting the hypothesis that stock returns are equally distributed over the week. However, Tuesday's rather than Monday's returns are the lowest in Australia and Japan. Indeed, the significantly lower returns on Tuesday are not unique to the Australian and Japanese stock markets. Agrawal and Tandon (1994) report that Monday's returns are the lowest in nine out of the 18 markets they examined, while Tuesday's returns are the lowest in eight of the markets. A recent study by Högholm *et al.* (2010) investigated 18 countries within the European Union, some of which are not members of the European Monetary Union. They show that the weekend effect is present, but the seasonal pattern differs across markets. The authors fail to find a link between the weekend seasonal pattern and whether or not a country is a member of the European Monetary Union.

Emerging-market studies have addressed this puzzling empirical regularity. Their findings are largely in line with their developed-market counterparts. The vast majority of studies offer empirical evidence in support of the argument that the weekend effect is a local instead of a global phenomenon. Brooks and Persand (2001) provide mixed evidence on the presence of a day-of-the-week effect over the period 1989 to 1996 in five South Asian markets

(Thailand, Malaysia, Taiwan, South Korea, and the Philippines). They report that the markets of Malaysia, Taiwan, and South Korea exhibit significant differences in average daily returns between the days of the week, while the returns in the other two markets do not show significant seasonal effects. Ajayi *et al.* (2004) investigate 11 East European markets and show that the mean return for Monday is negative in six markets but is statistically significant only in two markets. The remaining markets, however, display positive Monday mean returns but these are only statistically significant in one of these markets. Furthermore, only in one out of the two markets that exhibit significantly negative Monday returns are these returns found to be significantly lower than on the other days of the week. Basher and Sadorsky (2006) consider a large sample comprising 21 emerging markets over the period 1992 to 2003. Their results largely resemble those of other studies in that the weekend seasonal pattern differs across markets. Alagidede (2008a) arrives at a similar conclusion using a sample of seven African stock markets. Lean *et al.* (2007) examine the stock markets of Hong Kong, Taiwan, Japan, Malaysia, Singapore, Indonesia, and Thailand over the period 1988 to 2002 by using a stochastic-dominance approach. They show that Monday returns are dominated by other weekdays, and that Friday dominates other weekdays; they conclude that this effect could be exploited by means of a simple trading rule.

The weekend effect has received mounting attention in the GCC region. Al-Loughani and Chappell (2001) investigate this effect in the Kuwait stock exchange. They show that stock returns are significantly higher in the first day of the trading week (Saturday). In contrast, the return patterns in developed markets exhibit lower returns in the first trading day of the week (Monday). However, more recent GCC studies do not support this conclusion. Al-Khazali (2008) finds no traces of the day-of-the-week effect in the United Arab Emirates (UAE) after adjusting the data set for thin trading. Using the same methodology, Al-Khazali and Zoubi

(2010) reject the day-of-the-week effect in three GCC markets (Bahrain, Kuwait, and Saudi Arabia). In a study that investigates the day-of-the-week effect among other calendar-time anomalies in all GCC markets, Bley and Saad (2010) use conventional OLS methodology to detect seasonality in daily returns. Nonetheless, excluding Saturday from the analysis casts doubt on the reliability of their results, as it is the first trading day in the markets of Saudi Arabia and Kuwait during most of their sample period. Ariss *et al.* (2011) investigate the day-of-the-week effect in all GCC markets. By excluding data after June 2008 to avoid the effect of the global financial crisis, they provide evidence in support of the weekend effect in the Saudi market, but on different days to those of their international counterparts. They refer to it as the "Wednesday effect", as returns are significantly higher on Wednesday—the last trading day of the week in the Saudi market. It is significantly lower on Saturday—the first trading day.

The literature on the weekend effect is vast. A summary of the studies that examine the weekend effect is presented in Table 2A.2 in the appendix to this chapter. In this summary, a number of aspects are considered: the market under examination, the sample period, the days considered (the definition of the weekend period employed in the study), the econometric technique used to measure the weekend effect, and whether or not the study controlled for other seasonal effects. The main conclusions are stated.

2.4 The Holiday Effect

Persistent seasonal patterns in stock returns around holidays have long fascinated economists and financial practitioners. Anomalous patterns on the day that falls immediately before holidays was first uncovered by Fields (1931). By using DJIA data, he found that a large fraction of up market-movements occurs in the last trading day preceding a holiday. He attributed the pre-holiday abnormal returns to the tendency of speculators to exit their short positions before market closure. Indeed, several stock market analysts confirmed the findings of Fields (1931). For example, Merrill (1966) investigates the DJIA over the period 1897 to 1965 and shows that the market went up 67.9 percent of the times on the last trading day preceding holidays. Fosback (1976) examines the S&P 500 over the period 1929 to 1975, producing results indicating that the returns realised on the last two days before a holiday are nearly double the returns realised over the rest of the days throughout the 48-year sample period. Numerous other studies have been undertaken to investigate this effect further (for example Ariel, 1990; Kim and Park, 1994; Lakonishok and Smidt, 1988; Pettengill, 1989; Ziemba, 1991). The empirical findings generated by these studies reveal a strong and persistent seasonal pattern in stock returns for the days prior to the holidays; the returns for post-holiday days are not significantly different from those realised on typical days.

In a significant study, Ariel (1990) documents a strong holiday effect using the CRSP value-weighted and equally weighted index returns over the 1963 to 1982 period. The empirical results indicate that pre-holiday returns are substantially larger than returns on non-holiday trading days, and that the difference between the pre-holiday days' mean returns and that of non-holiday days is statistically significant for both the value-weighted and equally weighted indices; the effect is relatively stronger in larger capitalisation stocks. Specifically, Ariel (1990) reports that the means of pre-holiday returns are 9 and 14 times larger than the means of non-pre-holiday periods (typical days) for the equally weighted index and the value-weighted index, receptively. Moreover, he notes that 34.7 per cent of the value-weighted continuously compounded returns over the 20-year sample period were generated over the eight pre-holiday days. The exceptionally high return over pre-holiday days is shown to be robust after controlling for the day-of-the-week, the January, and the small-firm effects.

In accordance with the findings of Ariel (1990), Lakonishok and Smidt (1988) use a long time series of stock returns (spanning the period 1897 to 1986) and report that slightly more than 50 percent of the returns on the DJIA are generated, approximately, during eight annual pre-holiday days. They also show that this effect is distinct from other seasonal anomalies. In another study, Pettengill (1989) examines the S&P 500 and CRSP equally weighted indices over the period 1962 to 1986. His empirical results confirm the conclusions of prior studies such as Ariel (1990) and Lakonishok and Smidt (1988). Fabozzi *et al.* (1994) investigate a wide range of futures contracts. The results indicate that the holiday effect is also present in futures markets. Kim and Park (1994) provide out-of-sample evidence by investigating the presence of this anomaly in the UK and Japanese markets using a more rigorous approach. They construct size-decile portfolios. Their findings confirm that the holiday effect is not confined to the US and it is not related to firm size, after controlling for other effects. Other non-US based studies include, among others, Cadsby and Ratner (1992) and Meneu and Pardo (2004). The main conclusion that emerges from these studies is that the holiday effect is present in non-US markets, and that the holiday patterns documented in these markets are independent of those of the US.

Notwithstanding the robustness of the holiday effect, the explanations put forward to account for its presence are diverse and are not universally accepted. By using intra-day data, Ariel (1990) examines a number of hypotheses that are suggested to explain the holiday effect, and shows that the measurement-error explanation is highly unlikely to be sound, as positive returns are generated throughout the pre-holiday day, well before market closure. In addition, the impact of other seasonal effects on the strength of the holiday effect is also rejected by the data as a cause for the holiday effect. Ariel argues against the conventional explanation that market participants tend to exit their short position prior to market closure. He is sceptical about linking the holiday effect to the unwinding of short positions. He also shows that the returns realised over pre-holiday close to post-holiday open are positive, which is at odds with the proposition that the short positions should be reinstituted at the market opening.

Pettengill (1989) demonstrates that the holiday effect is not simply a consequence of market closure. He argues that if the holiday returns are a result of market closure, the return generated over the day that falls immediately before non-holiday announced market closures should be similar to those generated over pre-holiday day market closures. By the same token, if a holiday is not accompanied by market closure, the returns generated over the day that falls immediately before this holiday should not be different from other trading days. Using data for announced market closures due to increase trading volumes in NYSE during the year 1968, he found that the returns generated over the days that fall immediately before market closures that are not associated with a holiday are substantially lower when compared to pre-holiday returns. Furthermore, he shows that the returns generated immediately before the New Year holiday are high, irrespective of whether the market is closed or not.

Fabozzi *et al.* (1994) provide empirical evidence in support of the notion that market participants are more reluctant to take positions—short positions in particular—prior to holiday market-closures. They find that the trading volume for the pre-holiday days is significantly lower than on non-preholiday days, while that of post-holiday days is significantly higher. This suggests that traders rebalance their portfolios. Nonetheless, this explanation is partial, at best, because they find that pre-holiday patterns also exist for open market-holidays, albeit less consistently.

As with the previously discussed seasonal anomalies, there is no satisfactory explanation for the occurrence of this holiday anomaly. In the light of the above literature, Kim and Park (1994, p. 156) write:

> The persistence of the holiday effect across countries suggests that the holiday effect is not driven by institutional arrangements unique to the stock market of a country. Therefore, institutional factors such as trading methods, clearing mechanism, settlement procedures, and bid-ask spreads cannot be possible explanations for international evidence of the holiday effect because these institutional factors are different across countries. Also, our results show that, after controlling for the day-of-the-week effect and the pre-New-Year's-Day effect, the size effect is not present in mean returns on pre-holidays. Therefore, any explanations that are based on the relationship between the holiday effect and firm size should be re-examined.

The majority of papers in the extant literature accept the proposition of holiday-homogeneity proposed by Ariel (1990). This proposition implies that holiday returns are uniformly high across different holidays, firm sizes, and years. While early papers support the validity of this assumption (for example Ariel, 1990; Lakonishok and Smidt, 1988), a number of studies do not. Pettengill (1989) and Fabozzi *et al.* (1994) indicate that post-holiday returns, in particular, vary across weekdays. Tsiakas (2010) examines the DJIA constituents and classifies holidays, on the basis of the weekday on which they occur, into four categories. He finds statistical and economic evidence in support of conditioning on the four holidays. Easton (1990) examines the Australian stock market; McGuinness (2005) investigates the market of Hong Kong; and Akyol (2011) studies the Turkish stock market—they all show that the magnitude of the pre-holiday returns is positively correlated with the duration of the holiday. Hiraki and Maberly (1995) show that high pre-holiday returns are limited to the golden-week period in the Japanese stock market. Marrett and Worthington (2009) examine the Australian stock market and find that while the holiday effect is present in broad market indices, these findings do not apply to a number of industry indices. Chong *et al.* (2005) study the markets of the US, UK, and Hong Kong; Vergin and McGinnis (1999) examine four US broad market indices; and Marquering *et al.* (2006) investigate the DJIA—they all show that the preholiday returns have substantially declined over the years. On the other hand, Lucey and Pardo (2005) examine the Irish and Spanish markets and show that the holiday effect is growing stronger over time.

Indeed, the holiday effect is not confined to secular festivities, as a growing body of literature documents anomalous patterns in returns around cultural and religious holidays, not only in the Middle East and Far East, but also in the US. In an interesting paper, Frieder and Subrahmanyam (2004) explore the impact of religious and cultural occasions on investors' sentiment by analysing stock returns and trading volumes in the US market. Indeed, this study differs from prior studies of holiday seasonality in that such occasions occur at the times when the market remains open. The occasions considered by the authors are Rosh Hashanah, Yom Kippur, and St Patrick's Day. Their sample, using the S&P 500 index, spans the period 1946 to 2000. The results reveal that the mean returns of the two days that fall prior to St Patrick's Day and Rosh Hashanah (festive in nature) are significantly higher than the mean returns of other days. However, mean returns over the two days that fall after Yom Kippur (solemn in nature) are lower than the mean returns of other days, especially during the 1973 to 2000 period where the 1973 war coincided with Yom Kippur.

In a related paper, Kaplanski and Levy (2012) use a sample for the period from 1990 to 2008 to investigate the presence of holiday seasonality in the Tel Aviv Stock Exchange, where the market closes during the Jewish holidays of Rosh Hashanah and Yom Kippur. They argue that specific holidays, in particular Yom Kippur which coincided with the 1973 war, are associated with conflicting negative and positive sentiments. Therefore, a careful examination of its impact on the market is warranted. Their results show that the mean return for the day that falls immediately before the Yom Kippur holiday is not statistically different from other days, while the post-holiday mean returns are negative and significantly lower than for other days; this is largely consistent with the findings of Frieder and Subrahmanyam (2004). On the other hand, the pre-holiday mean returns for the remaining holidays are significantly higher than for typical days, while no meaningful difference is detected for the post-holiday day, which is in line with prior studies in this strand of the literature.

A number of studies document the presence of religious and cultural seasonal effects in several Asia-Pacific markets. Ho (1990) tests for several seasonal effects in 10 such markets—Australia, Hong Kong, Japan, Korea, Malaysia, New Zealand, the Philippines, Singapore, Taiwan, Thailand—in addition to the US and the UK over the period 1975 to 1987. He finds evidence for a turn-of-the-lunar-year effect in the markets of Hong Kong, Taiwan, and Malaysia. In accordance with the findings of Ho (1990), Chan *et al.* (1996) show that cultural and religious holiday effects are stronger than secular and state holidays in some Asian markets. Their analysis is conducted utilising data from the stock markets of India, Malaysia, Thailand, and Singapore. They find evidence for the Chinese New Year effects in the markets of Malaysia and Singapore. Moreover, the Islamic New Year and Vesak effects are also present in the Malaysian market.

In a recent study of the Middle East, Bley and Saad (2010) investigate a number of Islamic and state holidays in the GCC markets (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE) over the period 2000 to 2009. A subset of the Islamic holidays they examined occur in times when some markets, at least, are open. For example the markets of Saudi Arabia and Qatar are open during Al-Isra and Al-Mi'raj, the Prophet Mohammad's birthday, Ashura, and the Hijri New Year. The authors document significantly higher returns one day prior to Eid Al-Fitr in Oman, Qatar, and the UAE; higher returns in Saudi and Kuwaiti markets occur two days before this holiday. Furthermore, the Al-Isra and Al-Mi'raj effect is present only in the

Bahraini market; the Islamic New Year effect is only found in the market of Qatar. All of these holiday effects are positive, implying that returns during the days surrounding these holidays are higher than the returns realised during typical days. In addition, a negative effect on returns around Ashura is documented, but only in the UAE market. No abnormal patterns are detected in stock returns around other holidays. In the present study, we only examine the festivities which are public holidays. This implies that pre and post-holiday dummies are constructed for each market separately. This allows a more refined analysis of the holiday effect, which is documented by the majority of prior studies as a regularity in stock returns that on days that precede market closure.

The literature on the holiday effect is vast, which makes an in-depth review of all studies beyond our scope. However, a summary of the studies that examine the holiday effect is presented in Table 2A.3 in the appendix to this chapter. In this summary, a number of aspects are considered: the market under examination, the sample period, the days considered (the definition of the holiday dummies), whether the holiday causes a market closure or not, the econometric technique used to measure the holiday effect, and whether or not they control for other seasonal effects. The main conclusions are also stated.

2.5 The January Effect

The documentation of seasonal patterns in stock returns around the turn of the year dates back to the 1940s. Wachtel (1942) noticed anomalous patterns around the turn of the year in the Dow Jones Industrial Average (DJIA) over the period 1927 to 1942. He observed persistent price run-ups between December and January in 11 out of the 15 years examined. More rigorous empirical work was conducted subsequently (for example Keim, 1983; Reinganum, 1983; Rozeff and Kinney, 1976). The empirical results of the these later studies are consistent with Wachtel’s (1942) findings, in that returns are significantly higher in

January than in the other 11 months of the year. Rozeff and Kinney (1976) investigate monthly seasonality in the New York Stock Exchange (NYSE) by analysing a broad market index for the period 1904 to 1974. They find that returns in January are significantly higher than in the rest of the year, except for the period 1929 to 1940. More elaborate analysis has been conducted in studies such as Keim (1983) and Reinganum (1983); they form size portfolios on the basis of market capitalisation of the stocks traded in the NYSE. The empirical results reported in these studies confirm the presence of the January effect. Furthermore, both studies indicate that this effect is more pronounced in small stocks. These economists, among others, put forward a number of hypotheses to explain the January effect, including the tax-loss selling (TLS), market micro-structural explanations, the behaviour of portfolio managers who engage in window dressing at the turn of the year, and the timing of information releases.

The most widely accepted explanation is the TLS hypothesis, which postulates that stocks with the worst performance in the previous year tend to earn significantly higher returns in the January of the subsequent year (Gultekin and Gultekin, 1983; Keim, 1983; Reinganum, 1983; Rozeff and Kinney, 1976). This outcome arises because investors sell poorly performing stocks prior to the tax-year end in order to benefit from the tax deductibility of the capital losses incurred by selling underperforming stocks. The selling pressure results in excess supply of these stocks that, in turn, translates into a decline in their returns in December. In January, prices revert to their equilibrium level, as the excess supply of stocks is eliminated by investors at the beginning of the new year. Roll (1983) called this phenomenon the turn-of-the-year effect, rather than the January effect, as he observed that this effect gradually dies away as January wears on.

Ritter (1988) extends the TLS explanation and provides the parking-then-proceed hypothesis. He claims that buying pressure at the beginning of January is initiated by idle cash in individual investors' accounts from TLS, Christmas bonuses, other year-end financial proceeds, and the perception among individual investors that these small stocks are undervalued .This explanation of the turn-of-the-year effect as a small-stock phenomenon is supported by the empirical results obtained using the buy:sell ratio of individual investors' data from Merrill Lynch. Recent empirical evidence supports Ritter's findings that this effect is generally confined to small stocks and individual investors, as D'Mello *et al.* (2003) observe a significant decline in the average trade size for poorly performing stocks before the year end.

Another explanation for this pervasive anomaly is provided by the proponents of the efficient-market hypothesis, who posit that small stocks are characterised by high transaction costs which potentially consume the profits that can be earned from exploiting regular patterns in stock returns. This is the reason why these anomalous patterns cannot be arbitraged away (Reinganum, 1983; Roll, 1983; Stoll and Whaley, 1983). An alternative point of view is frequently referred to in the literature as the "window-dressing" hypothesis, or more, generally portfolio rebalancing. The window-dressing hypothesis postulates that the remuneration system in most managed funds depends largely on the performance at the end of the year (31 December). Therefore, portfolio managers may be induced to sell poorly performing stocks around the turn of the year and thus bid up the prices of the stocks included in their portfolios (Lakonishok and Smidt, 1984). In a subsequent paper, Ritter and Chopra (1989) argue that following their year-end window-dressing activities, fund managers tend to buy small risky stocks in order to outperform their passive benchmark. In addition, individual investors reinvest the proceeds from their tax-motivated selling. These portfolio-rebalancing activities generate the abnormally high returns on small risky stocks in January. Ritter and Chopra (1989) report empirical evidence in support of their conjecture.

The information hypothesis is among the early suggested alternative explanations for the January effect. Keim (1983) and Rozeff and Kinney (1976) conjecture that January coincides with the release of accounting information and other corporate announcements, which leads to an increase in uncertainty that fuels speculation and boosts stock returns. This hypothesis, possibly motivated by the findings of international studies, poses serious threats to the external validity of the TLS hypothesis. These international studies cover countries with similar tax laws to those of the US, but they are characterised by different tax-year end dates. An interesting case that received considerable attention is the Australian stock market. Australian tax laws resemble their American counterparts, but with a June to July tax year. In spite of that tax year in Australia, stock returns exhibit significant patterns from December to January, in addition to the expected July to August seasonality under the TLS (Brown *et al.*, 1983).

Indeed, the empirical results are mixed *vis-à-vis* the validity of the information hypothesis. Reinganum and Gangopadhyay (1991) report empirical results that do not lend support to this hypothesis. This is because they find that firms with a non-December fiscal-year end do not exhibit abnormal returns at the end of the fiscal year, whereas small firms are characterised by high January returns regardless of their fiscal-year end. Nonetheless, the empirical results from more recent studies are consistent with the information hypothesis. In particular, Kim (2006) constructs a common risk factor related to information uncertainty caused by earnings volatility. He employs a two-factor model containing the market risk factor and the common factor to show that the factor that proxies for information uncertainty caused by earnings volatility accounts for the January effect. Thus, Kim (2006) concludes that what are thought to be anomalous returns in January could be a risk premium for assuming information-uncertainty risk concerning earnings and unexpected earnings surprises, and that higher returns in January are a consequence of using a mis-specified model in adjusting for risk. Kim (2010) provides an out-of-sample validity check using data from the developed stock markets of Canada, the UK, Germany, France, Japan, Hong Kong, and Australia. The findings of this study are consistent with those of Kim (2006). Evidence from a recent study suggests that it is not only accounting information that has an influence on returns in January, but macroeconomic announcements do too. For example Gerlach (2007) examines the response of market participants to macroeconomic announcements and shows that they partially explain the higher returns in January.

Early studies of the US generally accept the TLS hypothesis (for example Keim, 1983; Reinganum, 1983; Rozeff and Kinney, 1976). However, Brown *et al.* (1983) provide evidence against the TLS hypothesis utilising Australian data. This empirical finding highlights the importance of international studies that provide useful insights into the nature and the prevalence of seasonality in stock returns. Although developed markets are the primary focus of the majority of international studies that address the January effect, the emerging markets of South East Asia and South America have been receiving mounting attention. The evidence on the prevalence of the January effect internationally is, indeed, mixed. While the January effect is widely documented in developed markets, the presence of this anomaly in emerging markets is limited to just a few of them.

Gultekin and Gultekin (1983) investigate the presence the January effect in 17 industrialised economies. Their data set comprises monthly stock returns that span the period 1959 to 1979. They show that the January effect is present in the stock returns of the majority of their sample and this provides support for the TLS hypothesis; all the countries under investigation show significantly higher returns around the turn of the tax year, with Australia being the exception. Furthermore, they indicate that the January effect is not confined to small firms, unlike the US where the value-weighted index does not exhibit any seasonal patterns in January. Agrawal and Tandon (1994) update the work of Gultekin and Gultekin (1983) by expanding the sample of countries to include five more, and they cover the period from 1971 to 1987. Consistent with Gultekin and Gultekin (1983), they find that the January effect is not confined to the US and small firms. Furthermore, although they find no traces of significantly higher returns around the turn of the tax year in five out of 18 of the markets under investigation, they conclude that their empirical findings overall support the TLS hypothesis.

The proliferation of studies that investigate seasonality in stock returns in emerging markets is induced by the findings of Nassir and Mohammad (1987). While they find evidence for the existence of the January effect in the Malaysian stock market, their results reject the TLS hypothesis, as Malaysia does not have a capital gains tax. Pang (1988) arrives at the same conclusion using data from the Hong Kong stock market. Ho (1990) provides evidence from the Asia-Pacific region by using data on seven emerging markets, in addition to the developed markets of Australia, New Zealand, and Japan. He shows that daily returns are significantly higher in January in the majority of these markets; the TLS hypothesis is not supported. Using an updated data set from the Asia-Pacific region, and employing the stochastic-dominance approach, Lean *et al.* (2007) find that the January effect has vanished in recent years for all markets except Singapore.

While the Asia-Pacific emerging markets received most of the attention, recent studies broadened the focus to include emerging markets from other regions. For example Fountas and Segredakis (2002) test for the January effect in 18 emerging market across the globe (Argentina, Chile, Colombia, Greece, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, and Zimbabwe). Over the period 1987 to 1995 they use monthly data, and weekly data for 1989 to 1996 period. They find limited evidence in favour of the January effect and the TLS hypothesis. However, other monthly seasonal patterns are detected.

Despite the wide range of emerging markets examined in the above-mentioned studies, empirical work that involves the GCC markets remains scarce, which may be attributable to data-availability issues. Among the first studies conducted using data from the GCC is Al-Saad and Moosa (2005), who utilise monthly stock returns data derived from a general index of the Kuwait stock market over the period 1984 to 2000. They employ an OLS regression and a structural time series technique and obtain results that provide evidence in support of a positive July effect. They suggest a summer-holiday effect as an explanation for the existence of this seasonal effect. Al-Deehani (2006) extends the Al-Saad and Moosa (2005) analysis by examining a more recent period using monthly average indices for the market and its nine sectors covering the period 1996 to 2004. Al-Deehani documents seasonal positive effects that correspond to April or June in the market index and mixed evidence for seasonality in the sectors' indices. Bley and Saad (2010) examine the existence of calendar-time anomalies using data from all GCC countries. In accordance with Al-Saad and Moosa (2005) and Al-Deehani (2006), based on market index data, they find no evidence for the presence of the January effect. However, they show that when firm-level data are examined to identify foreign ownership, traces of both the January and Monday effects are detected. They argue that this is a result of tax-selling-motivated slipovers, particularly in stocks that are characterised by higher foreign-ownership limits.[8]

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[8] The GCC countries are tax-free.

2.6 The Halloween Effect

This seasonal effect was discussed in 1964 in the *Financial Times*, and since then the popular financial press disseminated the phrase "Sell in May and go away". Surprisingly, this effect had not been formally investigated before the important study undertaken by Bouman and Jacobsen (2002). They show, that over the period 1970 to 1998 in 36 out of 37 developed and emerging markets stock returns are significantly higher from November to April than for the rest of the year. Furthermore, they report that this anomalous pattern in stock returns is exploitable using a simple trading strategy based on the conventional wisdom "Sell in May and go away". This trading rule involves buying a market portfolio at the end of October then selling it at the beginning of May and investing the proceeds in a risk-free asset. This strategy is shown to outperform the buy-and-hold strategy on a risk-adjusted basis and to possess market-timing ability.

The empirical findings of Bouman and Jacobsen (2002) have been criticised on methodological grounds by Maberly and Pierce (2004), who posit that the Halloween effect in the US market vanishes when a reasonable change in the methodology is made. They empirically show that two outliers are responsible for the Halloween effect: the October 1987 crash and the collapse of the hedge fund Long Term Capital Management in August 1998. In addition, they extend the investigation to include the S&P 500 index futures. The empirical results show that the Halloween effect is not present in the S&P 500 index futures, even when there is no control for the outliers. In line with the argument presented by Maberly and Pierce (2004), it is demonstrated that the Halloween effect in the Japanese market is confined to the period prior to the internationalisation of the Japanese stock exchange and the introduction of index futures in the mid-eighties (Maberly and Pierce, 2003). More recent research, nonetheless, refutes the findings of Maberly and Pierce (2004) and Maberly and Pierce (2003) and demonstrates that the Halloween effect documented by Bouman and Jacobsen (2002) is resilient to outliers. For example, Witte (2010) criticises the methodology employed by Maberly and Pierce (2004) (particularly) for their subjective choice of outliers. He demonstrates, using a number of robust econometric estimation techniques, that the Halloween effect is not sensitive to model specification, as is claimed by Maberly and Pierce (2004).

In an insightful paper, Jacobsen and Visaltanachoti (2009) examine the Halloween effect using portfolios based on sector and industry. They use a data set that spans the period 1926 to 2006 (obtained from the Fama and French website). Their empirical findings show that the strength of the Halloween effect varies from sector to sector, as the effect is absent in consumer sectors. They suggest that a sector-rotation strategy can generate higher risk-adjusted returns. Later evidence provided by Haggard and Witte (2010) examines the Halloween effect using data from 37 developed and emerging markets. They employ two robust econometric estimation techniques in addition to the conventional OLS regression. Furthermore, they examine the viability of the Halloween-effect-based trading strategy. The empirical results show that the Halloween effect is significant in the US and is robust to the different estimation techniques over the period 1954 to 2008, but not earlier. Moreover, the trading strategy based on the Halloween effect outperforms the buy-and-hold strategy. In addition, the results derived from non-US markets indicate that this effect is statistically significant in 17 out of the 37 markets under investigation.

While the anomalies were attributed to numerous and diverse factors that range from the regulatory environment to the market microstructure, the explanations proposed for the Halloween effect are predominantly behavioural in nature. These explanations are based on the findings of research in psychology. Kamstra *et al.* (2003) show that there is a seasonal affective disorder (SAD) in stock returns. Experimental psychological research suggests that this disorder is correlated with the fewer hours of daylight during autumn. This disorder has an impact on risk-taking behaviour, such that the investors become more risk averse in times of fewer hours of daylight. Thus, returns move in tandem with the length of the day. This effect is shown to be more pronounced in countries further away from the equator and increases with latitude (Dowling and Lucey, 2008).

In an interesting paper, Cao and Wei (2005) use the findings of psychological studies to motivate the relationship between stock returns and temperature. They refer to psychological studies that examine the impact of extreme temperature levels on human behaviour and find that stock returns are negatively related to temperature, which is consistent with the Halloween effect. They argue that exposure to low temperatures results in aggression, less risk avoidance and higher returns. Exposure to high temperatures leads either to apathy or aggression, to less or more risk avoidance, and to higher or lower returns depending on which behaviour dominates. Hong and Yu (2009) link low summer returns to the vacation season in 51 developed and emerging markets. They show that low summer returns are associated with low trading volume due to the slowdown in economic activity, especially in stock markets.

2.7 Conclusion

Seasonal patterns in stock returns have long fascinated finance practitioners and academics alike. In spite of the increasing number of the documented seasonal effects, the explanations put forward to account for the *raison d'être* of these effects are diverse and often lack external validity. Therefore, we have surveyed the literature on seasonal effects in stock returns to shed light on these limitations. We found that the studies that investigate seasonal patterns in the GCC markets are sparse, and that the present GCC studies largely focus on the weekend and the January effects, while paying little attention to the other widely established seasonal patterns such as the holiday, the turn-of-the-month, and the Halloween effects. In addition, the majority of prior GCC research employs unsophisticated statistical techniques, which rest on very strong statistical assumptions that do not necessarily hold in practice, and they also implicitly assume that seasonal patterns are fixed over time. In fact, the conclusions that emerge from the reviewed studies indicate that such simplistic assumptions are potentially misleading. We are, therefore, motivated to test a wider range of seasonal patterns using several econometric techniques and to investigate whether or not seasonal effects are fixed over time. We turn to this in Chapter 3.

APPENDIX TO CHAPTER 2
SUMMARY OF PRIOR STUDIES

This appendix contains tabulated summaries of the daily seasonality literature (particularly, the turn-of-the-month, weekend, and holiday effects). Tables 2A.1, 2A.2, and 2A.3 display a summary of several relevant studies pertaining to the turn-of-the-month, weekend, and holiday effects, respectively. These tables report several aspects of the reviewed studies, including the markets under examination, the sample period, the days considered (that is, the definition of seasonality period employed in the study), the econometric technique used, and whether the study controls for other seasonal effects. The main conclusions are stated.

Table 2A.1: Studies of the turn-of-the-month effect

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Cadsby and Ratner (1992)	Eleven stock market indices from 10 different countries: the US (the CRSP equal weighted and value weighted), Canada, Japan, Hong Kong, the UK, Australia, Italy, Switzerland, West Germany, and France	US, 1962-87 CA, 1975-87 JP, 1979-88 HK,1980-89 UK,1983-88 AU,1980-89 IT,1980-89 CH,1980-89 DE, 1980-89 FR,1980-89	-1 to +3 trading days of each calendar month	The OLS dummy variables regression	No	The find a significant effect in six of the 10 markets
Oğuzsoy and Güven (2006)	Istanbul Stock Exchange (ISE): ISE National 100 Composite Index and individual stock from the 30 most highly traded ISE stocks	1988-1999	–4 to +9, –1 to +2, and 1 to +4 trading days of each calendar month	OLS dummy variables regression	No	The results indicate that the mean returns over first to the fourth (1 to +4) trading days of the month are significantly higher than the mean returns generated during the rest of the month period, but at a marginal significance level of 10 percent, and only for the ISE National 100 Composite Index; only seven out of the 30 individual stocks analysed are statistically significant. In contrast, the combined –4 to –2 and +5 to +9 period mean returns are significantly lower than the mean return during the rest of the month.
Freund *et al.* (2007)	The National Stock Exchange of India (NSE): S&P CNX Nifty index	1992-2004	-1 to +3 trading days of each calendar month	OLS dummy variables regression with HAC standard errors and the nonparametric Wilcoxon test	Yes, the day-of-the-week and January dummies	The mean returns during the turn-of-the-month time interval are significantly higher than the mean returns over the rest of the month. The findings are robust to the inclusion of the day-of-the-week and January dummies. Furthermore, the results obtained from the nonparametric Wilcoxon test paint a similar story.

Table 2A.1 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Freund *et al.* (2007)	The National Stock Exchange of India (NSE): S&P CNX Nifty index	1992-2004	-1 to +3 trading days of each calendar month	OLS dummy variables regression with HAC standard errors and the nonparametric Wilcoxon test	Yes, the day-of-the-week and January dummies	The mean returns during the turn-of-the-month time interval are significantly higher than the mean returns over the rest of the month. The findings are robust to the inclusion of the day-of-the-week and January dummies. Furthermore, the results obtained from the nonparametric Wilcoxon test paint a similar story.
Floros (2008)	Greek stock market: General ASE Index, FTSE/ASE-20, and FTSE/ASE Mid 40 indices	General ASE 1996-2002 FTSE/ASE-20 1997-2001 FTSE/ASE Mid 40 1999-2001	The first fortnight of the calendar month (1 to15) and the second fortnight of the calendar month (16 to 31)	OLS dummy variables regression	No	The results are mixed. While the first fortnight mean returns are higher than the second fortnright for the General ASE index, the converse is true for the FTSE/ASE-20 and FTSE/ASE Mid 40 indices. Indeed, the difference between the two means of the first and second fortnight of the month is statistically insignificant across all indices.
Nikkinen *et al.* (2009)	Finland stock market: OMXH25	2001-2007	First half of the trading month (-1 to +8) and the second half of the trading month (-10 to -2); also divides the trading month into thirds: the first (-1 to +6), second (+7 to +13), third (+14 to +20)	GARCH(1,1)	Yes, US macroeconomic announcements	The results indicate that the turn-of-the-month effect is present across different model specifications. However, once macroeconomic announcements are taken into consideration, the turn-of-the-month loses statistical significance in every case.
Blandón (2011)	Four market indices from four Latin American markets: Argentina (Merval index), Brazil (Bovespa index), Mexico (Ipc index), and Chile (Ipsa index)	1999-2008	The first five trading days of each calendar month	AR(1) GARCH (1,1)	Yes, the weekend, the turn-of-the-year, the holiday	The results show that the turn-of-the-month effect is present only in the market of Chile at the marginal statistical significance level of 10 percent over entire sample period. However, when the period that corresponds to the GFC is deleted from the data set, the-turn-of-the-month effect strengthens in the market of Chile and become statistically significant in Brazil.

Table 2A.1 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Blandón (2011)	Four market indices from four Latin American markets: Argentina (Merval index), Brazil (Bovespa index), Mexico (Ipc index), and Chile (Ipsa index)	1999-2008	The first five trading days of each calendar month	AR(1) GARCH(1,1)	Yes, the weekend, turn-of-the-year, the holiday effect	The results show that the turn-of-the-month effect is present only in the market of Chile at the marginal statistical significance level of 10 percent over the entire sample period. However, when the period that corresponds to the GFC is deleted from the data set, the-turn-of-the-month effect strengthens in the market of Chile and become statistically significant in Brazil.
McGuinness and Harris (2011)	Eight indices for the stock markets of Hong Kong and China: Hong Kong (the Hang Seng "Blue-Chip", "H-Share index", "Red-Chip" and "Small Cap" indices); China (the Shanghai A and B indices as well as the Shenzhen A and B indices)	1994-2010	-1 to +3 trading days of each calendar month	OLS dummy variables regression	Yes, the Chinese New Year, the Western New Year, Hong Kong and Chinese other public holidays	The TOM effect is strongly present in the market of Hong Kong. In mainland China, the TOM effect is only found in B-stock indices, while only weak evidence for the TOM effect is found in domestically traded indices; that is, A-stock indices.
Maher and Parikh (2013)	The National Stock Exchange of India (NSE): BSE 30 (Sensex), BSE Midcap, and BSE Smallcap indices	2003-2011	-1 to +2 trading days of each calendar month	OLS dummy variables regression, GARCH (1,1), EGARCH (1,1) and the nonparametric Wilcoxon test	Yes, the quarter-end, calendar, and tax-year-end effects	The TOM is shown as present in the various size-conditioned and econometric techniques over the entire sample period. However, when the sample is dichotomised on the basis of market movements into upturn and downturn periods, the TOM effect is shown to be confined to upturn market periods.

Table 2A.1 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Compton *et al.* (2013)	Six different stock and bond market indices from Russia and the US: Russia (RTS and MICEX stock market indices in addition to the RUX and CBI TR bond indices); The US (S&P 500 stock index and the Dow Jones Corporate Bond Index)	Stock,1998-2008 Bond, 2003-2008	-1 to +3 trading days of each calendar month	OLS dummy variables regression, the nonparametric Wilcoxon signed-rank and sign test	No	The results show that the turn-of-the-month effect is strongly present in Russian stock and bond markets, as the returns generated during the four trading days around the turn of the month significantly exceed the returns accrued over the rest of the month. On the other hand, the pattern around the turn of the month is relatively weaker in the US stock and bond markets.
Sharma and Narayan (2014)	The US: The CRSP equal-weighted and value-weighted indices and 560 firms categorised into 14 portfolios formed on the basis of the Global Industry Classification Standard; also, firm size is considered	2000-2008	-1 to +3 trading days of each calendar month	GARCH(1,1)	No	The TOM effect is found to be statistically significant in aggregated data as well as sector portions. However, the strength of the TOM in stock returns and volatilities varies across market sectors and firm size. In general, stock return (volatility) on the TOM interval is significantly higher (lower) than returns during the rest of the month. The impact of the TOM effect on stock return and volatility is more pronounced in small-size firms than large firms.

Table 2A.2: Studies of the weekend effect

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Bessembinder and Hertzel (1993)	Fifteen time series: equities; US and Japanese broad market indices in addition to US size-ranked and OTC stock portfolios. Futures; market indices (S&P 500), commodities (gold, silver, live cattle, wheat, and cotton); exchange rates (Japanese Yen and Deutsche Mark) and fixed-income securities (treasury bills and bonds)	Vary across markets	Five trading days of the week with a focus on Monday	AR(1) dummy variables regression with HAC standard errors	Pre-holiday	The results show a persistent pattern in autocorrelation of securities returns. The authors find that the correlation between the returns on the first day after a market closure and returns on the following day are significantly lower than the autocorrelation of other days. In contrast, the correlation between the returns on the day that immediately precedes a market closure and returns on the day that immediately follows a market closure are significantly higher than the autocorrelations of other days. This pattern is shown to be robust across different markets and sample periods.
Abraham and Ikenberry (1994)	US market indices: The CRSP equal-weighted index and 10 size deciles	1963-1991	Five trading days of the week with a focus on Monday	t-test to test the equality of means with heteroscedasticity-consistent standard errors; the Chi square test to test the equality of the positive returns, frequencies, and first order autocorrelation	Yes, direction of market movement for the previous day	The day-of-the-week effect is present in its traditional form; that is, negative mean Monday returns that are significantly lower than the means of other days. When conditioning the mean return on the direction of the market movement is the previous day, the mean returns for Monday are positive if the preceding Friday returns are positive; if Friday's returns are negative, the returns for Monday are negative 80 percent of the time. The correlation between Friday's and Monday's returns is the highest among other days of the week. The pattern is even more pronounced in small and middle-sized companies.

Table 2A.2 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Easton and Faff (1994)	Australian indices: the Sydney Stock Exchange Statex-Actuaries Price and Accumulation Indices and the US S&P 500 index	1974-85	Five trading days of the week	OLS, MAD, TLS, IWLS, and the GARCH(1,1) regression in addition to employing Bayesian analysis in testing the joint hypothesis of the equality of the mean across the week days	Yes, pre-holiday	The results show that the evidence for the presence of the day-of-the-week effect is weakened when the test statistic is adjusted to account for the large sample size. However, despite the documented violation of the OLS assumptions, the day-of-the-week effect is fairly robust to the different estimation techniques. Finally, the day-of-the-week effect in the Australian market is shown to independent of the pattern documented in the US market.
Jaffe and Westerfield (1985)	Five stock market indices from five different countries: the US (the S&P 500 index), Canada (the Toronto stock exchange equal weighted index), Japan (the Nikkei Dow index), the UK (the Financial times ordinary Share index), Australia (the Statex Actuaries Index)	US, 1962-83 CA, 1976-83 JP, 1970-83 UK,1950-83 AU,1973-82	Five trading days of the week for all countries except Japan, where six trading days are observed	t-test to test the equality of means, OLS dummy variables regression and F test to test collectively if the means of the days of the week are different from each other	Yes, US market returns	There is a strong and statistically sound daily seasonality in all markets. The mean return for Monday is negative for all five countries and the lowest compared to mean returns for other days of the week in the markets of the US, Canada, and the UK; the mean return for Tuesday is the lowest in the case of Japan and Australia. In addition, the mean return for the last trading day of the week (Friday for all countries except Japan, where the last trading day of the week is Saturday) is, across the five markets, significantly higher than the mean of other days of the week. The days-of-the-week seasonality in the non-US market is found to be independent of seasonal effects in the US market. The "the time zone" partly accounts for the Tuesday seasonality in Australia, but not in Japan. The authors rule out measurement error or settlement procedure as causes for the days-of-week effect.

Table 2A.2 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Jaffe *et al.* (1989)	Five stock market indices from five different countries: the US (the S&P 500 index), Canada (the Toronto stock exchange equal weighted index), Japan (the Nikkei Dow index), the UK (the Financial times ordinary Share index), Australia (the Statex Actuaries Index)	US, 1930-81 CA, 1976-83 JP, 1970-83 UK,1950-83 AU,1973-82		t-test to test the equality of means and OLS dummy variables regression	Yes, the previous week returns	The Monday's negative is strongly correlated with the previous week's returns. When the mean Monday returns are conditioned on the previous week's market up-movement, the statistical significance of negative Monday mean returns is greatly weakened for the US and the UK markets, whereas it is no longer negative for the other markets.
Steeley (2001)	The UK (the Financial Times 100 Share index)	1991-98	Five trading days of the week	The parametric *F* test to test collectively if the means of the days-of-the-week are different from each other, the nonparametric Kruskal-Wallis test, the Turkey pair-wise test, and OLS regression	Yes, macroeconomic announcements in addition to the direction of market movement for the previous day	There is no discernible pattern in any particular day of the week. However, when the returns are dichotomised on the basis of their sign into negative and positive, the means of negative return for Mondays and Fridays are found to be statistically different from other trading days of the week. The means of positive returns, however, do not display any interesting pattern. It is shown that macroeconomic announcement clusters on the middle of the week (Tuesday to Thursday) which lowers the cost of trading on Friday and Monday. Indeed, when macroeconomic announcements are controlled for, the patterns documented during down market-movement on Monday disappear.
Al-Loughani and Chappell (2001)	Kuwait Investment Company price index	1993-1997	Five trading days of the week	AR(2) GARCH-M regression model	No	The returns on Saturday (the first day of the week in the Kuwaiti market) is positive and significantly higher than the returns for any other day.

Table 2A.2 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Mehdian and Perry (2001)	Four US broad market indices: NASDAQ, S&P 500, DJIA, and the Russell 2000	1964-1998 Russell 2000, 1979-1998	Five trading days of the week	OLS dummy variables regression and Chow test for structural breaks	Yes, for breakpoints identified by the Chow test, the weeks of the month, and the previous week returns	The results obtained using the entire sample confirm the widely documented traditional weekend effect, that is, negative Monday returns, which are lower than the returns generated over the other days. Furthermore, the positive correlation between the returns for Monday and the prior week's return is also supported. These findings hold for all the market indices examined. However, the results of the Chow test indicate there are a number of structural breaks in the returns series used. When the data are segmented into three subsamples on the basis of the identified breakpoints, the results show that the weekend effect varies across indices and time periods. In general, during more recent periods, the weekend effect is reversed (Monday returns became positive on average) and uncorrelated with the preceding week’s return for large cap market indices, while the weekend effect remained largely unchanged for the small cap indices.
Faff and McKenzie (2002)	Seven broad market indices for developed countries: Australia (All Ordinaries), Spain (IBEX 35), Germany (DAX 100), Japan (NIKKEI 225), Switzerland (SWISS MI), UK(FTSE 100), US (S&P 500)	AU,1980-1999 SP,1987-1999 DE,1973-1999 JP,1980-1999 CH, 1988-1999 UK,1969-1999 US,1969-1999	Five trading days of the week with a focus on Monday	AR(1) GARCH(1,1) regression model	No	The results indicate that the day-of-the-week seasonality in the mean returns has weakened after the introduction of futures contracts, particularly for the markets of the US, Switzerland, Japan, and Australia. However, the introduction of futures contracts has no significant impact on the seasonality in autocorrelation and volatility, albeit that some changes in the latter have been detected.

Table 2A.2 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Kohers *et al.* (2004)	Eleven MSCI Indices for the world's largest stock markets: US, Japan, the UK, France, Germany, Canada, Italy, the Netherlands, Switzerland, Hong Kong, and Australia, in addition to the MSCI World stock market index	1980-2002	Five trading days of the week	The parametric ANOVA test and nonparametric Kruskal-Wallis test	No	The day-of the-week effect is documented in the majority of markets over the first subsample: 1980-90. Indeed, most markets displayed the extensively documented seasonal weekly pattern of negative Monday returns and negative Tuesday returns for the markets in Japan and Australia over the first subsample period. However, when the sample spanning the period 1991-2002 is analysed, the day-of the-week effect is compromised.
Ajayi *et al.* (2004)	Eleven East European markets: Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russia, Slovakia, Slovenia	1999-2002 1994-2002 1995-2002 1995-2002 1997-2002 1998-2002 1995-2002 1997-2002 1995-2002 1995-2002 1994-2002	Five trading days of the week	OLS dummy variables regression and F test to test the equality of variances	No	The results indicate that the mean return for Monday is negative in six markets but is only statistically significant in two markets, namely, Estonia and Lithuania. One the other hand, positive Monday mean returns are documented for the remaining markets but are statistically significant only in the case of Russia. Furthermore, the mean return for Monday is significantly lower than the mean return over the rest of the week only in the market of Estonia. In addition, the volatility of Monday's return is significantly higher than the volatility of the rest of the week's return for four out of the 11 markets.
Lucey (2004)	Four Irish stock market indices: ISEQ price index, ISEQR; a financial sector index, ISEFIN; and a general market index, ISEGEN	1988-98	Five trading days of the week	The nonparametric Levene and the Kruskal-Wallis tests, the OLS, LAD, TLS and GARCH(1,1) regression models, and resampling analysis	No	The results indicate that the evidence for the presence of the day-of-the-week is fairly weak. This conclusion is reached because of sensitivity of the results to different estimation techniques.

Table 2A.2 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Brusa *et al.* (2005)	Four US market indices: CRSP value-weighted index in addition to NASDAQ, S&P 500, and DJIA indices	All but NASDAQ,1963-98 NASDAQ, 1973-1998	Five trading days of the week with a focus on Monday	OLS dummy variables regression with HAC standard errors	No	During the post-1988 period, they document a reversal in the Monday effect—returns on Monday become positive. Furthermore, the finding that firm size is associated with the strength of the reversal pattern, that is, large firms exhibit more pronounced reversal in Monday returns. The researchers suggest that the reversal of the Monday effect may be attributed to the increased activity of institutional investors, particularly during the more recent sample period, as they tend to trade large stocks.
Basher and Sadorsky (2006)	Twenty-one emerging stock markets using the MSCI country index: Argentina, Brazil, Chile, Colombia, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela, and South Africa, in addition to the MSCI World stock market index	1992-2003	Five trading days of the week	OLS dummy variables regression	Yes, for MSCI world stock market index returns and to the direction of the market movement for the previous day	The results are mixed. Although the days-of-the-week effect is present in a number of markets, the days on which seasonal patterns are documented largely differ, not only across markets, but also across model specifications.
Baker *et al.* (2008)	S&P/TSX composite price index from the Toronto Stock Exchange	1977-2002	Five trading days of the week	AR(21) GARCH(1,1) regression with four different specifications of the error distribution	No	The day-of-the-week effect is present in the Canadian market. Monday's returns are shown to be the lowest, while the highest returns are generated on Friday. However, the findings are shown to be sensitive to the specification of the error distribution.

Table 2A.2 *(Continued)*

Study (authors & pub. date)	Markets	Sample Period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Alagidede (2008a)	Seven stock market indices from seven African countries: Nigeria (NSE All Share Index), Kenya (NSE20 index), Tunisia (Tunnindex), Morocco (MASI index), South Africa (FTSE/JSE All Share index), Egypt (CASE30 Share Index) and Zimbabwe (ZSE Industrial Index), in addition to the FTSE All World Price Index	NG, 1995-2006 KE, 2001-2006 TN,1998-2006 MA, 2001-2006 ZA, 2001-2006 EG, 2001-2006 ZW,1996-2001	Five trading days of the week	OLS dummy variables regression and the GARCH(1,1) regression	Yes, for the FTSE All World Price Index returns	The results are mixed. The OLS model detects seasonality only in the markets of Nigeria and Zimbabwe. The GARCH(1,1) model appears to be more powerful, revealing seasonal patterns in the markets of South Africa and Tunisia, in addition to Nigeria and Zimbabwe. However, the days on which seasonal patterns occur largely differ, not only across markets, but also across model specifications. The results obtained from the variance equation of the GARCH(1,1) indicate that the seasonality in volatility is strong, particularly in the market of Nigeria.
Doyle and Chen (2009)	Thirteen broad market indices from 11 major stock markets: USA (NYSE, Amex and the Nasdaq), Japan (Nikkei225), UK (FTSE100), Germany (DAX30), France (CAC40), and Hong Kong (Hang Seng), China (Shanghai A Shares, Shanghai B Shares, Shenzhen A Shares, Shenzhen B Shares) and India (Sensex30)	1993-2007	Five trading days of the week	The ARMA(20,1) GARCH(1,1) regression	Yes, yearly dummies and the previous week's mean return	The assumption of fixed seasonality is tested using interactive dummy variables (the day-of-the-week dummies multiplied by yearly dummies). The results reveal that the day of the week is not fixed, but instead wanders over the years. The strength of the day-of-the-week effect is shown to persist over the sample period with no sign of weakening. The researchers show that time variance in the day-of-the-week effect is not a manifestation of the conditional weekday effect—the 'twist on the Monday effect'.

Table 2A.2 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Högholm *et al.* (2010)	Eighteen countries within the European Union using the MSCI country index in addition to the MSCI European Common Market index	2000-2006	Five trading days of the week	The parametric F test to test collectively if the means of the days-of-the-week effect are different from each other, the nonparametric Kruskal-Wallis test, the Brown-Forsythe statistic to test the equality of variances and AR-EGARCH regression model	Yes, for common European market index returns in addition to the first order autocorrelation and the direction of the market movement for the previous day simultaneously	The results obtained from the unconditional and the conditional analysis differ drastically. When the unconditional tests are employed, only six out of the 19 series exhibit days-of-the-week seasonality. However, when a conditional regression model is used, the days-of-the-week effect is shown to be present in the majority of the markets under investigation. Indeed, only four out of the 19 series show no traces of the days-of-the-week effect. In addition, the days-of-the-week pattern is local in nature and varies across markets. The conditional regression model incorporates first order autoregressive terms, market direction dummies for the previous day, and an interaction term for both. The researchers attribute the difference in the results between the conditional and the unconditional analysis to the autocorrelation structure in daily stock returns, and asymmetry in the first order autocorrelation and volatility.

Table 2A.2 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Keef *et al.* (2009)	Fifty countries stock indices	1994-2006	Monday	Panel regression model	Economic climate factor constructed using factor analysis from a number of economic indicators and the direction of market movements on the previous day	The results derived from conditional analysis show that there is no statistically significant difference between the returns on Monday and the other days of the week if Monday is preceded by an up market-movement. However, when Monday is preceded by a down market-movement, the returns on Monday are substantially lower than the returns for the other days of the week. When the countries included in the sample are classified on the basis of the "Economic climate" factor into rich and poor, there is a clear difference between countries as to the state of market efficiency and its evolution over time. Indeed, the prior-day effect is documented to be stronger in poor countries compared to their rich counterparts; nonetheless, this effect weakens at a faster pace in poor countries. In addition, the difference in the return on the Mondays which are preceded by a down market-movement and other days of the week has declined over time for rich countries and virtually reached zero in 2008; for poor countries, the Monday effect remain present.

Table 2A.2 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Bley and Saad (2010)	SHUAA Capital indices for each of the six GCC markets: Bahrain, Kuwait, Qatar, Oman, Saudi Arabia, and the United Arab Emirates	2000-2009	Five trading days of the week	OLS dummy variables regression	No	The results show GCC stock market indices exhibit some form of day-of-the-week seasonality. The mean for Thursday returns (the last trading day of the week) is positive and statistically different from zero, whereas no meaningful pattern is found for Sunday (the first trading day of the week), except for the market of Bahrain where a negatively significant mean return is documented. However, in countries where foreign ownership is allowed (Oman and the UAE), when portfolios are formed on the basis of the proportion of allowed foreign ownership, the portfolios of high foreign ownership display the well-documented reversed weekend effect: that is, positive and statistically significant returns on Monday, although it is not the first trading day in these markets. Further, no discernible pattern is observed on the first trading day of the week in portfolios of high foreign ownership.
Ariss *et al.* (2011)	Seven market indices from the six GCC countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE (Abu Dhabi and Dubai markets)	Inception-2008	Five trading days of the week	OLS dummy variables regression with robust standard errors obtained using the Huber-White sandwich estimator	Ramadan effect	The day-of-the-week seasonality is documented in the GCC markets, but nonetheless these are on different days than for other developed and emerging markets. Indeed, in accordance with other markets, the mean return for the last trading day of the week is positive and statistically significant. Furthermore, the authors show that this pattern is weaker during the month of Ramadan.

Table 2A.2 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	days considered	Econometric techniques	Control for other seasonal effects	Conclusion
Chan and Woo (2011)	H-shares index in Hong Kong	2000-2008	Five trading days of the week	EGARCH regression model	Yes, US market index and Shanghai A-share index	The days-of-the-week effect is present in the form of significantly high returns for Monday and Friday. When market risk is allowed to vary across the trading days of the week, the returns for Friday become insignificant. The results that emerge from the variance equation reveal that the volatility over Monday is significantly larger than the volatility of the other days. The researchers, therefore, concluded that the high returns on Monday are more likely to be compensation for bearing higher risk instead of being caused by a settlement procedure. Finally, the returns on Monday are not high enough to justify the implementation of a trading rule to exploit them.
Blose and Gondhalekar (2013)	COMEX front month gold futures contract	1975-2001	Five trading days of the week with a focus on Monday	t-test to test the equality of means and, the nonparametric Wilcoxon test and OLS dummy variables regression	Yes, three different bull and bear market phases	The results obtained from the unconditional analysis indicate that Monday mean returns are negative and significantly lower than the mean returns over the other days of the week. However, when the sample of returns is partitioned into three bull and bear market phases, the negative Monday mean return is shown to be confined to the bear market phase; during two bull market phases no statistically meaningful pattern is documented.
Auer (2014)	Closing prices for Brent crude oil	1987-2013	Five trading days of the week	The nonparametric Kruskal-Wallis test, GARCH-M, TGARCH and CGARCH regression models, in addition to a trading rule designed on the basis of the day-of-the-week effect	Yes, bull and bear market phases	The Monday returns (volatility) are shown to be significantly lower (higher) than the returns for the other days of the week. The findings are shown to be reasonably robust to alternative model specification. The trading rule formulated on the basis of the day-of-the-week effect generated higher Shape ratios compared to the buy-and-hold passive strategy; nonetheless, the difference between the two is not statistically significant.

Table 2A.3: Studies of the holiday effect

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Pettengill (1989)	The S&P 500 and CRSP equal-weighted indices	1962-1986	Pre-holidays, post-holidays, and other days	The US public holidays	Yes	t-test to test the equality of means and the F test to test the equality of variances	Yes, the days-of-the-week effect, the January, and firm-size effects	The results indicate that the pre-holiday mean returns are significantly higher than the mean returns of other days. The findings are robust across different firms, time periods, and days of the week. The post-holidays returns, however, show weaker patterns. Indeed, higher returns during post-holidays are confined to those which fall on Fridays.
Ariel (1990)	The US: The CRSP equal-weighted and value-weighted indices	1963-86	Pre-holidays and other days	The US public holidays	Yes	t-test to test the equality of means, the Chi square test to test the equality of the positive returns frequencies, and the Ordinary Least Squares (OLS) dummy variables regression	Yes, the days-of-the-week effect, and the January and the small-firm effects	The pre-holiday effect is significant in the US market indices and is not a manifestation of other well-established seasonal anomalies.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Easton (1990)	Sydney and Melbourne All Ordinaries	Syd, 1958-80 Melb, 1963-80	Pre-holidays, post-holidays and other days	Australian public holidays	Yes, at least for one market	The nonparametric Wilcoxon test; the difference in returns according to the length of the duration of market closures is tested using the Jonckheere nonparametric directional test.	No	The Wilcoxon test results indicate that returns on the days that immediately fall before and after a holiday are significantly higher than the other non-holiday periods "typical days". Further, for holidays on which only one of the markets is closed, the returns generated on the days that immediately precede the holiday are higher for the market that is closed, compared to that which remains open. Moreover, there is a positive association between the magnitude of returns that are generated before a holiday and the duration of the holiday.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Cadsby and Ratner (1992)	Eleven stock market indices from 10 different countries: the US (The CRSP equal-weighted and value-weighted), Canada (the Toronto stock exchange equal-weighted index), Japan (the Nikkei index), Hong Kong (the Hang Seng index), the UK (the Financial Times 500 Share index), Australia (the All Ordinaries index), Italy (the Banca Commerciale index), Switzerland (the Swiss Bank Corporation Industrials index), West Germany (the Commerz-bank index), and France (the Compagnie des Agent de Change General index)	US, 1962-87 CA, 1975-87 JP, 1979-88 HK,1980-89 UK,1983-88 AU,1980-89 IT,1980-89 CH,1980-89 DE, 1980-89 FR,1980-89	Pre-holidays and other days	Public holidays for each country as well as the US public holidays	Yes	The OLS dummy variables regression	No	The pre-holiday mean return significantly exceeds the mean returns for non-pre-holiday mean returns. The difference between the two means is highly significant at the 1 percent level for the US equal and value-weighted indices and the market indices for Canada, Japan, Hong Kong, and Australia; the difference is marginally significant for the Italian market index. There is, however, not sufficient evidence for the holiday effect in the remaining European markets. Furthermore, the markets that exhibit holiday seasonality do so only with respect to national (local) public holidays, except for the Hong Kong market which is shown to be affected by US public holidays. Indeed, no apparent pattern in returns is documented during post-holidays.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Kim and Park (1994)	Five stock market indices from three different developed countries: the US (the NYSE, AMEX, and NASDAQ indices), UK (the FT30 index), and Japan (Nikkei-Dow index)	NYSE,1963-86 AMEX, 1963-86 NASDAQ, 1973-86 FT30, 1972-87 Nikkei-Dow, 1972-87	Pre-holidays, post-holidays and other days	Public holidays for each country as well as the US public holidays	Yes	t-test to test the equality of means, the nonparametric Z-statistic to test the quality of medians and the OLS dummy variables regression	Yes, the days-of-the-week, the January, and firm-size effects, but only for the US data	The analysis conducted using the US data reveals that pre-holiday mean returns are significantly higher than other days across all indices. The results hold after controlling for other seasonal effects. Furthermore, the authors fail to find a significant difference in the strength of the holiday effect across different size deciles. The results obtained from analysing the UK and Japanese data confirm the presence of the holiday effect when the local public holidays of each country are considered. However, the US unique public holidays have no bearing on either the UK or the Japanese market. In fact, no meaningful pattern of returns is documented during the post-holiday days.

Table 2A.3 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Liano and White (1994)	The US: the S&P 500 and the NASDAQ indices	1962-91 1972-91	Pre-holidays and other days	The US public holidays taking the business-cycle phases into consideration	Yes	The OLS dummy variables regression with GMM-corrected standard errors, the nonparametric Kruskal-Wallis test, and Levene test for the equality of variance	No	The results show that pre-holiday mean returns are significantly higher than other days mean returns over the entire sample period for both the S&P 500 and the NASDAQ indices. Furthermore, during expansionary periods, the pre-holiday returns are stronger for the NASDAQ whose constituents are small firms; during contractionary periods, the S&P 500, which includes only large firms, exhibits more pronounced pre-holiday returns compared to the NASDAQ. Therefore, the researchers conclude that the holiday effect is influenced by firm size and the phase of the business cycle.

Table 2A.3 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Hiraki and Maberly (1995)	Tokyo Stock Exchange Price Index (TOPIX) and the Tokyo Stock Exchange Small Firm Price Index (TOPIXSF)	1976-90	Pre-holidays, post-holidays and other days	Japanese public holidays divided into three groups: "other" holidays, Golden Week, and New Year's Day	Yes	t-test to test the equality of means, the F test to test the equality of variances, and the OLS dummy variables regression	Yes, the day-of-the-week and the January effects	The results obtained by analysing the close-to-close returns indicate that the significant high pre-holiday mean returns compared to other trading days are limited to the Golden Week period. However, mean return during the rest of the holidays is not statistically different from the mean return of other days. Although the findings are not robust to firm size and holiday classification, the holiday effect is not a manifestation of the days-of-the-week effect. The analysis conducted using the intra-day data reveals that most of the return on the pre-holiday accrued on during the afternoon session. Further, those "other" pre-holiday gains, specifically, are reversed over the lunch session on the day that immediately follows a holiday.
Chan *et al.* (1996)	Four stock market indices from three different Asian countries :Malaysia, India, Thailand, and Singapore	MY,1974-92 IN,1979-92 TH, 1969-92 SG, 1975-91	Three days prior to a holiday and three days following a holiday	Relevant cultural and state holidays for each country	No	The OLS dummy variables regression	Yes, monthly dummies	The results indicate that cultural-holiday mean returns are significantly higher than the mean return of other days in all markets except Thailand. However, the researchers fail to find any discernible pattern in returns around state holidays across all markets.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Meneu and Pardo (2004)	Five of the most traded stocks in the Spanish market which are listed in the US and Germany: Telefonica, Banco Bilbao Vizcaya Argentaria, Banco Santander Central Hispano, Repsol YPF, and Endesa, in addition to the IBEX-35 index	1990-2000	Pre-holidays and other days	Spanish public holidays: New Year's Day, Epiphany, Maundy Thursday, and Good Friday, All Saints Day, Christmas Eve and Christmas Day, as well as the US and German holidays	Yes	Seemingly unrelated regressions (SUR), Brown-Forsythe's statistic to test the equality of variances, parametric F test, and nonparametric Kruskal-Wallis test	Yes, the weekend, the January, and the turn-of-the-year effects	The pre-holiday mean return is significantly larger than the non-pre-holiday "typical"days mean returns for the IBEX-35 index at the 1 percent level, and two out the five most heavily traded stocks in the Spanish market at the 5 percent level; no discernible post-holiday pattern is evident. Although these individual stocks are listed in the US and the German markets, they exhibit pre-holiday seasonality with respect to Spanish holidays only. The pre-holiday effect remains robust when controlling for other seasonal anomalies.
Frieder and Subrahmanyam (2004)	S&P 500 Index	1946-2000	Two days prior to holiday; holiday and two days following a holiday	St Patrick's Day, Rosh Hashanah and Yom Kippur	No	The OLS dummy variables regression and the Chi square test to test the equality of the positive returns frequencies	Yes, the weekend effect and monthly dummies (not reported)	The results reveal that the mean return of the two days that fall prior to St Patrick's Day and Rosh Hashanah (festive in nature) are significantly higher than the mean return of other days. Indeed, the Chi square test paints a similar picture. However, mean returns over the two days that fall after Yom Kippur (solemn in nature) are lower than the mean returns of other days, especially during the 1973-2000 period when the 1973 war coincided with Yom Kippur.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Chong *et al.* (2005)	Three stock market indices from three different countries: the US (the S&P 500 index), the UK (the FT30 index), and Hong Kong (the Hang Seng index)	1973-2003	Pre-holidays and other days	Public holidays for each country	Yes	t-test to test the equality of means, the Chi square test to test the equality of the positive returns frequencies, and the OLS regression with a time-trend variable to examine the persistence of the holiday effects	No	The pre-holiday mean return is significantly larger than the non-pre-holiday "typical" days mean returns across the three markets when the entire sample period is considered. The Chi square test results tell a similar story. However, when a simple OLS regression with a time-trend variable is fitted, the pre-holiday returns appear to be declining over time, albeit that they are only statistically significant in the case of the US. The results that emerge from segmenting the sample into five subsamples of equal length reveal that the strength of the holiday effect does not systematically decline over time; that is, the holiday effect is not confined to the early sample periods.

Table 2A.3 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Lucey and Pardo (2005)	Five most actively traded stocks in the Spanish market in addition to the IBEX-35 index; three most actively traded stocks in the Irish market: Allied Irish Banks, Bank of Ireland, Cement Roadstone Holdings, in addition to the official stock market index, that is, ISEQ	SP,1990-2000 IE,1996-2000	Pre-holidays and other days	Spanish public holidays for the Spanish data and Irish public holidays for the Irish data	Yes	The Brown-Forsythe Modified Levene's statistic and the Kruskal-Wallis test. The OLS regression with a time-trend variable to examine the persistence of the holiday effects. Further, a trading rule is used to test the economic significance the holiday effect.	No	The results indicate that pre-holiday returns are significantly higher than on other days for all the stocks and market indices under examination across both markets. In addition, the results obtained from the OLS regression with a time trend reveal that the pre-holiday returns are upward trending across the board, although not reaching statistical significance in some cases. Furthermore, a trading rule formulated on the basis of the holiday effect is tested out-of-sample over the period 2001 to 2002. The results show that the returns obtained using the simple rule outperform the buy-and-hold passive strategy. The findings are confirmed by means of a simulation methodology.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
McGuinness (2005)	Hang Seng Index and Hang Seng London Reference Index	1975-2005	Pre-holidays and other days	Hong Kong and US public holidays	Yes	t-test to test the equality of means and the Mann-Whitney nonparametric test, in addition to OLS dummy variables regression	Yes, the day-of-the-week and the turn-of-the-month effects, the duration of holidays, and US pre-holiday dummies and lagged returns	The results indicate that the holiday effect remains strong and is largely driven by the Chinese Lunar New Year effect. The duration of the market closure is shown to have a positive effect on pre-holiday returns. Furthermore, the strength of the weekend effect is not affected by the other seasonal effects. Moreover, in the recent sample period, the impact of US holidays on the Hong Kong market has greatly weakened, which reflects the decline in the strength of the holiday effect in the US.
Al-Loughani *et al.* (2005)	Kuwait stock exchange: the Global Investment House general price index	1984-2000	Pre-holidays, post-holidays, and other days	Kuwaiti official public holidays	Yes	t-test to test the equality of means and the Mann-Whitney nonparametric test	Yes, the day-of-the-week effect	The result reveals that no traces of the holiday effect were found in either the pre-invasion or the post-liberation samples. Indeed, the high post-holiday returns during the post-liberation sample are shown to be driven by high returns on Saturdays. Therefore, once the post-holiday returns that fall on a Saturday are removed, the post-holiday pattern ceases to be statistically significant.

Table 2A.3 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Alagidede (2008b)	Seven stock market indices from seven different African countries: Nigeria (NSE All Share Index), Kenya (NSE20 index), Tunisia (Tunnindex), Morocco (MASI index), South Africa (FTSE/JSE All Share index), Egypt (CASE30 Share Index), and Zimbabwe (ZSE Industrial Index)	NG, 1990-2009 KE, 1990-2009 TN,1997-2006 MA,2002-2006 ZA, 1997-2006 EG,1997-2006 ZW,1995-2006	Pre-holidays and other days	Public holidays for each country	Yes	OLS dummy variables regression	No	The results reveal that pre-holiday mean returns are positive and significantly higher than the mean return of other days only in the market of South Africa. Indeed, the F test reveals that the pre-holiday mean returns are significantly higher than the mean returns of other days in the market of Zimbabwe; nonetheless, both the pre-holiday and other days mean returns are negative over the sample period. No meaningful patterns are documented for the rest of the markets under investigation.
Kaplanski and Levy (2012)	Twenty-one stock price series from the Tel Aviv Stock exchange (TASE): the TA 100, 75, and 25, and industry indices, as well as portfolios formed on the basis of size, volatility, and return	1990-2008	Pre-holidays, post-holidays and other days	Israeli public holidays with a special focus on Yom Kippur which coincides with the 1973 war	Yes	OLS dummy variables regression with five autoregressive terms and an event-study methodology	Yes, the days-of-the-week, the first trading days of the taxation year, the period of September to October	The results indicate that for all public holidays, except Yom-Kippur, the pre-holiday mean returns are significantly larger than for other days at the 1 percent level; the post-holiday returns are not significantly different from other days. However, for Yom Kippur, the pre-holiday mean returns are not significantly different from other days; the post-holiday mean returns are significantly lower than for the other days at the 1 percent level. The results are largely robust across different market indices, formed portfolios, model specifications, and subsamples.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Marrett and Worthington (2009)	Twelve Australian stock market indices: the All Ordinaries and the Small Ordinaries indices, as well as 10 ASX/S&P industry indices	1996-2006	Pre-holidays, post-holidays and other days	Eight Australian national holidays	Yes	OLS dummy variables regression	No	The pre-holiday mean returns significantly exceed the other days mean returns for the All Ordinaries and the Small Ordinaries and the retail indices. However, no apparent holiday seasonality is documented for other industry indices. Furthermore, no evidence is found for a statistically significant pattern on post-holidays.
Bley and Saad (2010)	SHUAA Capital indices for each of the six GCC markets: Bahrain, Kuwait, Qatar, Oman, Saudi Arabia, and the United Arab Emirates	2000-2009	Two days prior to a holiday and two days following a holiday	Islamic, state, and Western holidays	No	OLS dummy variables regression	No	The results show limited holiday seasonal patterns, especially prior to Eid Al Fitr. However, state and Western holidays do not appear to induce any meaningful price movement in the market indices of the GCC markets. However, when portfolios are formed on the basis of the proportion of allowed foreign ownership, the portfolios of high foreign ownership appear to be affected by the Western turn-of-the-year effect.

Table 2A.3 *(Continued)*

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Tsiakas (2010)	The constituents of the DJIA, the S&P 500, and the CRSP equal-weighted and value-weighted indices	1962-2005	Pre-holidays, post-holidays, pre-long weekends and post-long weekends	The US public holidays	Yes	Bootstrapping: two-sided t-tests, the data-mining robust *F* test of Hansen and Lunde (2003), and the stochastic volatility (SV) models	No	The results indicate that pre-holidays, post-holidays, and pre-long weekends are characterised by significantly higher mean and lower volatility than other days; the post-long weekends are found to have lower mean and higher volatility. In addition, the author shows that conditioning on the four holiday dummies provides economic value in the context of dynamic asset allocation.
Akyol (2011)	Istanbul Stock Exchange (ISE) National-100 index	2001-2010	Pre-holidays, post-holidays, other days	Turkish public holidays divided into short and long on the basis of the length of the period of market closures	Yes	Integrated Generalised Autoregressive Conditionally Heteroscedastic IGARCH(1, 1)	No	The intra-day analysis reveals that pre-holiday and post-holiday returns are positive. Furthermore, there is a noticeable difference in the behaviour of returns between the morning and afternoon sessions. The researcher shows that there is a mild association between the length of the market closure and the returns pattern around holidays. The pre-holiday morning session returns are more positive for long holidays compared to short holidays, while they are less positive over the morning session on the day that immediately follows a holiday "post-holiday" day.

Table 2A.3 ***(Continued)***

Study (authors & pub. date)	Markets	Sample period	Days evaluated	Holidays considered	Market closure	Econometric techniques	Control for other seasonal effects	Conclusion
Gama and Vieira (2013)	An equal-weighted average of the 50 Portuguese firms and five industry portfolios. The time series was compiled by the researchers from DataStream. Furthermore, trading-volume data are also used.	2003-2012	Pre-holidays, holidays, other days	Nine Portuguese specific holidays	No	OLS dummy variables regression with five autoregressive terms; HAC standard errors are used	Yes, the days-of-the-week effect	The results indicate that mean returns on pre-holiday days and post-holiday days are not statistically significant compared to the mean returns on other trading days. However, the mean returns on holidays are significantly higher than on other days; the trading volume and volatility are significantly lower during these holidays.

CHAPTER 3

SEASONALITY IN STOCK RETURNS: METHODOLOGY AND EMPIRICAL RESULTS

3.1 Testing for Seasonality

The majority of prior studies employ the standard OLS estimation technique to investigate the existence of seasonal patterns in stock returns (for example Ariel, 1987; Bouman and Jacobsen, 2002; Brown *et al.*, 1983; French, 1980; Gultekin and Gultekin, 1983; Lakonishok and Levi, 1982; Rozeff and Kinney, 1976; Swinkels and Van Vliet, 2012). This is achieved by regressing stock returns on the relevant seasonal dummy variables as:

$$r_t = \beta_0 + \sum_{i}^{q} \beta_i D_{i,t}^{Seasonality} + \varepsilon_t \qquad (3.1)$$

where r_t is the continuously compounded return on Day *t*, $D_{i,t}^{Seasonality}$ are dummy variables that take the value 1 on the trading days corresponding to the underlying seasonal effect and 0 otherwise, β_0 is the intercept representing the mean return for typical days, the slope β_i represents the difference between the mean return of the trading days corresponding to the seasonal effect and the mean return of typical trading days, while $\beta_0 + \beta_i$ represents the mean return of trading days corresponding to the seasonal effect, and ε_t is an error term assumed to be independently and identically distributed (iid). The null hypothesis is $H_0: \beta_i + \beta_{i+1} + \cdots + \beta_{q-1} + \beta_q = 0$. Notwithstanding the widespread use of this approach, it suffers from major drawbacks, particularly the assumptions that the error term of Eq. (3.1) is iid and that seasonality in stock return is deterministic and can be captured by deterministic seasonal dummy variables.

Indeed, it is widely established that the stylised facts of stock returns (Leptokurtosis, conditional heteroscedasticity, and autocorrelation) as revealed by Fama (1965) and Mandelbrot and Taylor (1967) violate the assumptions of the OLS regression model. Because the OLS estimation technique is designed to exploit these assumptions, the inferences derived from it are impacted upon more severely than are those obtained using other estimation techniques when these assumptions do not hold (Kennedy, 2008).[9] In response to this shortcoming, Connolly (1989) utilises several econometric estimation techniques in order to examine the sensitivity of inferences about the seasonal anomalies under investigation to the violation of the OLS assumptions. Connolly (1989) argues that while the violation of normality received little attention in the empirical finance literature, it can potentially affect the reliability of the OLS coefficients and their standard errors through the presence of outliers. Consistent with this conjecture, Maberly and Pierce (2004) point out that two outliers are responsible for the Halloween effect: the October 1987 crash and the collapse of the hedge fund Long Term Capital Management in August 1998. They show that no trace of the Halloween effect is found when the influential observations are removed from the return series.[10]

One approach to account for the fat-tailed distribution of stock returns is to employ robust estimation techniques (Connolly, 1989) where the estimators are insensitive to the assumptions made about the data-generation process (Andersen, 2008; Kennedy, 2008). Robust estimators have been utilised in several recent studies in this strand of literature (for example Haggard and Witte, 2010; Witte, 2010). Among the widely used robust estimators are the L-estimators and the M-estimators. Each estimator class finds parameter estimates in a

[9] If the error distribution is leptokurtic, OLS remains the Best Linear Unbiased Estimator (BLUE). Nonetheless, it is inferior to some nonlinear unbiased estimators, namely those referred to as robust estimators.

[10] An observation is said to be influential when its removal affects the OLS estimates (Andersen, 2008).

different fashion. While the OLS parameter estimates are found by minimising the sum of squared residuals $min \sum_{i=1}^{n}(y_i - \sum x_{i,j}\beta_j)^2 = min \sum_{i=1}^{n}(\varepsilon_i)^2$, the L-estimator parameter estimates are constructed by minimising the sum of the absolute value of the residuals $min \sum_{i=1}^{n}\left|y_i - \sum x_{i,j}\beta_j\right| = min \sum_{i=1}^{n}|\varepsilon_i|$. The L-estimator which assigns equal weights to positive and negative errors is a special case of the quantile regression method developed by Koenker and Bassett (1978). Although The L-estimator is less sensitive to outliers compared to OLS, L-estimator estimates have relatively low efficiency (Andersen, 2008). The M-estimator proposed by Huber (1964,1973) is held to be a compromise between the efficiency of OLS estimators and the resistance of the L-estimators (Andersen, 2008). The M-estimator parameter estimates are obtained by minimising the sum of a less rapidly increasing function of residuals, instead of minimising the sum of squared residuals as in the case of OLS, which is achieved using an iteratively reweighted least squares procedure (Andersen, 2008; Rousseeuw and Leroy, 2003).

Another violation of the OLS assumptions is autocorrelation. It is shown that there exists serious autocorrelation behaviour in daily returns—particularly at lags 5, 10, 15, and 20—which is in harmony with the daily seasonal effects (Copeland and Wang, 1994). To model autocorrelation, Doyle and Chen (2009) employ an ARMA(20,1) specification.[11] They follow this approach in order to investigate the sensitivity of the inferences *vis-à-vis* the daily seasonal effect (namely the day-of-the-week effect) to the presence of the ARMA terms. Thus, the regression equation is specified as:

$$r_t = \beta_0 + \sum_{i}^{q} \beta_i D_{i,t}^{Seasonality} + \sum_{i=1}^{k=20} \rho_i r_{t-i} + m\varepsilon_{t-1} + \varepsilon_t \qquad (3.2)$$

[11] The justification offered by Doyle and Chen (2009) for the choice of ARMA(20,1) process is that it is encompassing.

where k is the order of the autoregressive process (set to 20 in our case), ρ_i are the coefficients on the 20 lagged AR terms, and m is the coefficient on the MA term. If the seasonal effect remains robust to the inclusion of ARMA terms, the existence of daily seasonality cannot rest merely on the short-term memory of the ARMA window. The fact the stock returns are characterised by time-varying heteroscedasticity motivates the use of the autoregressive conditional heteroscedasticity (ARCH) model, introduced by Engle (1982), and the generalised autoregressive conditional heteroscedasticity (GARCH) model, proposed by Bollerslev (1986), for detecting daily seasonal patterns in financial time series (for example Al-Loughani and Chappell, 2001; Choudhry, 2000; Connolly, 1989; Doyle and Chen, 2009; McConnell and Wei, 2008). This estimation technique enables researchers to model the variance as conditional on the past variance and error, instead of assuming that it is constant throughout the series. Typically, a GARCH(p,q) model has p autoregressive lags, that is ARCH terms and q moving average lags (GARCH) terms. Subsequent to the pioneering work of Engle (1982), numerous variations of volatility models have been developed. Indeed, Moosa (2013, p. 66) humorously states that “there have been more sequels to ARCH than to Jaws, Rocky, Rambo and Die Hard put together [and that] these sequels include GARCH, EGARCH, XARCH and XYARCH, where X and Y can be replaced by any letter of the alphabet”. Nonetheless, GARCH(1,1) remains commonly employed in empirical finance research and, in particular, is endorsed by Engle (2001, p. 166) “[as] the simplest and most robust of the family of volatility models”. Therefore, Doyle and Chen (2009) and McConnell and Wei (2008), among others, model the conditional variance as a GARCH(1,1) process in the following fashion:

$$\sigma_t^2 = \omega + \alpha\varepsilon_t^2 + \gamma\sigma_{t-1}^2 \tag{3.3}$$

where α is the coefficient on the ARCH(1) component, γ is the coefficient on the GARCH(1) component and ω is the mean-reverting constant.

While these specifications assume that seasonal effects are fixed over time, an increasing number of more recent studies posit that seasonality in stock returns is diminishing over time as markets become more efficient (for example Kohers *et al.*, 2004; Marquering *et al.*, 2006; Tan and Tat, 1998; Worthington, 2010). Motivated by the notion of diminishing seasonality, Chong *et al.* (2005) propose the following regression model to test this conjecture:

$$r_t = \beta_0 + \beta_1 D_t^{Seasonality} + \emptyset Trend_t \times D_t^{Seasonality} + \varepsilon_t \qquad (3.4)$$

where $Trend_t$ is a deterministic trend variable equal to the elapsed number of days from the start of the sample period, $Trend_t \times D_t^{Seasonality}$ is the interaction term between the seasonal dummy variable and the deterministic trend variable, and $\emptyset$ captures the evolution direction of the seasonal effect under investigation. Thus, if the hypothesis $H_0\colon \emptyset = 0$ is rejected in favour of the alternative hypothesis $H_1\colon \emptyset < 0$, then the seasonal effect under investigation is confirmed to be declining.

An alternative perspective on seasonality is offered by Moosa (1995). He indicates that the usual position taken in the literature that seasonality is deterministic (constant) leads to a test of the null of no seasonality against the alternative of deterministic seasonality. This formulation ignores the likely possibility of stochastic (time-varying) seasonality. Al-Saad and Moosa (2005) argue that when testing for seasonality in stock returns, a more valid approach would be to test first for the presence of stochastic seasonality versus deterministic seasonality. To this end, they employ the structural time series model of Harvey (1990,1997) initially to discern whether seasonality is stochastic or deterministic. Once seasonality turns out to be deterministic, the results can be corroborated using the standard OLS estimation technique.

Another approach to test for time-varying seasonality is suggested by Doyle and Chen (2009), who estimate changing seasonality over time by including in Eq. (3.2) a year dummy and an interaction term of year and seasonal effect dummies. This is represented as:

$$\begin{aligned} r_t = \beta_0 + \sum_{i}^{q} \beta_i D_{i,t}^{Seasonality} + \sum_{j}^{m} \delta_j Year_{j,t} + \sum_{j}^{m}\sum_{i}^{q} \lambda_{j,i} Year_{j,t} \times D_{i,t}^{Seasonality} \\ + \sum_{i=1}^{k=20} \rho_i r_{t-i} + m\varepsilon_{t-1} + \varepsilon_t \end{aligned} \quad (3.5)$$

The null hypothesis is $H_0: \lambda_{j,i} = 0$ jointly for all $D_{i,t}^{Seasonality}$ and $Year_{j,t}$. If the null is rejected, then it can be concluded that seasonality does vary over time.

3.2 The Turn-of-the-month Effect

In this section we present the empirical results for the turn-of-the-month effect. Before the presentation of the results, we explain the operationalisation of variables and model specification.

Operationalisation of the Variables

There is no universally agreed definition for the turn-of-the-month effect. In his pioneering paper, Ariel (1987) employs a unique definition for the trading month that differs from that of the typical calendar month. In particular, he includes the last trading day of each month with the following month, and he excludes the last trading day of the respective month. In order to test for the presence of a monthly seasonal effect, Ariel (1987) splits the trading month equally into two parts (by deleting the odd day (if any) that falls in the middle of the month). Next, he tests the null hypothesis that the mean return for the first half of the trading month is equal to that of the last half. Several studies adopt this definition, including Ogden (1990), Booth *et al.* (2001), and Gerlach (2007).

An alternative more broadly used definition was suggested by Lakonishok and Smidt (1988), who were the first to refer to this as "the turn-of-the-month effect". Furthermore, they narrowed the definition to be the period that starts from the last day of the prior month, and the following three days from the subsequent month. Among the studies that employ this definition are Cadsby and Ratner (1992), Kunkel *et al.* (2003), Freund *et al.* (2007), McConnell and Wei (2008), McGuinness and Harris (2011), and Sharma and Narayan (2014). There are, however, numerous studies that slightly modify these two definitions on an *ad hoc* basis. For example Ziemba (1991) adjusts the definition of the turn of the month to run over the last five trading days of the prior month and the first two trading days of the following month; this is in order to match the payment cycle in Japan. Maher and Parikh (2013) only consider the last trading day of the month along with the first two days in the following month; some studies examine several definitions and include Oğuzsoy and Güven (2006) and Nikkinen *et al.* (2009).

Models Specification

In the spirit of Kunkel *et al.* (2003) and McConnell and Wei (2008), we first examine the 10 trading days around the turn of the month to determine whether any of the mean daily returns are significantly different from zero. To this end, we estimate the following OLS regression for each stock market:

$$r_t = \sum_{i=-5}^{5} \beta_i D_{i,t} + \varepsilon_t \tag{3.6}$$

where r_t is the return on Day *t*, $D_{i,t}$ are dummy variables that take the value 1 on the first and last five trading days of each month and 0 otherwise, $\beta_{-5}, \ldots, \beta_5$ measure the mean daily return during each of the days that fall around the turn of the month, and ε_t is an error term assumed to be iid. The null hypotheses are $H_{0,i}\colon \beta_i = 0 \;\; -5 \leq i \leq \; 5$.

We then test precisely for the presence of the turn-of-the-month effect by directly comparing the turn-of-the-month returns to the rest-of-the-month (ROM) returns. This is achieved by estimating the widely used model following the definition proposed by Lakonishok and Smidt (1988). Therefore, we run the following regression:

$$r_t = \alpha_0 + \alpha_1\, TOM_t + \varepsilon_t \qquad (3.7)$$

where r_t is the return on day t, TOM_t is a dummy variable for the turn-of-the-month period that takes the value 1 if the return at day t falls within the turn-of-the-month period (trading days -1 to 3) and 0 otherwise, α_0 is the intercept representing the mean return for the rest-of-the-month period, the slope α_1 represents the difference between the mean turn-of-the-month return and the mean rest-of-the-month return, while $\alpha_0 + \alpha_1$ represents the mean return over the turn-of-the-month period, and ε_t is an error term, which is assumed to be iid. The null hypothesis is: $H_0\colon \alpha_1 = 0$.

Motivated by the discussion pertaining to the consequences of the violation of the OLS assumptions, we conduct a battery of typical error-distribution specification tests for Eq. (3.7), closely following the approach of Connolly (1989). We employ the Jarque and Bera (1987) normality test to test the normality assumption, the Ljung-Box Q-statistic (Ljung and Box, 1978) to test for autocorrelation, and the time-varying heteroscedasticity test developed by Engle (1982). If the residuals obtained from Eq. (3.7) fail these tests, we examine the sensitivity of results to alternative model specifications. We use the following estimation techniques:

- Model 1: OLS with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)
- Model 2: M-estimator
- Model 3: L-estimator

- Model 4: ARMA(20,1) with the heteroscedasticity and autocorrelation consistent (HAC) standard errors of Newey and West (1987)
- Model 5: GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992)
- Model 6: ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992).

To examine the conjecture that seasonal effects vary over time, we run a rolling regression of Eq. (3.7) using the OLS estimation technique with a step of 20 trading days and a fixed 250 trading-days window. The rolling regression results are plotted in Figure 3.1. The estimates of the slope coefficient α_1 obtained from the rolling regression procedure are equivalent to a 20-step moving average with a window length of 250 of the difference between the turn-of-the-month return and the rest-of-the-month return.

To test the hypothesis that the turn-of-the-month effect is diminishing over time, we estimate the model proposed by Chong *et al.* (2005) using the OLS technique (with robust standard errors). For this purpose, the regression model is specified as:

$$r_t = \beta_0 + \beta_1 TOM_t + \beta_2 Trend_t \times TOM_t + \varepsilon_t \qquad (3.8)$$

If the null hypothesis $H_0: \beta_2 = 0$ is rejected in favour of the alternative hypothesis $H_1: \beta_2 < 0$, then the seasonal effect under investigation is confirmed to be declining. As a robustness check, Eq. (3.8) is estimated using several econometric techniques.

While seasonality in stock returns may not necessarily be declining, it could be potentially time-varying. Thus, we estimate the model proposed by Doyle and Chen (2009) using a model that is specified as:

$$r_t = \gamma_0 + \gamma_1 TOM_t + \sum_j^m \delta_j Year_{j,t} + \sum_j^m \lambda_j Year_{j,t} \times TOM_t + \sum_{i=1}^{k=20} \rho_i r_{t-i} + m\varepsilon_{t-1} + \varepsilon_t \tag{3.9}$$

The null hypothesis is $H_0: \lambda_j = 0$ jointly for all TOM_t and $Year_{j,t}$, which is done using a Wald test. If the null hypothesis is rejected, it can be concluded that the turn-of-the-month effect does vary over time. As a robustness check, Eq. (3.9) is estimated using several econometric techniques (the same as those used for Eq. (3.8)).

Empirical Results

Table 3.1 contains the regression results of Eq. (3.6) and Eq. (3.7) for the seven GCC markets. The first 10 columns report the estimated regression coefficients and their corresponding t-statistics (in parentheses) from Eq. (3.6). The estimated coefficients are equivalent to the mean daily returns for day -5, -4, -3, -2, -1, 1, 2, 3, 4, and 5. The eleventh, twelfth and thirteenth columns give the estimated regression coefficients and their corresponding t-statistics (in parentheses) from Eq. (3.7). The eleventh column reports the sum of the estimated intercepts and slopes $(\alpha_0 + \alpha_1)$, which amounts to the mean daily returns for the four-day turn-of-the-month interval (day -1 to day +3). The twelfth and thirteenth columns, respectively, show the estimated intercept and slope. The estimated intercepts (α_0) are equivalent to the mean daily returns of all of the other days of the month (the rest of the month) while the estimated slopes give the difference between the mean daily return for the turn-of-the-month interval and the mean return for all the other days of the month. In addition, columns 1 to 12 give the fraction of positive returns for each of the 10 days around the turn of the month, the turn-of-the-month four-day interval, and all the other days of the month. Indeed, the t-statistics in column 12 pertain to the hypothesis that the mean return over the turn of the month is significantly different from the mean return over all other days. This statistic is the focus of attention in drawing inferences about the presence of the turn-of-the-month effect in the GCC markets.

Panels A to G of Table 3.1 contain the estimation results for the seven GCC markets. Note from Panel A, which reports the results of the Abu Dhabi market index, that the mean daily return of the first and second days of the trading month are positive and statistically different from zero at the 5 percent significance level. In addition, the mean daily return over the four-day turn-of-the month interval $(\alpha_0 + \alpha_1)$ is 0.16 percent; it is statistically significant at the 1 percent level, while the mean daily return during the rest of the month (α_0) is shown to be negative; there is insufficient evidence to reject the hypothesis that it is equal to zero at the conventional significance levels.

Table 3.1: Daily stock returns around the turn-of-the-month

	Daily mean return around the turn of the month										TOM	ROM	Difference
Market	β_{-5}	β_{-4}	β_{-3}	β_{-2}	β_{-1}	β_1	β_2	β_3	β_4	β_5	$\alpha_0 + \alpha_1$	α_0	α_1
Panel A: Abu Dhabi													
Mean daily return	-0.04	-0.03	0.01	-0.06	0.11	0.23	0.22	0.07	0.03	-0.03	0.16	-0.01	0.16
t-Statistic	(-0.35)	(-0.31)	(0.09)	(-0.58)	(1.03)	(2.15)	(2.04)	(0.62)	(0.26)	(-0.30)	(2.92)	(-0.23)	(2.74)
Positive	0.51	0.52	0.55	0.55	0.52	0.60	0.61	0.58	0.53	0.51	0.58	0.51	
Panel B: Bahrain													
Mean daily return	-0.07	-0.06	-0.10	0.09	0.13	0.03	-0.10	-0.01	-0.01	0.14	0.01	0.00	0.01
t-Statistic	(-1.17)	(-0.96)	(-1.60)	(1.48)	(2.10)	(0.43)	(-1.61)	(-0.24)	(-0.22)	(2.30)	(0.34)	(0.19)	(0.22)
Positive	0.47	0.42	0.43	0.50	0.56	0.51	0.45	0.50	0.55	0.63	0.51	0.45	
Panel C: Dubai													
Mean daily return	-0.15	-0.05	-0.21	0.01	0.28	0.41	0.07	-0.14	0.05	-0.07	0.16	-0.02	0.17
t-Statistic	(-0.77)	(-0.27)	(-1.07)	(0.06)	(1.45)	(2.12)	(0.37)	(-0.72)	(0.25)	(-0.37)	(1.61)	(-0.37)	(1.62)
Positive	0.45	0.52	0.45	0.53	0.56	0.68	0.53	0.57	0.53	0.52	0.59	0.50	
Panel D: Kuwait													
Mean daily return	-0.01	0.10	-0.10	0.03	0.19	-0.04	0.14	0.19	0.22	0.14	0.12	0.03	0.09
t-Statistic	(-0.12)	(1.33)	(-1.33)	(0.38)	(2.44)	(-0.53)	(1.74)	(2.40)	(2.77)	(1.79)	(3.02)	(1.70)	(1.96)
Positive	0.60	0.59	0.48	0.55	0.66	0.54	0.63	0.61	0.68	0.66	0.61	0.57	

Table 3.1 *(Continued)*

	Daily mean return around the turn of the month										TOM	ROM	Difference
Market	β_{-5}	β_{-4}	β_{-3}	β_{-2}	β_{-1}	β_{1}	β_{2}	β_{3}	β_{4}	β_{5}	$\alpha_0 + \alpha_1$	α_0	α_1
Panel E: Oman													
Mean daily return	0.00	-0.16	-0.07	-0.12	0.11	0.27	0.02	0.04	0.15	0.19	0.11	0.04	0.07
t-Statistic	(-0.03)	(-1.58)	(-0.66)	(-1.25)	(1.13)	(2.78)	(0.24)	(0.37)	(1.51)	(1.94)	(2.25)	(1.63)	(1.31)
Positive	0.57	0.48	0.42	0.47	0.63	0.59	0.53	0.63	0.58	0.62	0.59	0.54	
Panel F: Qatar													
Mean daily return	-0.12	-0.02	-0.01	0.16	0.21	0.17	0.05	0.09	0.17	0.27	0.13	0.05	0.08
t-Statistic	(-0.85)	(-0.14)	(-0.09)	(1.16)	(1.50)	(1.21)	(0.37)	(0.61)	(1.20)	(1.94)	(1.85)	(1.48)	(1.01)
Positive	0.48	0.48	0.50	0.62	0.57	0.63	0.60	0.56	0.58	0.62	0.59	0.54	
Panel G: Saudi Arabia													
Mean daily return	0.14	-0.09	0.07	-0.07	0.25	0.11	-0.17	0.24	0.23	0.00	0.11	0.02	0.09
t-Statistic	(0.94)	(-0.57)	(0.43)	(-0.45)	(1.63)	(0.73)	(-1.10)	(1.56)	(1.47)	(0.02)	(1.41)	(0.56)	(1.04)
Positive	0.60	0.55	0.55	0.51	0.60	0.62	0.57	0.58	0.58	0.61	0.59	0.57	

Indeed, the hypothesis that the difference in mean daily returns between the four-day turn-of-the-month interval and the other days of the trading month is equal to zero, formally expressed as $H_0: \alpha_1 = 0$, is rejected at the 1 percent significance level indicating that a strong turn-of-the-month effect is present in the Abu Dhabi market.

The estimation results for the market index of Bahrain are displayed in Panel B. The pattern over the four-day turn-of-the-month interval is weaker compared to Abu Dhabi. Nonetheless, the mean daily return on the last trading day (0.13 percent with a *t*-statistic of 2.10) and the fifth trading day (0.14 percent with a *t*-statistic of 2.30) are positive and statistically significant at the 5 percent significance level. Over all, there is insufficient evidence to support the existence of the turn-of-the-month effect in the Bahraini market. The results for the Dubai market, which are shown in Panel C, paint a similar picture. It is clear that there is no distinctive pattern over the turn-of-the-month period, except for the significantly positive mean daily return on the last day of the month (0.41 percent with a *t*-statistic of 2.12).

Panel D contains the results for the Kuwaiti market index, which indicates a clear pattern around the turn of the month, but in a slightly different way. The mean daily return of the last trading day of the month, along with the first five trading days of the month (except the first day of the month), are statistically significant. The mean daily return of the fourth day of the trading month is 0.22 percent, which is highly significant at the 1 percent significance level. The mean daily return of the last and third trading days (0.19 and 0.19, respectively) are statistically significant at the 5 percent level; the second and fifth trading days are marginally significant at the 10 percent level. On balance, there is evidence in favour of the turn-of-the-month effect in the Kuwaiti market, as the hypothesis that the difference between the mean daily return over the turn-of-the-month interval and the mean daily return over the other days of the trading month is equal to zero is rejected at the 5 percent level.

The results of the stock market index of Oman are contained in Panel E. As with the markets of Dubai and Abu Dhabi, the mean daily return on the first day of the trading month (0.27 present) is highly significant at the 1 percent level; as is the case with the markets of Bahrain and Kuwait, the mean daily return on the fifth day of the trading month is marginally significant at the 10 percent significance level. However, there is insufficient evidence to support the presence of the turn-of-the-month effect in the Omani market. Panel F indicates no visible pattern around the turn-of-the-moth in the Qatar market, except for a marginally significant mean daily return on the fifth day of the trading month, similar to the markets of Oman, Kuwait, and Bahrain. Finally, the results in Panel G pertain to the Saudi Stock market index. It is remarkable to note that there no traces of statistical significance around the turn-of-the-month period in Saudi Arabia.

As discussed earlier, we perform the diagnostic tests described earlier on the estimated residuals of Eq. (3.7). Table 3.2 provides the results for these tests. The normality test of Jarque and Bera (1987) strongly rejects the null hypothesis of normality for all of the seven GCC markets. Therefore, in line with Connolly (1989) and Easton and Faff (1994), we find solid evidence of non-normality in the estimated residuals. The next two columns of Table 3.2 report the skewness and kurtosis estimates for the error distributions. Again, consistent with Connolly (1989) and Easton and Faff (1994), the estimated kurtosis is greater than 3 and skewness is negative across the board.

The final two columns of Table 3.2, respectively, contain the Ljung-Box Q-statistics testing for up to order 20 autocorrelation and the ARCH test proposed by Engle (1982), with one lag. Both the

Ljung-Box Q (20)-statistics and the ARCH test statistics are highly significant across all of the seven GCC markets. Given these findings, the use of alternative econometric specifications and estimation techniques (that are better equipped to deal with the data features) is warranted.

Table 3.2: Error-distribution specification test results for Eq. (3.7)

Market	Jarque-Bera	Skewness	Kurtosis	Q-Stat	LM-ARCH
Abu Dhabi	7068.12	-0.11	11.01	254.38	365.94
Bahrain	3122.50	-0.44	8.74	172.66	94.52
Dubai	2239.60	-0.03	8.03	64.15	339.69
Kuwait	1439.28	-0.60	6.55	346.17	238.03
Oman	26422.75	-0.97	18.86	348.24	723.93
Qatar	4047.20	-0.36	9.16	201.71	314.27
Saudi Arabia	7336.21	-0.86	10.86	70.85	149.30
$\chi^2(0.001)$	13.82			45.32	10.83

Therefore, we test for the presence of the turn-of-the-month effect using the models specified in section 3.2. To reiterate, Model 1 is simply given by computing the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987) for the OLS estimates of Eq. (3.7). This procedure can be thought of as a quick and dirty solution for the autocorrelation and time-varying heteroscedasticity problems. To deal with the fat-tailed distribution of the estimated residuals, Model 2 and Model 3 represent the L and M estimators of Eq. (3.7), respectively. To deal with autocorrelation in an alternative way, Model 4 makes use of an ARMA(20,1) specification with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987). Model 5 is used to estimate the coefficients of Eq. (3.7) using the GARCH(1,1) model with the robust standard errors of Bollerslev and Wooldridge (1992) to account for conditional heteroscedasticity. Finally, using Model 6 simultaneously deals with autocorrelation and conditional heteroscedasticity by employing the ARMA(20,1) GARCH(1,1) specification with robust standard errors of Bollerslev and

Wooldridge (1992). The results from estimating these models are shown in Table 3.3.

Table 3.3 contains the regression results of Eq. (3.7) for the seven GCC markets. Each column reports the estimated regression coefficients (the intercept and slope) and their corresponding *t*-statistics for Models 1 to 6. We omit the ARMA, ARCH, and GARCH terms to conserve space.[12] Panels A to G of Table 3.3 provide the estimation results for the seven GCC markets. A close look at Panel A—the results for the Abu Dhabi Market index—reveals that the coefficient estimates, as well as the *t*-statistics, display considerable sensitivity to alternative estimation techniques. While the turn-of-the-month effect is statistically significant under Models 1 to 4 (that is, the slope α_1 is statistically significantly different from zero at least at the 5 percent level), no evidence for the presence of a turn-of-the-month effect is found when Models 5 and 6 are used. Panel B—the estimation results for the market index of Bahrain—does not show any interesting pattern, as the turn-of-the-month effect is not detected under any of the models.

Table 3.3: Estimated regressions for Eq. (3.7) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
α_0	-0.010	0.030	0.020	-0.006	0.020	0.024
	(-0.20)	(1.51)	(1.38)	(-0.16)	(1.39)	(0.94)
α_1	0.160	0.110	0.090	0.145	0.040	0.043
	(2.16)	(2.71)	(2.46)	(2.00)	(1.36)	(1.09)
Panel B: Bahrain						
α_0	0.003	0.022	0.006	0.004	0.015	0.014
	(0.16)	(1.91)	(0.54)	(0.14)	(1.31)	(0.72)
α_1	0.008	-0.021	0.014	0.000	0.008	0.001
	(0.21)	(-0.82)	(0.52)	(0.01)	(0.30)	(0.03)

[12] The results are available upon request.

Table 3.3 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: Dubai						
α_0	-0.017	0.020	0.000	-0.019	0.026	0.022
	(-0.34)	(0.57)	(0.00)	(-0.28)	(0.99)	(0.59)
α_1	0.173	0.224	0.219	0.165	0.297	0.303
	(1.52)	(2.76)	(2.69)	(1.49)	(4.74)	(4.70)
Panel D: Kuwait						
α_0	0.033	0.093	0.095	0.032	0.093	0.090
	(1.36)	(5.95)	(5.85)	(0.82)	(7.27)	(3.82)
α_1	0.086	0.108	0.087	0.089	0.051	0.045
	(1.54)	(3.07)	(2.08)	(1.76)	(1.74)	(1.34)
Panel E: Oman						
α_0	0.039	0.061	0.052	0.042	0.051	0.051
	(1.40)	(4.41)	(3.70)	(1.23)	(4.53)	(3.17)
α_1	0.072	0.086	0.069	0.051	0.042	0.059
	(1.12)	(2.72)	(2.11)	(0.89)	(1.58)	(1.84)
Panel F: Qatar						
α_0	0.050	0.082	0.059	0.051	0.062	0.088
	(1.24)	(3.58)	(2.77)	(1.07)	(3.65)	(3.40)
α_1	0.079	0.130	0.135	0.086	0.065	0.040
	(0.89)	(2.46)	(2.67)	(1.02)	(1.54)	(0.77)
Panel G: Saudi Arabia						
α_0	0.020	0.140	0.118	0.019	0.117	0.126
	(0.54)	(6.64)	(5.98)	(0.42)	(5.25)	(4.42)
α_1	0.089	0.068	0.064	0.098	0.040	0.019
	(1.09)	(1.36)	(1.24)	(1.26)	(0.80)	(0.36)

Panel C shows the estimation results for the Dubai market index. As for the market of Abu Dhabi, the estimated coefficients, as well as the *t*-statistics, seem to be sensitive to alternative estimation techniques, albeit in a different manner. In this case, in contrast to the Abu Dhabi market, Models 1 and 4 fail to detect the turn-of-the-month effect. Furthermore, when we make use of Models 5 and 6 we find strong evidence for the presence of the turn-of-the-month effect at the 1 percent level. Indeed, the results of Models 3 and 4 are consistent with those of the Abu Dhabi market, as these models produce evidence for the turn-of-the-month-effect.

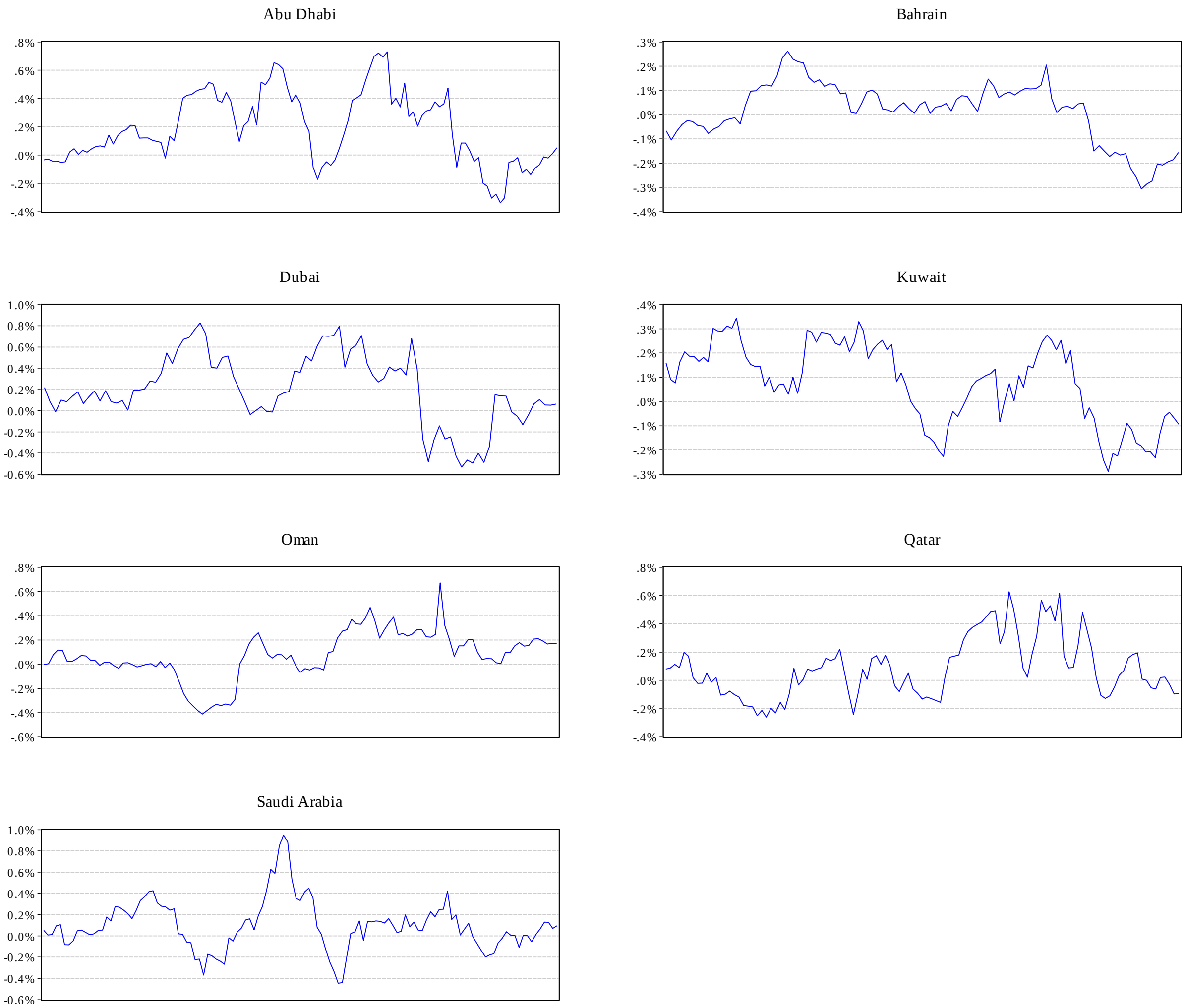
The results for the Kuwaiti market are displayed in Panel D and they show that the turn-of-the-month effect disappears when the standard HAC errors are used (Model 1); using Models 5 and 6 makes the turn-of-the-month effect weaker (marginally significant at the 10 percent level). As with the markets of Abu Dhabi and Dubai, the turn-of-the-month effect is found to be significant under Models 2 and 3. In accordance with the results of the Abu Dhabi market, no traces of the turn-of-the-month effect are detected under Model 6.

The results shown in Panels E and F, which correspond, respectively, to the markets of Oman and Qatar tell a similar story. While the OLS model fails to detect the turn-of-the-month effect in these markets, Models 2 and 3 produce a significant turn-of-the-month effect, at least at the 5 percent level. The rest of the models are consistent with the OLS estimation results. Finally, Panel G indicates that the turn-of-the-month effect is absent in the Saudi market, irrespective of which technique is used.

Overall, the turn-of-the-month effect appears to be sensitive to model specification and estimation technique. Indeed, it interesting to note that the when the robust estimators (the L-estimator and the M-estimator in Models 2 and 3, respectively) are used, the turn-of-the-month effect is detected in all GCC markets except for Saudi Arabia and Bahrain. The results derived from the rest of the models, nonetheless, are mixed. For example when the GARCH(1,1) model with and without ARMA(20,1) terms (Models 5 and 6 respectively) are used, the turn-of-the-month effect ceases to be significant in the Abu Dhabi market; the opposite occurs in the Dubai market—that is, the turn-of-the-month effect becomes significant when Models 5 and 6 are employed.

To investigate the behaviour of the turn-of-the-month effect over the sample period, we provide a visual representation of the evolution in the turn-of-the-month effect in Figure 3.1 for the seven GCC markets. An eyeball inspection of Figure 3.1 gives the impression that the difference between the mean daily return over the turn-of the-month interval and the mean daily return during the other days of the month (as represented by the slope coefficient α_1 estimates of Eq. (3.7)) is time-varying.

Figure 3.1: Evolution of the turn-of-the-month effect



Indeed, it is not clear that the turn-of-the-month effect is declining in the majority of the GCC markets. However, this casual observation is not sufficient to establish either that the turn-of-the-month effect is time-varying, or that it is declining over the sample period. Therefore, to test the hypothesis that the turn-of-the-month effect is declining over the sample period, we estimate the regression in Eq. (3.8).

The estimation results of Eq. (3.8) are shown in Table 3.4. We employ four estimation techniques and model specifications as robustness checks. The first column of Table 3.4 contains the OLS coefficient estimates of Eq. (3.8) and their corresponding *t*-statistics (in parentheses) calculated using the HAC standard errors of Newey and West (1987). The following three columns of Table 3.4 contain, respectively, the same set of results generated using the ARMA(20,1) with the HAC standard errors of Newey and West (1987), GARCH(1,1), and ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992). In this analysis we are particularly interested in the sign and statistical significance of the coefficient β_2 that captures the evolutionary direction of the turn-of-the-month effect over the sample period.

Table 3.4: Estimated regressions for Eq. (3.8) using four estimation techniques

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Panel A: Abu Dhabi								
β_0	-5.91E-05	(-0.20)	-7.00E-05	(-0.18)	2.28E-04	(1.39)	2.32E-04	(0.93)
β_1	0.002	(2.38)	0.002	(2.41)	0.001	(1.71)	0.001	(1.41)
β_2	-6.39E-07	(-0.74)	-6.30E-07	(-0.81)	-4.35E-07	(-0.81)	-3.83E-07	(-0.77)
Panel B: Bahrain								
β_0	0.003	(0.16)	0.004	(0.15)	0.015	(1.30)	0.012	(0.49)
β_1	-0.006	(-0.15)	-0.019	(-0.56)	-0.002	(-0.06)	-0.012	(-0.41)
β_2	4.68E-05	(0.94)	6.03E-05	(1.32)	4.05E-05	(1.00)	6.09E-05	(1.58)

Table 3.4 ***(Continued)***

Market	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Panel C: Dubai								
β_0	-0.017	(-0.34)	-0.019	(-0.28)	0.026	(1.02)	0.022	(0.59)
β_1	0.194	(1.65)	0.182	(1.60)	0.328	(4.81)	0.331	(4.71)
β_2	-7.53E-05	(-0.53)	-6.30E-05	(-0.45)	-1.27E-04	(-1.21)	-1.09E-04	(-1.06)
Panel D: Kuwait								
β_0	0.033	(1.36)	0.032	(0.84)	0.093	(7.28)	0.093	(3.94)
β_1	0.078	(1.24)	0.060	(1.04)	0.061	(1.90)	0.045	(1.25)
β_2	2.60E-05	(0.48)	7.81E-05	(1.45)	-2.90E-05	(-0.66)	-9.61E-07	(-0.02)
Panel E: Oman								
β_0	0.039	(1.40)	0.041	(1.22)	0.052	(4.58)	0.051	(3.14)
β_1	0.079	(1.08)	0.061	(0.89)	0.051	(1.75)	0.077	(2.17)
β_2	-2.15E-05	(-0.26)	-2.65E-05	(-0.33)	-3.07E-05	(-0.76)	-4.50E-05	(-1.27)
Panel F: Qatar								
β_0	0.050	(1.24)	0.052	(1.07)	0.062	(3.67)	0.086	(3.38)
β_1	0.059	(0.64)	0.077	(0.87)	0.088	(2.25)	0.088	(1.82)
β_2	6.13E-05	(0.60)	2.21E-05	(0.22)	-6.69E-05	(-0.73)	-1.09E-04	(-1.64)
Panel G: Saudi Arabia								
β_0	0.020	(0.54)	0.019	(0.42)	0.117	(5.27)	0.127	(4.43)
β_1	0.065	(0.67)	0.068	(0.73)	0.061	(1.10)	0.041	(0.69)
β_2	6.55E-05	(0.68)	8.44E-05	(0.88)	-7.29E-05	(-1.43)	-7.22E-05	(-1.32)

Panel A of Table 3.4 reports the results of the Abu Dhabi market index. The direction of evolution (β_2) is shown to be negative across all estimation techniques and model specifications. However, there is insufficient evidence to support the hypothesis that the turn-of-the-month effect is declining over the sample period in the Abu Dhabi market. On the contrary, the coefficient β_2 is persistently positive but is statistically insignificant in Panel B of Table 3.4, which contains the estimation results for the Bahrain market index. Indeed, the results of the market indices of Dubai and Oman (respectively, shown in Panels C and E) are largely consistent with the results reported for the Abu Dhabi market index; the results for the remaining markets are mixed. Taken together, there is insufficient evidence to establish that the turn-of-the-month effect evolves in a certain direction over the sample period for any of the seven GCC markets.

Next, we turn to the specification used to test for the evolution of the turn-of-the-month effect to answer the question of whether the turn-of the-month effect is time-varying over the sample period. This specification, in fact, does not impose any structure as to the direction of evolution of the turn-of-month effect, which is at odds with the previously discussed one which forces the turn-of-the-month effect to be either strengthening or weakening over the sample period in a linear fashion. Therefore, we estimate the regression Eq. (3.9) using the same estimation techniques and model specifications described earlier.[13] After the estimation of Eq. (3.9), we test the hypothesis that the turn-of-the-month effect is time-varying, as discussed previously, which amounts to a post-estimation Wald test. In this case, the test statistic has a $\chi^2(9)$ distribution for the markets of Abu Dhabi, Kuwait, Oman, Qatar, and Saudi Arabia (since there are nine restrictions on the values of the estimated coefficients), whereas in the cases of Bahrain and Dubai the Wald test statistic has, respectively, $\chi^2(8)$ and $\chi^2(7)$ distributions.[14]

We show the results of the post-estimation Wald test in Table 3.5. The first column of Table 3.5 contains the χ^2 test statistics with their corresponding *P-values* generated from the OLS with the HAC standard errors of Newey and West (1987). Displayed in the following columns are the results from the ARMA(20,1) with the HAC standard errors of Newey and

[13] The estimation results are not reported to conserve space.

[14] Because the markets of Abu Dhabi, Kuwait, Oman, Qatar, and Saudi Arabia have 10 years of data, we exclude one year to avoid falling into the dummy variable trap. Thus, we end up with 9 degrees of freedom. The same applies to the markets of Bahrain and Dubai.

West (1987), GARCH(1,1) and ARMA(20,1) GARCH(1,1), with the robust standard errors of Bollerslev and Wooldridge (1992).

Table 3.5: Wald test results for Eq. (3.9)

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	χ^2	*P-value*	χ^2	*P-value*	χ^2	*P-value*	χ^2	*P-value*
Abu Dhabi	5.02	0.8326	14.49	0.1059	6.82	0.6558	10.29	0.3279
Bahrain	2.14	0.9764	2.68	0.9529	3.41	0.9063	5.48	0.7050
Dubai	13.12	0.0693	14.95	0.0366	7.54	0.3748	8.95	0.2562
Kuwait	11.68	0.2321	13.95	0.1240	12.35	0.1942	12.29	0.1972
Oman	11.51	0.2422	10.88	0.2840	5.70	0.7696	9.57	0.3860
Qatar	14.12	0.1181	19.25	0.0232	15.72	0.0729	18.45	0.0303
Saudi Arabia	16.03	0.0662	14.61	0.1022	12.92	0.1661	11.42	0.2478

A close look at Table 3.5 reveals that there is insufficient evidence in favour of the hypothesis that the turn-of-the-month effect is time-varying in the majority of the GCC markets (Abu Dhabi, Bahrain, Dubai, Kuwait, and Oman); this conclusion is valid across all estimation techniques and model specifications.

The results for the remaining markets indicate that there is mild evidence in support of the time-varying turn-of-the-month hypothesis in the markets of Qatar and Saudi Arabia. However, these findings are sensitive to the estimation techniques and model specification used.

3.3 The Weekend Effect

In this section, we discuss the weekend effect, the second of the daily seasonal effects that we examine.

Operationalisation of the Variables

As discussed earlier, French (1980) proposed and tested two hypotheses to explain the stock-returns generating process. The first is the trading-time hypothesis, which states that the expected returns are equal for each day of the week. In order to test this hypothesis, French specified the following regression model:

$$r_t = \beta_0 + \sum_{i=2}^{5} \beta_i D_{i,t} + \varepsilon_t \tag{3.10}$$

where r_t is the return on Day t, $D_{i,t}$ is a dummy variable that takes the value 1 if the return at day t corresponds to corresponds to day i and 0 otherwise ($D_{2,t}$=Tuesday, $D_{3,t}$=Wednesday, etc.), β_0 is the intercept representing the mean return for Monday, and the slopes $\beta_2, \dots, \beta_5$ capture the difference between the mean return for Monday and the mean return of each of the other trading days of the week. If the trading-time hypothesis holds, the null hypothesis $H_0: \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ should not be rejected by the data.

The calendar-time hypothesis suggests that the expected returns for Monday (the first trading day of the week after regular market closures during the two-day weekend interval) is three times the expected return for the rest of the trading days of the week. To test this hypothesis, French (1980) reformulated Eq. (3.10) by adding the Monday dummy multiplied by 2 to the intercept term to produce the following model:

$$r_t = \beta_0(1 + 2D_{1,t}) + \sum_{i=2}^{5} \beta_i D_{i,t} + \varepsilon_t \tag{3.11}$$

where β_0 is the intercept representing one-third of the mean return for Monday, and the slopes β_2 through β_5 measure the difference between the mean return of the fraction of Monday's return and the mean return of each of the other trading days of the week. If the calendar-time hypothesis holds (the mean return for Monday is three times the mean return for any other day), the null hypothesis $H_0: \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ should not be rejected by the data.[15]

If any of the joint null hypotheses (the trading and calendar time) is rejected, then the null hypotheses for the single regression coefficients $H_{0,i}: \beta_i = 0 \; 2 \leq i \leq \; 5$ are tested. For example in the case of the trading-time hypothesis, which is tested using Eq. (3.10), the rejection of the null hypothesis $H_{0,2}: \beta_2 = 0$ implies that there is sufficient evidence to conclude that the expected returns on Tuesday and Monday are different.

While the first model (the trading-time) remains the most widely used, an increasing number of studies adopt alternative model specifications to test for the weekend effect. A popular alternative specification is proposed by Gibbons and Hess (1981) and is subsequently utilised, *inter alia*, by Jaffe and Westerfield (1985), Condoyanni *et al.* (1987), Solnik and Bousquet (1990), Ajayi *et al.* (2004), Bley and Saad (2010), and Ariss *et al.* (2011). This model is obtained by reformulating Eq. (3.10) as:

$$r_t = \sum_{i=1}^{5} \beta_i D_{i,t} + \varepsilon_t \tag{3.12}$$

where the coefficients $\beta_1, \dots, \beta_5$ represent the mean return for the corresponding day of the week (β_1 is the mean return for Monday, β_2 is the mean return for Tuesday, and so on). Following the estimation of the coefficients of Eq. (3.12), the joint null hypothesis that all of the expected daily returns are equal ($H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$) is tested. Likewise, if the joint hypothesis is rejected, then the null hypotheses for the single regression coefficients

[15] French (1980) shows that neither of the hypotheses is supported by the data. Instead, anomalous behaviour around regular market closures invoked by weekends is documented. In particular, the results indicate that the mean return for Monday is significantly negative, while the mean return for the other days of the week are significantly positive over the entire sample period. Numerous studies confirm the findings of French (1980).

$H_{0,i}: \beta_i = 0 \; 1 \leq i \leq \; 5$ are tested. However, the rejection of the null hypothesis $H_{0,2}: \beta_2 = 0$ merely indicates that there is sufficient evidence to conclude that the expected return on Tuesday is different from zero. Notwithstanding the widespread use of this model, the conclusions derived from it can be misleading. Alt *et al.* (2011, p. 449) write "the testing of the null hypotheses $H_{0,i}: \beta_i = 0 \; 1 \leq i \leq \; 5$, is questionable, to say the least. If there is some evidence that the expected daily returns are not equal, what is the logic behind the next step to test the null hypotheses that each expected daily return is equal to zero?"

Indeed, a number of recent studies focus on the Monday seasonality—for example, Brusa *et al.* (2005) and Keef *et al.* (2009). The model used in these studies is basically given by:

$$r_t = \beta_0 + \beta_1 D_{1,t} + \varepsilon_t \tag{3.13}$$

where β_0 is the intercept representing the mean return for days other than Monday, and β_1 measures the difference between the mean return for Monday and the mean return for the other trading days of the week; $\beta_0 + \beta_1$ represents the mean return on Monday. The null hypothesis is $H_0: \beta_1 = 0$. Furthermore, studies that investigate the profitability of trading on the basis of seasonal effects focus on for which higher returns are documented. Swinkels and Van Vliet (2012), for example, include a Friday dummy instead of Monday in their regression model as:

$$r_t = \beta_0 + \beta_1 D_{5,t} + \varepsilon_t \tag{3.14}$$

where β_0 is the intercept representing the mean return for the other trading days of the week, the slope β_1 captures the difference between the mean return for Friday and the mean return for the other trading days of the week; $\beta_0 + \beta_1$ represents the mean return on weekend days. The null hypothesis to be tested is $H_0: \beta_1 = 0$.

Trading days in the GCC markets differ from the rest of the world's markets. Even within the GCC, trading days vary slightly across member countries. Three countries (Kuwait, Saudi Arabia, and the UAE) have witnessed changes in their trading calendars. The markets of Bahrain, Oman, and Qatar traded from Sunday to Thursday over the entire sample period. On the other hand, during the bulk of the sample period, the Kuwaiti stock markets operated from Saturday to Wednesday, while the markets of Saudi Arabia and the UAE were open for six days from Saturday to Thursday. Furthermore, the trading calendar was altered such that trades are conducted from Sunday to Thursday in order to comply with other GCC and international markets. This applied from 24 September 2006 in the markets of the UAE (Abu Dhabi and Dubai) and about a year later in Kuwait from 1 September 2007; trading on Thursday was halted in the Saudi market from 15 June 2006. These differences and changes in the trading days add a layer of complexity to the analysis.

Although a number of studies examine the day-of-the-week effect in the GCC markets, they are either limited to one market or a subset of GCC markets (Al-Barrak, 2009; Al-Khazali, 2008; Al-Loughani and Chappell, 2001), or they are methodologically flawed (Ariss *et al.*, 2011; Bley and Saad, 2010). Ariss *et al.* (2011) and Bley and Saad (2010) fail to account appropriately for the modifications in trading calendars. Furthermore, the testing procedure used by both Ariss *et al.* (2011) and Bley and Saad (2010) suffers from major drawbacks. To test for the presence of the day-of-the-week effect, they employ the model represented by Eq. (3.12); they fail to conduct their analysis appropriately, as they directly test the equality of the individual coefficients to zero without testing the joint hypothesis of the equality of coefficients with each other. They weaken their findings through their obscure reporting of the results. Bley and Saad (2010) fail to report the regression coefficient for Saturday, which is the first trading day for the markets of Kuwait (up to September 2007), Saudi Arabia (over the entire sample period), and the UAE (up to September 2006). Similarly, Ariss *et al.* (2011) omit the regression coefficient for Saturday for Kuwait and for Thursday for Saudi Arabia. Al-Loughani and Chappell (2001) show that the returns for Saturday significantly exceed the returns for each other day of the week in the Kuwaiti market.

The majority of studies show that daily return seasonality is concentrated around regular market closures due to weekends. A carful investigation of this issue is warranted. It can be achieved by conducting a detailed descriptive analysis of the returns for the last trading day that immediately precedes—as well as the first day that directly follows—regular market closures caused by the weekend in the seven GCC markets over the sample period. By shifting the focus to the sequence of the trading days, we can deal with the complication created by the changes in the trading calendar. To reiterate, the construction of the dummy variables in this fashion facilitates the analysis if a change in the trading calendar occurs. In the case of the UAE markets (Abu Dhabi and Dubai), for example, the dummy variable $D_{first,t}$ takes the value 1 when the return at day t corresponds to Saturday, and 0 otherwise, up to 16 September 2006; from 24 September 2006 until the end of the sample period the dummy variable $D_{first,t}$ takes the value 1 when the return at day t corresponds to Sunday, and 0 otherwise. To obtain a first feel for the data, a descriptive analysis of the weekend effect is carried out. The results are reported in Table 3.6.

Table 3.6: Summary statistics for the weekend effect

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A: all days							
Mean	0.024	0.004	0.014	0.050	0.053	0.065	0.036
SD	1.19	0.63	1.90	0.86	1.08	1.53	1.69
Number of observations	2645	2220	2124	2455	2482	2520	2713
Fraction positive return days	0.525	0.508	0.515	0.575	0.548	0.547	0.571
Panel B: non first or last days of the week							
Mean	-0.018	-0.004	-0.048	0.018	0.0004	0.020	0.002
SD	1.20	0.62	1.91	0.84	1.10	1.56	1.60
Number of observations	1664	1337	1344	1498	1496	1519	1721
Fraction positive return days	0.516	0.490	0.512	0.565	0.529	0.536	0.553
Panel C: first day of the week							
Mean	0.099	-0.024	0.014	0.107	0.117	0.128	0.063
SD	1.319	0.623	2.178	1.042	1.121	1.710	2.273
Number of observations	488	437	389	469	501	500	496
Ratio of week beg returns to non-week beginning	-5.419	5.629	-0.288	5.925	269.862	6.503	34.825
Fraction positive return days	0.539	0.499	0.486	0.586	0.555	0.554	0.569
t-Statistic for difference of the means	1.91	-0.57	0.56	2.01	2.05	1.35	0.75
Chi-Square Test	0.373	0.147	1.288	0.205	0.088	0.084	0.010
Panel D: last day of the week							
Mean	0.092	0.057	0.228	0.093	0.150	0.141	0.127
SD	1.049	0.646	1.534	0.748	0.943	1.228	1.267
Number of observations	493	446	391	488	485	501	496
Ratio of pre-holiday returns to non-weekend	-5.053	-13.517	-4.769	5.126	346.134	7.195	70.399
Fraction positive return days	0.540	0.57	0.55	0.59	0.60	0.57	0.64
t-Statistic for difference of the means	1.81	1.81	2.51	1.71	2.59	1.52	1.54
Chi-Square Test	0.41	7.11	2.42	0.62	4.42	1.40	7.14

Panel A of Table 3.6 reports the mean, standard deviation, the number of observations, and the fraction of positive return days for all trading days, over the entire sample period, for each of the seven GCC markets. The same set of statistics is shown in Panel B for days that neither immediately precede nor follow a regular weekend market closure—in other words, the days that are neither the first nor the last days of the week. Panel C contains the same set of results as Panels A and B for the first day of the week, in addition to the parametric *t*-test of the equality of the mean return of days that are neither the first nor the last days of the regular week, and the mean return of the first days of the week. In order to account for the violation of the assumption of equal variances, the Welch (1951) version of the test statistic is utilised. For first day of the week, the *t*-statistic is calculated as:

$$t = \frac{\mu_{first} - \mu_{non\ first/last}}{\sqrt{\frac{\sigma^2_{first}}{N_{first}} + \frac{\sigma^2{}_{non\ first/last}}{N_{non\ first/last}}}} \tag{3.15}$$

The second test used in order to consider the presence of outliers is the nonparametric goodness of fit χ^2 test of the equality of the observed number of days with positive returns and the expected number of days with the same sign. The test statistic is calculated as:

$$\chi^2 = \frac{2(O_{first} - E_{first})^2}{E_{first}} \tag{3.16}$$

where O_{first} denotes the number of observed positive returns on the first day of the week and E_{first} is the expected number of positive returns on the first day of the week, which is obtained by multiplying the fraction of positive return days for all trading days by the number of first days of the week.

Panel D displays the results for the last days of the week—it is structured in the same fashion as Panel C. For the last day of the week, the *t*-statistic and the χ^2 statistic are calculated respectively as:

$$t = \frac{\mu_{last} - \mu_{non\ first/last}}{\sqrt{\frac{\sigma_{last}^2}{N_{last}} + \frac{\sigma^2{}_{non\ first/last}}{N_{non\ first/last}}}} \tag{3.17}$$

$$\chi^2 = \frac{2(O_{last} - E_{last})^2}{E_{last}} \tag{3.18}$$

where O_{last} denotes the number of observed positive returns on the last days of the week, and E_{last} is the expected number of positive returns on the last days of the week that is obtained by multiplying the fraction of positive return days for all trading days by the number of last days of the week.

Examining Panels A and B, we find that the mean return of non-first or last days of the week is lower than the mean return of all days, across the seven GCC markets. Moreover, the mean return of non-first and last days even turns out to be negative in three of the GCC markets (Abu Dhabi, Bahrain, and Dubai). The results in Panel C reveal that the mean return of the first day of the week exceeds the mean return of the non-first or last days of the week in all the GCC markets except for the Bahrain market where the mean return of the first day of the week is negative. Furthermore, the difference between the two means is statistically significant in three out of the seven GCC markets. In fact, the difference is significant at the 5 percent level in the markets of Kuwait and Oman, while being marginally significant at the level of 10 percent in the Abu Dhabi market. The goodness of fit χ^2 test statistics, however, are statistically insignificant at all conventional levels, which suggests that some extreme positive observations may be behind the significantly higher mean return for the first day of the week in the markets of Kuwait, Oman, and Abu Dhabi.

We turn to the last-day-of-the-week results which are shown in Panel D. The results indicate that the mean return of the last day of the week exceeds the mean return of non-first or last days of the week across the seven GCC markets. The difference between the two means is statistically significant in five out of the seven GCC markets. Notably, the difference is highly significant at the 1 percent level in the Omani market, while being significant at the 5 percent level in the Dubai market, and marginally significant at the 10 percent level for Abu Dhabi, Bahrain, and Kuwait. On the other hand, the *t*-test fails to confirm that the mean return for the first day of the week exceeds significantly the mean return of non-first or last days for the remaining markets, namely Qatar and Saudi Arabia. The results of the goodness of fit χ^2 test statistics tell a different story: while the χ^2 test statistics confirm the results obtained using the *t*-test in the markets of Bahrain and Oman, the rest of the markets produce contradictory results. Particularly, the χ^2 test statistic is highly statistically significant at the 1 percent level in the Saudi market, whereas the *t*-test is found to be insignificant. This, indeed, suggests the presence of return outliers in the case of Saudi Arabia, Abu Dhabi, Dubai, and Kuwait.

Model Specification

Based on the results reported in Table 3.6, the focus on the trading days that immediately fall before and precede a weekend is justified. Furthermore, the results that emerge from the goodness of fit χ^2 test suggest the presence of returns outliers. Thus, to be able to conduct a further investigation of return characteristics by using diagnostic tests, we specify the following regression model:

$$r_t = \beta_0 + \beta_1 D_{first,t} + \beta_2 D_{last,t} + \varepsilon_t \tag{3.19}$$

where $D_{first,t}$ is a dummy variable that takes the value 1 if the return at day t corresponds to the first trading day of the week that immediately follows a weekend, and 0 otherwise; $D_{last,t}$ is a dummy variable that takes the value 1 if the return at day t corresponds to the last trading day of the week that immediately falls before a weekend; β_0 is the intercept representing the mean return for days other than the first and last trading days of the week; β_1 measures the difference between the mean return for the first trading day of the week and the mean return for the other trading days of the week, excluding the last trading day of the week; and β_2 captures the difference between the mean return for the last trading day of the week and the mean return for the other trading days of the week, excluding the first trading day of the week; ε_t is an error term assumed to be independently and identically distributed (iid). The null hypotheses are: $H_0\colon \beta_1 = 0$ and $H_0\colon \beta_2 = 0$.

We test the assumption on the error term after estimating Eq. (3.19) using OLS in the same way as was done previously. The results are qualitatively the same.[16] Based on the previous discussion with regard to the consequences of the violation of the OLS assumptions, we conduct a battery of typical error-distribution specification tests for Eq. (3.19), closely following the approach of Connolly (1989). We employ the Jarque and Bera (1987) test of normality, the Ljung-Box Q-statistic (Ljung and Box, 1978) to test for autocorrelation, and the time-varying heteroscedasticity test developed by Engle (1982). If the residuals obtained from Eq. (3.19) fail these tests, we examine the sensitivity of the results to alternative model specifications, using the following estimation techniques:

- Model 1: OLS with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)
- Model 2: M-estimator
- Model 3: L-estimator
- Model 4: ARMA(20,1) with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)

[16] The results are available upon request.

- Model 5: GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992)
- Model 6: ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992).

To examine the conjecture that seasonal effects vary over time, we run a rolling regression of Eq. (3.19) using the OLS estimation technique with a step of 20 trading days and a fixed 250-trading-days window. The estimates the of slope coefficients β_1 and β_2 obtained from the rolling regression are plotted in Figures 3.2 and 3.3 to offer a visual insight to the change in the weekend effect through time.

To test the hypothesis formally that the weekend effect is diminishing over time, we estimate the model proposed by Chong *et al.* (2005). For this purpose, the regression model is specified as:

$$r_t = \beta_0 + \beta_1 D_{first,t} + \beta_2 D_{last,t} + \beta_3 Trend_t \times D_{first,t} + \beta_4 Trend_t \times D_{last,t} + \varepsilon_t \quad (3.20)$$

Here, we are interested in testing the hypotheses $H_0: \beta_3 = 0$ and $H_0: \beta_4 = 0$. If the null hypotheses are rejected in favour of the alternative hypotheses $H_1: \beta_3 < 0$ and $H_1: \beta_4 < 0$, the weekend effect is confirmed to be declining. As a robustness check, Eq. (3.20) is estimated using several econometric techniques: OLS with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987), ARMA(20,1) with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987), GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992), and an ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992).

While seasonality in stock returns may not necessarily be declining, it could be potentially time-varying. Thus, we estimate the model proposed by Doyle and Chen (2009). For this purpose, the model is specified as:

$$r_t = \gamma_0 + \gamma_1 D_{first,t} + \gamma_2 D_{last,t} + \sum_{j}^{m} \delta_j Year_{j,t} + \sum_{j}^{m} \lambda_j Year_{j,t} \times D_{first,t} + \sum_{j}^{m} \psi_j Year_{j,t} \times D_{last,t} + \sum_{i=1}^{k=20} \rho_i r_{t-i} + m\varepsilon_{t-1} + \varepsilon_t \tag{3.21}$$

The null hypothesis is $H_0: \lambda_j = \psi_j = 0$ jointly for all $D_{first,t}$, $D_{last,t}$ and $Year_{j,t}$. This is achieved by using the post-estimation Wald test. If the null hypothesis is rejected, it can be concluded that the weekend effect does vary over time. As a robustness check, Eq. (3.21) is estimated using several econometric techniques (the same as those used with Eq. (3.20)).

Empirical Results

We estimate Eq. (3.19) using OLS and perform the diagnostic tests on the estimated residuals. The diagnostic test results are qualitatively similar to those reported in Table 3.2, that is, the OLS residuals estimates of Eq. (3.19) fail the diagnostic tests for normality, autocorrelation, and homoscedasticity.[17] These findings justify the use of alternative econometric specifications, and estimation techniques that are better equipped to handle the data features.

Table 3.7 contains the regression results from Eq. (3.19) for the seven GCC markets. Each column reports the estimated regression coefficients: the intercept and slopes and their corresponding *t*-statistics for Models 1 to 6. We omit the ARMA, ARCH, and GARCH terms

[17] For brevity, these results are not reported here; they are available upon request.

to conserve space.[18] Panels A to G of Table 3.7 provide the estimation results for the seven GCC markets obtained using the six different models.

The results in Panel A of Table 3.7—which reports the results from using the Abu Dhabi Market index—indicate that the coefficient estimates, as well as the *t*-statistics, display some sensitivity to alternative model specifications and estimation techniques. While the coefficient estimates obtained from Models 1, 4, 5, and 6 support the presence of some kind of weekend effect, Models 2 and 3 reveal no traces of such an effect. The intercept coefficient β_0 estimates obtained from Models 1, 4, 5, and 6 are found to be negative but statistically indistinguishable from zero at the conventional significance levels. This suggests that the returns generated during days that fall between the first and last days of the week are virtually zero. Only Model 2 shows that β_0 is positive and statistically significant, albeit at the (marginal) 10 percent level. Furthermore, the first slope coefficient (β_1) estimates obtained using Models 1, 4, and 6 are found to be positive and significant at least at the 10 percent level, indicating that the returns realised on the first day of the week significantly exceed the returns generated during days that fall between the first and last days of the week. On the other hand, the slope coefficient β_1 computed by using Models 2, 3, and 5 are not statistically different from zero, in spite of being positive. Indeed, the results are more conclusive for the second slope coefficient (β_2) for which Models 1, 4, 5, and 6 generate statistically significant estimates. This confirms that the returns earned on the day that immediately precedes a regular weekend are significantly higher than the returns realised on days that fall between the first and last days of the week.

Panel B gives the estimation results for the Bahraini market. The coefficient estimates are remarkably consistent across different models, particularly in terms of statistical significance.

[18] Results are available upon request.

β_1

The results indicate that the estimates of the intercept and the first slope coefficients (β_0 and β_1) are statistically insignificant; the second slope coefficient (β_2) estimates are persistently positive and statistically significant at least at the significance level of 10 percent. These findings emphasise the importance of the last day of the week in the Bahraini market.

Panel C, which displays the estimation results for the market index of Dubai paints a similar picture. As for the market of Bahrain, the intercept and first slope coefficients (β_0 and β_1) are statistically insignificant across different models. Nonetheless, the second slope coefficient (β_2) estimates are shown to be statistically significant, at least at the 5 percent level. The exception to this is when Model 3 is used where no statistical significance is detected.

The estimation results for the market index for Kuwait are shown in Panel D. The results are mixed with respect to whether weekly seasonality is present, and of which form. However, weekly seasonality is more evident over the first day of the week immediately following a regular weekend market closure, as four out of the six models indicate that the first slope coefficient (β_1) is significantly different from zero, at least at the 10 percent level; the second slope coefficient (β_2) is found to be significant when the OLS models (Models 1 and 4) are used, albeit at the (marginal) 10 percent level.

Table 3.7: Estimated regressions for Eq. (3.19) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
β_0	-0.018	0.033	0.026	-0.021	-0.004	-0.006
	(-0.56)	(1.74)	(1.43)	(-0.50)	(-0.22)	(-0.21)
β_1	0.117	0.028	0.036	0.129	0.061	0.071
	(1.86)	(0.70)	(0.92)	(2.11)	(1.39)	(1.79)
β_2	0.111	0.032	0.038	0.091	0.119	0.115
	(2.06)	(0.81)	(1.01)	(1.81)	(3.07)	(3.03)

Table 3.7 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel B: Bahrain						
β_0	-0.004	-0.001	-0.004	-0.008	-0.001	-0.006
	(-0.21)	(-0.04)	(-0.37)	(-0.29)	(-0.06)	(-0.24)
β_1	-0.020	0.020	0.004	-0.007	0.005	0.010
	(-0.61)	(0.74)	(0.18)	(-0.21)	(0.18)	(0.38)
β_2	0.061	0.074	0.054	0.062	0.079	0.082
	(1.74)	(2.81)	(2.14)	(1.78)	(2.45)	(2.58)
Panel C: Dubai						
β_0	-0.048	0.008	0.034	-0.061	0.042	0.032
	(-0.91)	(0.21)	(0.80)	(-0.88)	(1.33)	(0.77)
β_1	0.062	0.107	-0.072	0.097	0.028	0.063
	(0.51)	(1.29)	(-0.82)	(0.84)	(0.33)	(0.77)
β_2	0.276	0.180	0.119	0.292	0.169	0.175
	(2.95)	(2.16)	(1.46)	(3.22)	(2.29)	(2.32)
Panel D: Kuwait						
β_0	0.018	0.099	0.093	0.005	0.091	0.080
	(0.69)	(5.49)	(5.03)	(0.13)	(6.03)	(3.19)
β_1	0.089	0.087	0.044	0.154	0.043	0.087
	(1.72)	(2.36)	(0.96)	(2.88)	(1.13)	(2.33)
β_2	0.075	0.002	0.049	0.072	0.020	0.025
	(1.93)	(0.06)	(1.31)	(1.70)	(0.63)	(0.77)
Panel E: Oman						
β_0	0.000	0.053	0.045	0.005	0.040	-0.001
	(0.01)	(3.30)	(2.71)	(0.13)	(2.77)	(0.00)
β_1	0.117	0.052	0.062	0.103	0.031	0.041
	(2.07)	(1.63)	(1.65)	(1.93)	(0.92)	(1.37)
β_2	0.150	0.068	0.058	0.131	0.074	0.067
	(3.11)	(2.10)	(1.96)	(2.60)	(2.55)	(2.53)

Table 3.7 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel F: Qatar						
β_0	0.020	0.077	0.059	0.025	0.028	0.048
	(0.45)	(2.86)	(2.34)	(0.51)	(1.31)	(1.63)
β_1	0.108	0.087	0.057	0.115	0.118	0.139
	(1.33)	(1.61)	(1.02)	(1.43)	(2.25)	(2.80)
β_2	0.122	0.071	0.047	0.099	0.116	0.114
	(1.85)	(1.32)	(1.04)	(1.54)	(2.28)	(2.46)
Panel G: Saudi Arabia						
β_0	0.002	0.111	0.090	0.005	0.068	0.081
	(0.05)	(4.60)	(3.89)	(0.10)	(3.30)	(3.13)
β_1	0.061	0.131	0.077	0.045	0.131	0.112
	(0.57)	(2.57)	(1.25)	(0.45)	(1.89)	(1.66)
β_2	0.125	0.114	0.112	0.126	0.195	0.168
	(1.86)	(2.25)	(2.78)	(1.83)	(2.57)	(2.59)

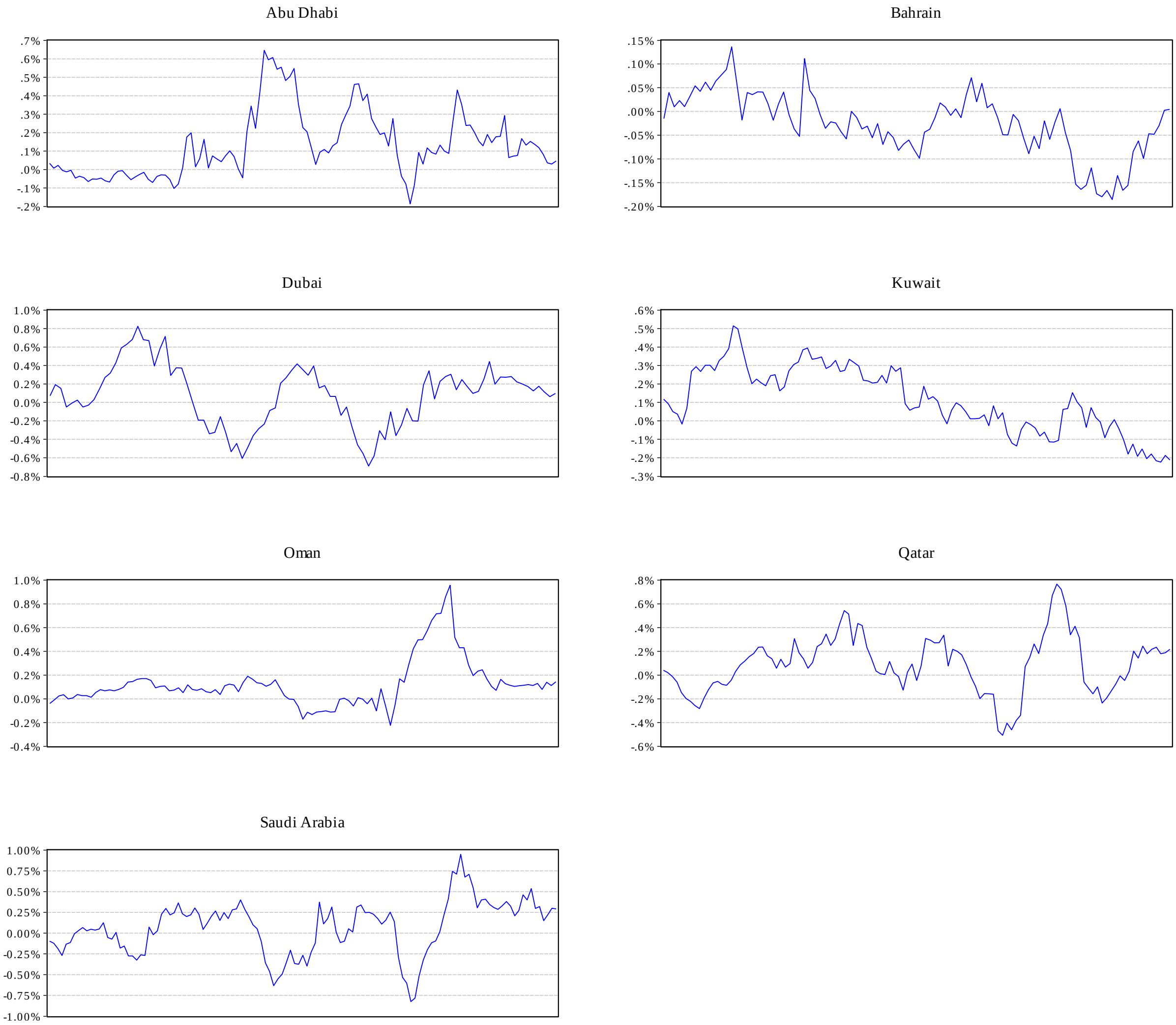
Panel E reports the estimation results for the market index of Oman. They reveal that weekly seasonality is more pronounced for the last trading day that falls immediately before a regular weekend. In fact, the second slope coefficient β_2 estimates are consistent both in terms of sign and statistical significance across different models—all β_2 estimates are found to be statistically significant, at least at the 5 percent level.

Panel F shows the estimation results for the market index of Qatar. The weekly seasonal pattern is strongly detected only by Models 5 and 6 (GARCH-type models), and the slope coefficient β_0 estimates are indistinguishable from zero; both the first and second slope coefficients $\beta_1$and β_2 are found to be statistically significant at the 5 percent level.

The results in Panel G for the market index of Saudi Arabia show that weekly seasonality during the last day of the week is more pronounced. While the results for the first slope coefficients β_1 are sensitive to the model used, the second slope coefficients β_2 are statistically significant at least, at the 10 percent level, across all different models.

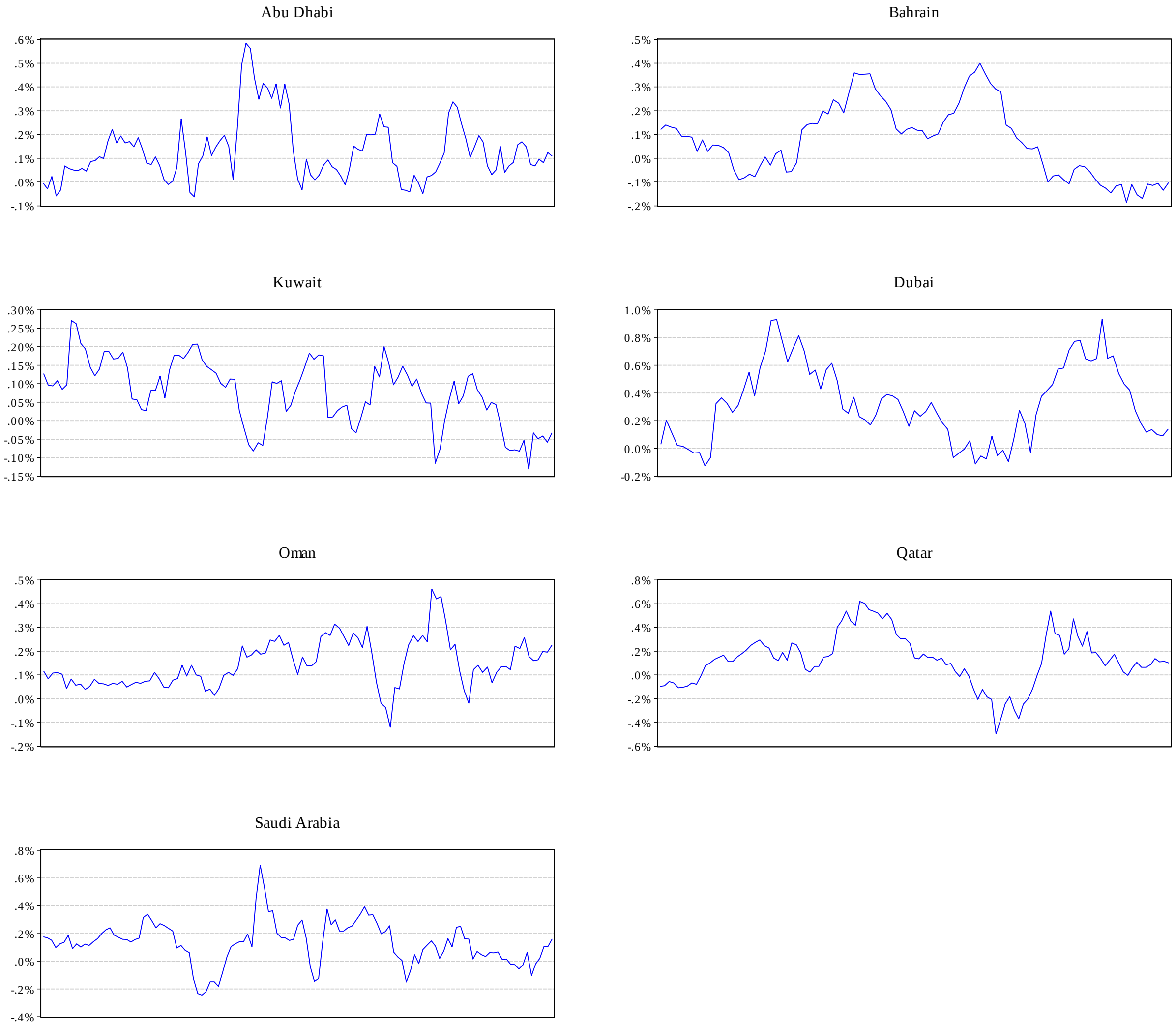
We now investigate the behaviour of the weekend effect over the sample period by providing a visual representation in Figures 3.2 and 3.3 of the evolution of the weekend effect for the seven GCC markets.

Figure 3.2: Evolution of the weekend effect—the first trading day of the week coefficient (β_1)



A careful look at Figure 3.2 gives the impression that the first slope coefficient (β_1) OLS estimate of Eq. (3.19) is time-varying,[19] while β_1 is evidently declining in the markets of Kuwait and Bahrain; such a pattern is not clearly apparent in the remaining markets.

Figure 3.3: Evolution of the weekend effect—the last trading day of the week coefficient (β_2)



Moreover, the OLS rolling regression coefficient estimates of the second slope β_2 of Eq. (3.19), depicted in Figure 3.3, show a similar yet less-pronounced decline for the markets of Kuwait and Bahrain.[20] Other markets, however, do not exhibit such a pattern.

19 As discussed earlier, the first slope coefficient β_1 represents the difference between mean daily return over the return of the first day of the week that immediately follows a regular weekend market closure, and the mean daily return during the days that fall between the first and last days of the regular trading week.

However, this casual observation is not sufficient to establish that either the weekend effect is time-varying or that it is declining over the sample period. Therefore, to find out if the weekend effect is declining over the sample period, we estimate Eq. (3.20); the results are shown in Table 3.8. We employ four estimation techniques or model specifications as robustness checks. The first column of Table 3.8 contains the OLS coefficient estimates of Eq. (3.20) and their corresponding *t*-statistics (in parentheses) calculated using the HAC standard errors of Newey and West (1987). The following three columns of Table 3.8 contain, respectively, the same set of results generated using the ARMA(20,1) model with the HAC standard errors of Newey and West (1987), GARCH(1,1), and ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992). In this analysis we are particularly interested in the sign and statistical significance of the coefficients β_3 and β_4 that capture the evolution of the weekend effect that manifests in the first and last trading days of the week, respectively, over the sample period.

Table 3.8: Estimated regressions for Eq. (3.20) using four estimation techniques

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Panel A: Abu Dhabi								
β_0	-1.83E-04	(-0.56)	-2.06E-04	(-0.50)	-4.40E-05	(-0.22)	-5.66E-05	(-0.20)
β_1	0.002	(1.89)	0.001	(1.06)	0.001	(1.33)	0.000	(0.37)
β_2	0.002	(2.49)	0.001	(1.60)	0.001	(2.22)	0.001	(1.85)
β_3	-2.90E-07	(-0.55)	3.24E-07	(0.60)	-4.07E-08	(-0.11)	4.25E-07	(1.23)
β_4	-6.74E-07	(-1.52)	-2.26E-07	(-0.50)	-1.19E-07	(-0.26)	-2.12E-09	(-0.00)

[20] The second slope coefficient β_2 represents the difference between the mean daily return over the last day of the week that immediately precedes a regular weekend market closure and the mean daily return during the days that fall between the first and last days of the regular trading week.

Table 3.8 ***(Continued)***

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Panel B: Bahrain								
β_0	-4.23E-03	(-0.21)	-6.97E-03	(-0.28)	2.61E-05	(0.00)	-2.64E-03	(-0.14)
β_1	0.131	(2.78)	0.090	(1.77)	0.127	(3.27)	0.116	(2.94)
β_2	0.266	(4.85)	0.215	(3.65)	0.191	(3.72)	0.173	(3.26)
β_3	-1.37E-04	(-3.57)	-8.83E-05	(-2.08)	-1.27E-04	(-4.17)	-1.11E-04	(-3.57)
β_4	-1.82E-04	(-4.09)	-1.36E-04	(-2.78)	-1.15E-04	(-2.86)	-9.60E-05	(-2.24)
Panel C: Dubai								
β_0	-0.048	(-0.91)	-0.058	(-0.86)	0.045	(1.43)	0.036	(0.88)
β_1	0.340	(1.65)	0.277	(1.33)	0.205	(1.54)	0.177	(1.33)
β_2	0.517	(3.50)	0.433	(2.78)	0.249	(2.11)	0.182	(1.53)
β_3	-2.49E-04	(-1.60)	-1.66E-04	(-1.04)	-1.69E-04	(-1.69)	-1.14E-04	(-1.10)
β_4	-2.19E-04	(-2.12)	-1.33E-04	(-1.16)	-7.88E-05	(-0.83)	-1.14E-05	(-0.11)
Panel D: Kuwait								
β_0	0.018	(0.69)	0.006	(0.16)	0.093	(6.18)	0.081	(3.65)
β_1	0.460	(4.58)	0.459	(4.14)	0.381	(5.66)	0.412	(5.59)
β_2	0.280	(4.19)	0.206	(2.46)	0.170	(2.79)	0.132	(2.00)
β_3	-2.99E-04	(-4.67)	-2.45E-04	(-3.58)	-2.49E-04	(-5.63)	-2.36E-04	(-4.87)
β_4	-1.68E-04	(-4.10)	-1.08E-04	(-2.06)	-1.17E-04	(-3.13)	-8.21E-05	(-2.04)
Panel E: Oman								
β_0	0.000	(0.01)	0.005	(0.13)	0.040	(2.77)	0.043	(2.42)
β_1	0.138	(2.36)	0.103	(1.79)	0.043	(0.96)	0.036	(0.85)
β_2	0.228	(4.10)	0.119	(2.31)	0.082	(1.91)	0.069	(1.73)
β_3	-1.74E-05	(-0.31)	-1.68E-08	(-0.00)	-1.13E-05	(-0.31)	3.25E-06	(0.09)
β_4	-6.28E-05	(-1.44)	9.63E-06	(0.19)	-8.06E-06	(-0.27)	-4.54E-06	(-0.16)
Panel F: Qatar								
β_0	0.020	(0.45)	0.025	(0.51)	0.027	(1.29)	0.047	(1.63)
β_1	0.189	(1.80)	0.177	(1.77)	0.078	(1.15)	0.108	(1.53)
β_2	0.237	(2.62)	0.187	(2.19)	0.121	(1.93)	0.170	(2.53)
β_3	-6.42E-05	(-0.79)	-4.89E-05	(-0.61)	3.48E-05	(0.73)	2.88E-05	(0.60)
β_4	-9.11E-05	(-1.56)	-6.90E-05	(-1.21)	-3.80E-06	(-0.07)	-4.94E-05	(-1.04)

Table 3.8 *(Continued)*

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Panel G: Saudi Arabia								
β_0	0.002	(0.05)	0.005	(0.10)	0.068	(3.31)	0.078	(2.94)
β_1	-0.013	(-0.09)	-0.039	(-0.28)	0.074	(0.62)	0.031	(0.27)
β_2	0.301	(3.41)	0.217	(2.59)	0.088	(1.23)	0.029	(0.39)
β_3	5.19E-05	(0.53)	6.20E-05	(0.61)	4.98E-05	(0.73)	7.81E-05	(1.18)
β_4	-1.23E-04	(-2.77)	-6.69E-05	(-1.34)	8.25E-05	(0.89)	1.11E-04	(1.30)

Panel A of Table 3.8 reports the results for the market index of Abu Dhabi. The direction of evolution for the first day of the trading week, coefficient β_3, is shown to vary across techniques and model specifications, but the estimates lack statistical significance. Likewise, the last day of the trading week, coefficient β_4, is persistently negative but the estimates are indistinguishable from zero. Thus, there is insufficient evidence to support the hypothesis that the weekend effect is declining over the sample period in the Abu Dhabi market.

The results for the market index of Bahrain reported in Panel B are more conclusive. Both coefficients (β_3 and β_4) are persistently negative and statistically significant, at least at the 5 percent significance level. Indeed, the results for the market indices of Dubai (shown in Panel C) are mixed for both β_3 and β_4. Generally, weak support is offered for the declining weekend effect, as the results are not robust across the different techniques and model specifications.

The results in Panel D, which pertain to the market index of Kuwait, are striking. Both β_3 and β_4 are persistently negative and statistically significant at the 1 percent level for β_3, and at least at the 5 percent level for β_4. The results in Panels E to G pertain to the market indices of

Oman, Qatar, and Saudi Arabia, respectively. They are largely inconclusive, as the coefficient estimates are not robust to alternative techniques and model specifications.

Taken together, the results suggest that we can safely conclude that the weekend effect is diminishing over time in the markets of Bahrain and Kuwait. However, there is insufficient evidence to establish that the weekend effect, in any form, evolves in a certain direction over the sample period for the markets of Abu Dhabi, Dubai, Oman, Qatar, and Saudi Arabia.

Next, we turn to the alternative specification to test for the evolution of the weekend effect to find out whether the weekend effect is time-varying over the sample period. This specification does not impose any structure on the direction of the evolution of the weekend effect, which is at odds with the specification represented by Eq. (3.20); it forces the weekend effect to be either strengthening or weakening over the sample period in a linear fashion. Therefore, we estimate Eq. (3.21) using the same estimation techniques and model specifications defined previously.[21] Following the estimation of Eq. (3.21), we test the hypothesis that the weekend effect is time-varying, which amounts to a post-estimation Wald test, where the test statistic has a $\chi^2(18)$ distribution for the markets of Abu Dhabi, Kuwait, Oman, Qatar, and Saudi Arabia (since there are nine restrictions on the values of the estimated coefficients); in the case of Bahrain and Dubai, the test statistic has respectively $\chi^2(16)$ and $\chi^2(14)$ distributions.[22]

We show the results of the post-estimation Wald test in Table 3.9. The first column contains the χ^2 test statistics with their corresponding *P-values* generated from OLS with the HAC standard errors of Newey and West (1987). In the following three columns we display the

[21] The estimation results are not reported to conserve space.

[22] Because the markets of Abu Dhabi, Kuwait, Oman, Qatar, and Saudi Arabia have 10 years of data, we exclude one year to avoid falling into the dummy variable trap. Thus, we end up with 18 degrees of freedom. The same applies to the markets of Bahrain and Dubai.

same set of results from the ARMA(20,1) with the HAC standard errors of Newey and West (1987), GARCH(1,1), and ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992). Examining Table 3.9, it appears that there is strong support for the hypothesis that the weekend effect is time-varying, but only in the Bahraini market where the null hypothesis that the weekend effect is the same over the years is rejected at least at the 5 percent level. This is across all estimation techniques and model specifications. The results pertaining to the market of Kuwait are surprising. While clear evidence in support of a diminishing weekend effect is documented, only partial evidence for the time-varying hypothesis is found. Likewise, the results for markets of Dubai and Saudi Arabia are mixed. However, the results for the remaining markets, namely Abu Dhabi and Oman and Qatar, indicate that there is no evidence for the time-varying weekend effect.

Table 3.9: Wald test results for Eq. (3.21)

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	χ^2	*P-value*	χ^2	*P-value*	χ^2	*P-value*	χ^2	*P-value*
Abu Dhabi	13.20	0.78	22.50	0.21	14.73	0.68	19.26	0.38
Bahrain	38.42	0.00	44.47	0.00	29.83	0.02	35.41	0.00
Dubai	18.47	0.19	22.40	0.07	28.76	0.01	28.41	0.01
Kuwait	18.10	0.45	28.38	0.06	21.52	0.25	26.38	0.09
Oman	24.75	0.13	22.24	0.22	14.58	0.69	22.21	0.22
Qatar	19.25	0.38	19.11	0.39	13.95	0.73	15.56	0.62
Saudi Arabia	24.67	0.13	21.21	0.27	33.61	0.01	38.36	0.00

3.4 The Holiday Effect

This section discusses the third of the daily seasonal effects, which is the holiday effect.

Operationalisation of the Variables

While the layman's definition of a holiday is largely clear, Brockman and Michayluk (1998) note that this definition is a subject of disagreement among researchers. One widely acknowledged definition is put forward by Lakonishok and Smidt (1988). They posit that a holiday is a day on which the stock market is closed, exclusive of typical weekend days (Saturday and Sunday). Keef and Roush (2005) argue that this definition is crude, as it includes exceptional events, such as the funerals of presidents and natural disasters. They tentatively argue that the one-off event irregular market closures may not share similar characteristics with regular holidays. Other researchers, on the other hand, focus on cultural and religious occasions that occur when the market is open (Frieder and Subrahmanyam, 2004). Such an approach may be subject to data-snooping bias, as the researchers can arbitrarily hand-pick occasions that simply coincide with distinctive patterns in stock returns. In this case, causality between these occasions and stock returns is hard to establish due to the absence of the temporality condition.

The empirical evidence on the holiday effect in the GCC markets is sparse. The studies that investigate the presence of the holiday effect in the GCC markets are either limited to one market or are flawed by a lack of precision in defining holidays. In addition, these studies do not account for other seasonal effects and they use unsophisticated estimation techniques that rest on the foundation of strong statistical assumptions that are shown to be violated by the data. Al-Loughani *et al.* (2005) examine the holiday effect in the stock market of Kuwait over the period 1984 to 2000. They consider the official public holidays (both Islamic and secular) when the stock market is closed. Their empirical results are that no traces of the holiday effect are found over the sample period. While their definition of a holiday is valid, the evidence is limited to one market. A more recent paper of Bley and Saad (2010) investigates the presence the holiday effect separately (among other seasonal effects) in the six GCC countries over the period 2000 to 2009. Although this paper investigates the holiday effect in all six GCC countries, some of the holidays they include are largely irrelevant to the majority of the GCC markets. Such holidays include Christmas Day on which the GCC markets remain open, and Ashura Day that is a public holiday only in Bahrain. Furthermore, they ignore a number of secular holidays that invoke market closures in some GCC countries, particularly Labour Day in Bahrain, Renaissance Day in Oman, and the Currency and Exchange holiday in Qatar. In fact, while the GCC countries share the same culture and language, the public holidays in these countries differ substantially. In our analysis, we carefully distinguish between the GCC markets by considering the official public holidays that cause market closure in each market separately.

Table 3.10: Holidays in GCC countries

Country	Public holidays included for applicable years
Bahrain	*Religious:* Ashura, Eid Al-Fitr, Eid Al-Adha, Islamic New Year, and Prophet Muhammad's birthday *Secular:* Gregorian New Year, Labour Day, and National Day
Kuwait	*Religious:* Al-Isra and Al-Mi'raj, Eid Al-Fitr, Eid Al-Adha, Islamic New Year, and Prophet Muhammad's Birthday *Secular:* Gregorian New Year and National Day
Oman	*Religious:* Al-Isra and Al-Mi'raj, Eid Al-Fitr, Eid Al-Adha, Islamic New Year, and Prophet Muhammad's Birthday *Secular:* Gregorian New Year and National Day, Renaissance Day
Qatar	*Religious:* Eid Al-Fitr and Eid Al-Adha *Secular:* Gregorian New Year and National Day, and Currency and Exchange holiday
Saudi Arabia	*Religious:* Eid Al-Fitr and Eid Al-Adha *Secular:* National Day
United Arab Emirates	*Religious:* Al-Isra and Al-Mi'raj, Eid Al-Fitr, Eid Al-Adha, Islamic New Year, and Prophet Muhammad's Birthday *Secular:* Gregorian New Year and National Day

Table 3.10 contains a list of the regular public holidays that invoke market closure for each of the six GCC countries. These public holidays are classified into two categories: religious and secular. The religious public holidays are Islamic occasions, most of which are festive. The Islamic *alias* the Hijri calendar is used to determine the proper days on which these occasions are celebrated. On the other hand, the secular public holidays (which include state holidays such as the National Day in addition to global holidays, particularly the Gregorian New Year) are all based on the Gregorian calendar. In other developed and emerging markets, which only use one calendar, public holidays are mutually exclusive. However, in the GCC markets and other predominantly Islamic countries that use the Islamic calendar in conjunction with Gregorian calendar, this is not necessarily the case (that is, two public holidays can, potentially, occur on the same day).

The Islamic calendar is a purely lunar calendar. It is unique in the sense that the beginning of the new month is based on the sighting of the crescent moon on the 29th day of each lunar month, shortly after sunset. If the crescent moon is sighted, the present month has 29 days, otherwise the month has 30 days. The Islamic calendar year is persistently shorter than the Gregorian calendar year. Therefore, the Islamic holidays shift with respect to the Gregorian calendar. This situation results in holidays clustering, or even occurring as the possibility of two public holidays occurring simultaneously. In addition, some of the GCC countries occasionally—if a public holiday falls in a weekend—observe no substitute public holiday. Thus, the number of public holidays may vary on a year-to-year basis, which motivates a careful investigation of this issue. To this end, we conduct a detailed descriptive analysis of public holidays in the seven GCC markets over the sample period.

The results are reported in Table 3.11. Panel A of Table 3.11 reports the mean, standard deviation, the number of observations, and the fraction of positive return days for all trading days over the entire sample period for each of the seven GCC stock markets. The same set of statistics is shown in Panel B for days that neither precede nor follow a holiday. Panel C contains the same set of results as Panels A and B for religious pre-holiday days exclusive of secular pre-holiday days, simultaneous religious and secular pre-holiday days (a secular holiday and a religious holiday falling on the same date), and the aggregated pre-holiday days. In addition, we report the results of two statistical tests: the first is the parametric *t*-test of the equality of the mean returns of days that neither precede nor follow a holiday, and the mean return of aggregated pre-holiday days. In order to account for the violation of the assumption of equal variance, the Welch (1951) version of the test statistic is utilised. For pre-holiday days and post-holiday days, the *t*-test calculated as:

$$t = \frac{\mu_{pre} - \mu_{non\,pre/post}}{\sqrt{\frac{\sigma_{pre}^2}{N_{pre}} + \frac{\sigma^2{}_{non\,pre/post}}{N_{non\,pre/post}}}} \tag{3.22}$$

To account for the presence of outliers, the second test is the nonparametric goodness of fit χ^2 test of the equality of the observed number of days with positive returns and the expected number of days with that sign. The test statistic is calculated as:

$$\chi^2 = \frac{2(O_{pre} - E_{pre})^2}{E_{pre}} \tag{3.23}$$

where O_{pre} denotes the number of observed pre-holiday positive returns and E_{pre} is the expected number of pre-holiday positive returns, which is obtained by multiplying the fraction of positive return days for all trading days by the number of pre-holiday days.

Panel D displays the results for the post-holiday days, structured in the same fashion as Panel C. For post-holiday days, the *t*-statistic is calculated as:

$$t = \frac{\mu_{post} - \mu_{non\ pre/post}}{\sqrt{\frac{\sigma_{post}^2}{N_{post}} + \frac{\sigma^2{}_{non\ pre/post}}{N_{non\ pre/post}}}} \tag{3.24}$$

While goodness of fit χ^2 test is given by:

$$\chi^2 = \frac{2(O_{post} - E_{post})^2}{E_{post}} \tag{3.25}$$

where O_{post} denotes the number of observed post-holiday positive returns and E_{post} is the expected number of post-holiday positive returns, which is obtained by multiplying the global fraction of positive return days (for all trading days) by the number of post-holiday days.

Table 3.11: Summary statistics for the holiday effect

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A: All days							
Mean	0.024	0.004	0.0142	0.0499	0.0532	0.0653	0.0358
SD	1.19	0.63	1.903	0.864	1.080	1.531	1.689
N	2645	2220	2124	2455	2482	2520	2713
Fraction positive return days	0.525	0.508	0.515	0.575	0.548	0.547	0.571
Panel B: Non-pre-holiday or post-holiday days							
Mean	0.010	0.005	-0.0143	0.0476	0.0423	0.0603	0.0225
SD	1.17	0.63	1.880	0.857	1.079	1.523	1.675
N	2518	2085	2032	2319	2377	2450	2659
Fraction positive return days	0.519	0.508	0.504	0.572	0.543	0.543	0.568

Table 3.11 ***(Continued)***

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel C: Pre-holiday days							
Mean (Religious)	0.173	0.113	0.808	0.246	0.155	0.438	1.243
SD (Religious)	0.911	0.444	1.807	0.730	0.706	1.307	1.436
N (Religious)	43	42	33	49	32	19	20
Mean (Secular)	0.261	0.043	0.0460	-0.0270	0.2099	-0.2371	-0.0193
SD (Secular)	1.326	0.439	2.434	0.917	0.509	0.945	0.559
N (Secular)	17	21	11	15	12	14	6
Mean (Religious and Secular)	-0.339	0.528	0.865	0.465	0.795	0.526	1.538
SD (Religious and Secular)	1.117	0.884	0.487	0.687	1.577	0.858	NA
Number (Religious and Secular)	4	5	2	4	9	2	1
Mean (total)	0.164	0.122	0.629	0.198	0.276	0.173	0.973
SD (total)	1.038	0.489	1.937	0.772	0.890	1.176	1.364
N (total)	64	68	46	68	53	35	27
Fraction positive return days	0.56	0.59	0.72	0.66	0.66	0.63	0.81
t-Statistic for difference of the means	1.17	**1.94**	**2.25**	1.59	**1.90**	0.57	**3.66**
Chi-Square test	0.35	1.72	**7.31**	1.77	2.45	0.85	**5.62**
Panel D: Post-holiday days							
Mean (Religious)	0.140	-0.054	0.279	-0.003	0.29515	0.06134	0.61452
SD (Religious)	1.959	0.497	2.514	1.135	1.008	2.981	2.959
N (Religious)	43	42	33	49	32	19	20
Mean (Secular)	1.205	-0.309	1.872	-0.199	0.034	0.568	-0.738
S (Secular)	1.732	0.513	2.842	1.246	1.268	0.941	2.171
N (Secular)	17	21	11	15	12	14	6
Mean (Religious and Secular)	0.401	-0.033	0.284	0.389	0.873	0.837	3.033
SD (Religious and Secular)	0.666	0.416	0.480	0.770	1.762	1.428	NA
Number (Religious and Secular)	4	5	2	4	9	2	1
Mean (total)	0.439	-0.131	0.660	-0.0228	0.3342	0.3084	0.4036
SD (total)	1.887	0.504	2.601	1.136	1.223	2.276	2.812
N (total)	64	68	46	68	53	35	27
Fraction positive return days	0.70	0.41	0.78	0.59	0.68	0.74	0.63
t-Statistic for difference of the means	**1.82**	**-2.19**	**1.77**	-0.51	**1.74**	0.65	0.72
Chi-Square test	**7.76**	2.48	**12.79**	0.04	**3.34**	**4.90**	0.33

Examining Panels A and B of Table 3.11, we find that the mean return of non-pre-holiday or post-holiday days is lower than the mean return for all days in all markets except for Bahrain. In fact, the mean return of non-pre-holiday or post-holiday days in the market of Dubai turns out to be negative. However, in the case of the Bahraini market, the mean return of non-pre-holiday or post-holiday days exceeds the mean return for all days—this is attributed to the deletion of the post-holiday days means which are negative, on average, in that market.

The results in Panel C are striking. The mean return for religious pre-holiday days exceeds the mean return for secular pre-holiday days in the majority of GCC markets; the exceptions are the markets of Abu Dhabi and Oman. It is interesting to note that the mean return for secular pre-holiday days is negative in the markets of Kuwait, Qatar, and Saudi Arabia. Furthermore, the mean return of pre-holiday days when religious and secular holidays occur on the same day is higher than religious and secular pre-holiday days means across all GCC markets, except for Abu Dhabi.

The mean return of the aggregated pre-holiday days exceeds the mean return of non-pre-holiday and post-holiday days across the seven GCC markets. Indeed, the magnitude of the aggregated pre-holiday mean returns relative to the mean returns of non-pre-holiday and post-holiday days is quite startling. For example in the case of Saudi Arabia, the mean return on the aggregated pre-holidays is 0.973 percent compared to 0.0225 percent on non-pre-holiday or post-holiday days; this is a ratio of 43 to 1. In the case of Dubai, moreover, the mean return on the aggregated pre-holidays is 0.629 percent compared to a negative mean return of -0.0143 percent on non-pre-holiday or post-holiday days.

The differences between the two means are both economically and statistically significant in four out of the seven GCC markets. Notably, the difference is highly significant at the 1 percent level in the Saudi market, while it is significant at the 5 percent level for the Dubai market, and marginally significant, at the level of 10 percent, for the markets of Bahrain and Oman. The results of goodness of fit χ^2 test statistics tell a slightly different story: while the test statistics confirm the results obtained using the *t*-test in the markets of Dubai and Saudi Arabia, they fail to support the presence of pre-holiday seasonality in the markets of Bahrain and Oman. It may suggest the presence of return outliers in the cases of Bahrain and Oman.

The post-holiday results that are displayed in Panel D of Table 3.11 are mixed. The mean return of religious post-holiday days is higher than the mean return of secular post-holiday days in four out of the seven GCC markets. We find that that mean return of religious as well as secular post-holiday days is negative in the markets of Bahrain and Kuwait. Furthermore, the mean return of post-holiday days when religious and secular holidays occur on the same day is higher than what is realised on religious and secular pre-holiday days across all GCC markets; exceptions are Abu Dhabi and Dubai. The aggregate mean return of the post-holiday days exceeds the mean return of non-pre-holiday or post-holiday days for five out of the seven GCC markets. These are the markets of Abu Dhabi, Dubai, Oman, Qatar, and Saudi Arabia. On the other hand, the mean returns of post-holiday days are found to be negative for the Bahraini and Kuwaiti markets—they are also lower than the mean returns of non-pre-holiday and post-holiday days.

We find that the differences between the two means (post-holiday and non-pre-holiday or post-holiday) are not positive in every case. Specifically, the difference is negative in the markets of Bahrain and Kuwait, while being positive in the remaining markets. The magnitude of the post-holiday mean returns relative to the mean returns for non-pre-holiday or post-holiday days is economically meaningful, amounting to a ratio of more than 46 to 1 for the market of Dubai.

With respect to statistical significance, the difference between the two means is statistically significant for four out of the seven GCC markets. Notably, the difference is negative and significant at the 5 percent level in the Bahraini market, while being positive and significant at the marginal level of 10 percent for Abu Dhabi, Dubai, and Oman. The results of goodness of fit χ^2 test statistics tell a slightly different story: while the χ^2 test statistics confirm the results obtained from the *t*-test in the markets of Dhabi, Dubai, and Oman, they fail to support the presence of pre-holiday seasonality in the markets of Bahrain. Furthermore, the χ^2 test detects post-holiday seasonality in the Qatari market, whereas the *t*-test fails to do so. This result suggests the presence of return outliers in the cases of Bahrain and Qatar.

The results that emerge from the descriptive analysis confirm the presence of distinctive patterns around public holidays in the GCC markets, and thus validate the merits of categorising the holidays into religious and secular. A careful investigation of the holiday effect in the GCC markets is warranted. To this end, we utilise a number of model specifications in order to disentangle the factors that drive the holiday effect. Furthermore, we employ several econometric techniques to examine the robustness of empirical results to different estimation techniques.

Model Specification

As a first pass, we utilise a simple regression model to test for the presence of the holiday effect in the GCC markets' returns, which is similar to that used by Ziemba (1991). This model is specified as:

$$r_t = \beta_0 + \beta_1 PreHol_t + \beta_2 PostHol_t + \varepsilon_t \qquad (3.26)$$

where r_t is the return on day *t*; $PreHol_t$ is a dummy variable that takes the value 1 if the returns at day t correspond to a pre-holiday day; $PostHol_t$ is a dummy variable that takes the value 1 if the return on day t corresponds to a post-holiday day; β_0 is the intercept representing the mean return of typical trading days that do not correspond to pre or post-holiday days. The slope β_1 represents the difference between the mean pre-holiday return and the mean of a typical trading day's return, while the slope β_2 captures the difference between the mean post-holiday days return and the mean of a typical trading day's return; ε_t is error term, assumed to be iid. The null hypotheses to be tested here are: $H_0: \beta_1 = 0$ and $H_0: \beta_2 = 0$.

Following the literature, we omit the post-holiday dummy ($PostHol_t$) from Eq. (3.26) such that the regression model is rewritten as:

$$r_t = \beta_0 + \beta_1 PreHol_t + \varepsilon_t \tag{3.27}$$

where β_0 is the intercept representing the mean return of a typical trading day's return that does not correspond to pre-holiday days returns (but includes post-holiday days). The slope β_1 represents the difference between the mean pre-holiday days return and the mean of a typical trading day's return, including post-holiday days. The null hypothesis is: $H_0: \beta_1 = 0$.

The bulk of the literature on the holiday effect assumes holiday homogeneity. For instance, Ariel (1990, p. 162) writes that “the implicit assumption is made that all pre-holidays are treated as multiple draws from a single pre-holiday distribution despite the fact that the mean returns on different pre-holidays for the value-weighted index differ substantially…”. Several recent studies, however, have refuted this assumption.

Testing the holiday-homogeneity assumption is warranted. As shown in Table 3.10, public holidays in each GCC country are classified into religious and secular. Since religious and secular holidays are not mutually exclusive, we specify a model that explicitly takes into consideration the intricate nature of the holiday structure in GCC markets. To examine the impact of religious and secular holidays, given the fact they may have occurred on the same day during our sample, we propose the following specification:

$$\begin{aligned} r_t = \beta_0 + \beta_1 PreHol\_Rel_t + \beta_2 PreHol\_Sec_t + \beta_3 PreHol\_Both_t \\ + \beta_4 PostHol\_Rel_t + \beta_5 PostHol\_Sec_t + \beta_6 PostHol\_Both_t + \varepsilon_t \end{aligned} \tag{3.28}$$

where $PreHol\_Rel_t$ is a dummy variable that takes the value 1 if the return on day t corresponds to a religious pre-holiday; $PreHol\_Sec_t$ is a dummy variable that takes the value 1 if the return on day t corresponds to a secular pre-holiday; and $PreHol\_Both_t$ is a dummy variable that takes the value 1 if the return on day t corresponds to the coincidence of a simultaneous religious and secular pre-holiday. The variable $PostHol\_Rel_t$ is a dummy that takes the value 1 if the return on day t corresponds to a religious post-holiday; $PostHol\_Sec_t$ is a dummy variable that takes the value 1 if the return on day t corresponds to a secular post-holiday; and $PostHol\_Both_t$ is a dummy variable that takes the value 1 if the return on day t corresponds to the coincidence of a simultaneous religious and secular post-holiday. The intercept β_0 represents the mean return of typical trading days that do not correspond to either pre or to post-holidays. The slopes $\beta_1, \dots, \beta_6$ capture the difference between the corresponding holiday variable mean returns and the mean of typical trading days.

To maintain comparability with the extant literature, we omit the post-holiday variables from Eq. (3.28). Therefore, the model is expressed as:

$$r_t = \beta_0 + \beta_1 PreHol\_Rel_t + \beta_2 PreHol\_Sec_t + \beta_3 PreHol\_Both_t + \varepsilon_t \tag{3.29}$$

where β_0 is the intercept representing the mean return of typical trading days that do not correspond to pre-holidays (but do include post-holidays). The slopes $\beta_1, \dots, \beta_3$ capture the difference between the corresponding holiday variable mean returns and the mean of typical trading days.

To examine the incremental effect of the simultaneous occurrence of religious and secular holidays on the magnitude and significance of the religious and secular holidays, we reformulate the model as:

$$\begin{aligned} r_t = \beta_0 + \beta_1(PreHol\_Rel_t + PreHol\_Both_t) + \beta_2(PreHol\_Sec_t \\ + PreHol\_Both_t) + \beta_3(PostHol\_Rel_t + PostHol\_Both_t) \\ + \beta_4(PostHol\_Sec_t + PostHol\_Both_t) + \varepsilon_t \end{aligned} \tag{3.30}$$

We also estimate a model that excludes the post-holiday variables. By restricting β_3 and β_4 in Eq. (3.30) to zero, we obtain the following model:

$$\begin{aligned} r_t = \beta_0 + \beta_1(PreHol\_Rel_t + PreHol\_Both_t) \\ + \beta_2(PreHol\_Sec_t + PreHol\_Both_t) + \varepsilon_t \end{aligned} \tag{3.31}$$

We test the assumptions of the error term after estimating Eq. (3.26) using OLS. Based on the previous discussion in Section 3.1 with regard to the consequences of the violation of the OLS assumptions, we conduct a battery of typical error-distribution specification tests, closely following the approach of Connolly (1989). We employ the Jarque and Bera (1987) normality test, the Ljung-Box Q-statistic (Ljung and Box, 1978) to test for autocorrelation, and the time-varying heteroscedasticity test developed by Engle (1982). The results that emerge from the diagnostic tests show that the residuals obtained from Eq. (3.26) fail these tests.[23]Therefore, we examine the sensitivity of our results to alternative model specifications, using the following estimation techniques:

- Model 1: OLS with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)
- Model 2: M-estimator
- Model 3: L-estimator

[23] The results are available upon request.

- Model 4: ARMA(20,1) with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)
- Model 5: GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992)
- Model 6: ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992).

As before, we examine the conjecture that the seasonal effect varies over time. We run a rolling regression of Eq. (3.26) using OLS with a step of 20 trading days, and a fixed 250-trading-days window. The estimates the of slope coefficients β_1 and β_2 obtained from the rolling regression are, respectively, plotted in Figures 3.4 and 3.5 to offer visual insight to the change in the holiday effect through time.

To test the hypothesis that the holiday effect is diminishing over time, we estimate the model proposed by Chong *et al.* (2005). For this purpose, the regression model is specified as:

$$\begin{aligned} r_t = \beta_0 + \beta_1 PreHol_t + \beta_2 PostHol_t + \beta_3 Trend_t \times PreHol_t \\ + \beta_4 Trend_t \times PostHol_t + \varepsilon_t \end{aligned} \tag{3.32}$$

Here, we are interested in testing the hypotheses $H_0: \beta_3 = 0$ and $H_0: \beta_4 = 0$. If the null hypotheses are rejected in favour of the alternative hypotheses $H_1: \beta_3 < 0$ and $H_1: \beta_4 < 0$, the holiday effect is confirmed to be declining. As a robustness check, Eq. (3.32) is estimated using several econometric techniques: OLS with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987), ARMA(20,1) with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987), GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992), and an ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992).

While seasonality in stock returns may not necessarily be declining, it could potentially be time-varying. For this reason, we estimate the model proposed by Doyle and Chen (2009). For this purpose, the model is specified as:

$$r_t = \gamma_0 + \gamma_1 PreHol_t + \gamma_2 PostHol_t + \sum_{j}^{m} \delta_j Year_{j,t} + \sum_{j}^{m} \lambda_j Year_{j,t} \times PreHol_t + \sum_{j}^{m} \psi_j Year_{j,t} \times PostHol_t + \sum_{i=1}^{k=20} \rho_i r_{t-i} + m\varepsilon_{t-1} + \varepsilon_t \tag{3.33}$$

The null hypothesis is $H_0\colon \lambda_j = \psi_j = 0$ for all $PreHol_t$, $PostHol_t$ and $Year_{j,t}$. This is achieved by using the post-estimation Wald test. If the null hypothesis is rejected, it can be concluded that the weekend effect does vary over time. As a robustness check, Eq. (3.33) is estimated using several econometric techniques.

Empirical Results

Table 3.12 contains the regression results from Eq. (3.26) for the seven GCC markets. Each column reports the estimated regression coefficients, the intercept and the slopes, and the *t*-statistics for Models 1 to 6. We omit the ARMA, ARCH, and GARCH terms to conserve space.[24] Panels A to G of Table 3.12 provide the estimation results for the seven GCC markets obtained using the six different models.

Panel A reports the results for the Abu Dhabi market index, which indicate that the coefficient estimates and the *t*-statistics are consistent across alternative model specifications and estimation techniques. We find evidence in favour of holiday seasonality that manifests

[24] Results are available upon request.

on post-holiday days. The intercept coefficient β_0 estimates obtained using Models 1, 4, 5, and 6 are found to be positive but statistically indistinguishable from zero at all conventional significance levels. This suggests that the returns generated during non-pre-holiday days and post-holiday days are virtually zero. Only Models 2 and 3 show that β_0 is positive and statistically significant. The coefficient estimates pertaining to pre-holiday days β_1 are found to be indistinguishable from zero at all conventional significance levels, except for Model 4 where β_1 is significant at the marginal level of 10 percent. The coefficient estimates for the post-holiday days (β_2) are statistically significant across the board at least at the 5 percent level. This indicates that the returns realised on post-holiday days significantly exceed the returns generated during non-pre-holiday days or post-holiday days in the Abu Dhabi market.

Panel B gives the estimation results for the market index of Bahrain. In line with the results for Abu Dhabi, only weak evidence is obtained in support of high returns on pre-holiday days. Only Model 1 indicates that coefficient β_1 is significant. However, it seems that the Bahraini market reacts negatively to the end of the holiday or to the market opening, as the coefficient estimates β_2 pertaining to post-holiday days are significant at least at the 5 percent level, except in Model 3 which fails to detect this pattern.

Panel C displays the estimation results for the market index of Dubai, which are striking. We find strong evidence in favour of the presence of holiday seasonality. Indeed, the coefficient estimates are remarkably consistent across the different models, particularly in terms of statistical significance. The intercept coefficient β_0 estimates are statistically indistinguishable from zero, except for Model 5 (GARCH-type model), suggesting that the returns generated during non-pre-holiday days and post-holiday days are virtually zero. It is interesting to note that both the first and second slope coefficients (β_1 and β_2 pertaining to the pre and post-holiday days, respectively) are positive and statistically significant across all specification and estimation techniques.

The estimation results for the market index of Kuwait, which are shown in Panel D, are mixed as to whether holiday seasonality is present and, if so, in which form. In fact, holiday seasonality is more pronounced on pre-holiday days compared to post-holiday days, as four out of the six models indicate that the first slope coefficient β_1 is significantly different from zero. On the other hand, the second slope coefficient β_2 pertaining to post-holiday days is found to be significant only in three out of the six models used. Moreover, β_2 is found to be negative when Models 1 and 4 (OLS) are used, although it is statistically insignificant.

Table 3.12: Estimated regressions for Eq. (3.26) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
β_0	0.010	0.034	0.026	0.004	0.024	0.023
	(0.36)	(2.21)	(1.78)	(0.09)	(1.53)	(0.98)
β_1	0.147	0.105	0.100	0.205	-0.077	-0.058
	(1.23)	(1.07)	(1.00)	(1.84)	(-0.76)	(-0.63)
β_2	0.427	0.374	0.348	0.473	0.317	0.310
	(2.02)	(3.79)	(2.28)	(2.58)	(3.07)	(3.09)
Panel B: Bahrain						
β_0	0.005	0.019	0.006	0.005	0.019	0.016
	(0.29)	(1.76)	(0.64)	(0.20)	(1.88)	(0.72)
β_1	0.119	0.084	0.095	0.090	0.116	0.095
	(1.88)	(1.42)	(1.51)	(1.43)	(1.63)	(1.40)
β_2	-0.138	-0.122	-0.087	-0.139	-0.188	-0.182
	(-2.22)	(-2.05)	(-1.18)	(-2.22)	(-2.55)	(-2.61)

Table 3.12 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: Dubai						
β_0	-0.014	0.030	0.015	-0.019	0.058	0.058
	(-0.31)	(0.95)	(0.46)	(-0.30)	(2.35)	(1.61)
β_1	0.643	0.641	0.864	0.669	0.642	0.568
	(2.21)	(3.01)	(5.09)	(2.26)	(3.20)	(2.79)
β_2	0.674	0.962	0.707	0.721	0.618	0.643
	(1.75)	(4.52)	(2.61)	(1.87)	(2.50)	(2.71)
Panel D: Kuwait						
β_0	0.048	0.104	0.107	0.047	0.096	0.092
	(2.05)	(7.22)	(7.07)	(1.25)	(8.45)	(4.09)
β_1	0.151	0.187	0.160	0.128	0.129	0.124
	(1.42)	(2.19)	(1.75)	(1.36)	(1.84)	(1.79)
β_2	-0.070	0.187	0.184	-0.070	0.150	0.138
	(-0.50)	(2.19)	(1.15)	(-0.55)	(1.82)	(1.75)
Panel E: Oman						
β_0	0.042	0.072	0.059	0.037	0.055	0.058
	(1.64)	(5.61)	(4.55)	(1.13)	(5.20)	(3.82)
β_1	0.228	0.108	0.141	0.276	0.089	0.059
	(1.84)	(1.25)	(2.16)	(2.25)	(1.22)	(0.80)
β_2	0.288	0.173	0.171	0.382	0.139	0.157
	(1.77)	(2.01)	(1.48)	(2.43)	(1.48)	(1.78)
Panel F: Qatar						
β_0	0.060	0.096	0.072	0.061	0.072	0.087
	(1.60)	(4.55)	(3.67)	(1.31)	(4.86)	(3.22)
β_1	0.113	0.179	0.218	0.095	-0.306	-0.297
	(0.56)	(1.01)	(1.20)	(0.49)	(-1.18)	(-1.49)
β_2	0.248	0.698	0.517	0.279	0.304	0.316
	(0.65)	(3.94)	(2.46)	(0.71)	(1.71)	(1.87)

Table 3.12 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel G: Saudi Arabia						
β_0	0.023	0.142	0.118	0.020	0.115	0.120
	(0.65)	(7.35)	(6.47)	(0.47)	(6.10)	(4.55)
β_1	0.951	0.584	0.615	1.092	0.438	0.486
	(4.32)	(3.02)	(3.66)	(4.55)	(2.91)	(3.10)
β_2	0.381	0.660	0.378	0.476	0.408	0.448
	(0.62)	(3.41)	(1.45)	(0.86)	(1.66)	(1.93)

The results pertaining to the market of Oman, which are shown in Panel E, are similar to those for Kuwait, except that the presence of a holiday effect is marginally more evident on post-holiday days. The coefficient β_1 estimates pertaining to pre-holiday days are found to be statistically significant across three out of the six models; the coefficient β_2 is statistically significant when calculated using four out of the six models used.

Panel F contains the results for the market of Qatar. By and large, the holiday effect is equivocal and limited to post-holiday days. As shown in Table 3.11, the nonparametric χ^2 goodness of fit test detects post-holiday seasonality when the parametric *t*-test fails to do so, which highlights the presence of returns outliers. This conjecture is confirmed here, as post-holiday seasonality is detected only by Models 2 and 3 (robust regression techniques). These findings emphasise the importance of using the appropriate econometric techniques.

The results for the Saudi market are exhibited in Panel G. A close look at these results reveals a remarkably clear seasonal pattern on pre-holiday days. The findings are highly robust to alternative model specifications and estimation techniques, particularly in terms of statistical significance. The coefficient β_1 estimates pertaining to pre-holiday days are highly significant at the 1 percent level across the board. We find, nonetheless, that the post-holiday seasonal regularity is relatively less-pronounced, as only three out of the six models reveal a significant post-holiday seasonal effect.

Table 3.13, which is similar to Table 3.12, reports the regression results for Eq. (3.27) for the seven GCC markets. Panels A to G provide the estimation results for the seven GCC markets which were obtained using the six different models. The findings are as expected: the omission of the dummy variable pertaining to the post-holiday days resulted in a change in the magnitude—and occasionally in the statistical significance—of the remaining dummy variables, the intercept (which now captures the post-holiday days return in addition to non-pre-holiday days), and consequently the coefficient pertaining to pre-holiday days, which measures the difference between the returns generated on pre-holiday days and other days (which are captured by the intercept coefficient β_0).

Table 3.13: Estimated regressions for Eq. (3.27) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
β_0	0.021	0.042	0.033	0.019	0.033	0.034
	(0.72)	(2.73)	(2.26)	(0.48)	(2.19)	(1.45)
β_1	0.144	0.101	0.094	0.068	-0.103	-0.142
	(1.21)	(1.02)	(0.93)	(0.61)	(-0.98)	(-1.49)
Panel B: Bahrain						
β_0	0.001	0.015	0.005	0.003	0.013	0.011
	(0.03)	(1.43)	(0.49)	(0.07)	(1.34)	(0.59)
β_1	0.121	0.086	0.097	0.125	0.121	0.117
	(1.92)	(1.44)	(1.46)	(2.04)	(1.62)	(1.68)

Table 3.13 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: Dubai						
β_0	0.001	0.048	0.034	-0.003	0.068	0.067
	(0.01)	(1.53)	(1.02)	(-0.04)	(2.80)	(1.83)
β_1	0.628	0.622	0.845	0.643	0.591	0.474
	(2.16)	(2.90)	(4.98)	(2.18)	(3.04)	(2.38)
Panel D: Kuwait						
β_0	0.046	0.108	0.109	0.045	0.100	0.096
	(1.95)	(7.59)	(7.13)	(1.17)	(8.92)	(4.29)
β_1	0.153	0.182	0.159	0.144	0.108	0.089
	(1.46)	(2.13)	(1.73)	(1.60)	(1.58)	(1.29)
Panel E: Oman						
β_0	0.048	0.075	0.061	0.047	0.059	0.066
	(1.88)	(5.94)	(4.74)	(1.46)	(5.54)	(3.69)
β_1	0.227	0.108	0.139	0.185	0.081	0.005
	(1.84)	(1.25)	(2.13)	(1.69)	(1.13)	(0.07)
Panel F: Qatar						
β_0	0.064	0.105	0.076	0.067	0.077	0.102
	(1.70)	(5.03)	(3.91)	(1.48)	(5.25)	(4.34)
β_1	0.109	0.169	0.214	0.016	-0.329	-0.392
	(0.54)	(0.95)	(1.18)	(0.07)	(-1.31)	(-2.19)
Panel G: Saudi Arabia						
β_0	0.026	0.146	0.120	0.025	0.120	0.126
	(0.74)	(7.59)	(6.56)	(0.58)	(6.38)	(4.80)
β_1	0.947	0.580	0.614	1.054	0.369	0.377
	(4.25)	(3.01)	(3.65)	(4.08)	(2.24)	(2.12)

Although the specification represented by Eq. (3.27) is widely used in the literature, it fails to unveil holiday seasonality, which is confined to post-holiday days in some of the markets that we investigate. In particular, when this specification is employed, no trace of holiday seasonality in any form is detected in the markets of Abu Dhabi and Qatar whose results are displayed in Panels A and F, respectively. Furthermore, the deletion of the post-holiday dummy masks the pronounced negative returns documented on post-holiday days and it slightly inflates the pre-holiday return differential captured by β_1, as shown in Panel B which reports the Bahraini market results.

As discussed above, the assumption of the homogeneity of holidays as to their impact on stock returns is rather restrictive. Therefore, we estimate Eq. (3.28) in order to obtain an insight into the impact of each category of holidays (religious and secular), separately, in addition to their impact when they occur simultaneously. Table 3.14 shows the regression results of Eq. (3.28) for the seven GCC markets. Table 3.14 is structured in a similar fashion to Tables 3.12 and 3.13. Panels A to G of Table 3.14 display the estimation results for the seven GCC markets which are obtained using the six different models. The results are overwhelming, which means that uniform conclusions are difficult to draw. With respect to econometric issues, the coefficient estimates computed using GARCH-type models are largely inconsistent with those calculated using other models. This could possibly be due to the small number of observations for some categories, in particular the category that captures the simultaneous occurrence of religious and secular holidays.

Table 3.14: Estimated regressions for Eq. (3.28) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
β_0	0.010	0.034	0.026	0.004	0.024	0.023
	(0.35)	(2.20)	(1.78)	(0.10)	(1.52)	(0.98)
β_1	0.154	0.039	-0.033	0.165	-0.117	-0.058
	(1.12)	(0.32)	(-0.28)	(1.18)	(-0.88)	(-0.63)
β_2	0.251	0.387	0.328	0.392	0.076	0.310
	(0.80)	(2.03)	(1.72)	(1.65)	(0.59)	(3.09)
β_3	-0.350	-0.366	0.087	-0.292	-0.143	-0.387
	(-0.72)	(-0.94)	(0.28)	(-0.71)	(-0.51)	(-0.80)
β_4	0.130	0.324	0.244	0.151	0.172	0.133
	(0.44)	(2.70)	(1.74)	(0.61)	(1.44)	(1.07)
β_5	1.195	0.646	0.950	1.212	0.619	-0.005
	(2.92)	(3.40)	(2.21)	(3.21)	(2.86)	(-0.19)
β_6	0.352	0.314	0.209	0.733	0.426	0.019
	(1.37)	(0.80)	(1.07)	(2.35)	(1.97)	(0.73)
Panel B: Bahrain						
β_0	0.005	0.019	0.006	0.005	0.019	0.016
	(0.28)	(1.75)	(0.60)	(0.20)	(1.88)	(0.72)
β_1	0.116	0.115	0.179	0.083	0.079	0.095
	(1.65)	(1.53)	(2.18)	(1.12)	(0.93)	(1.40)
β_2	0.038	0.030	-0.012	0.024	0.040	-0.182
	(0.40)	(0.29)	(-0.12)	(0.27)	(0.53)	(-2.61)
β_3	0.523	0.116	0.193	0.464	0.703	1.096
	(1.48)	(0.54)	(1.70)	(1.38)	(1.94)	(20.10)
β_4	-0.059	-0.032	-0.014	-0.073	-0.107	-0.117
	(-0.74)	(-0.43)	(-0.18)	(-0.87)	(-1.18)	(-2.75)
β_5	-0.319	-0.341	-0.314	-0.309	-0.313	0.014
	(-2.92)	(-3.22)	(-3.61)	(-2.87)	(-2.64)	(0.37)
β_6	-0.037	-0.027	-0.006	0.037	0.042	-0.030
	(-0.22)	(-0.12)	(-0.04)	(0.35)	(0.33)	(-0.84)

Table 3.14 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: Dubai						
β_0	-0.014	0.030	0.015	-0.019	0.058	0.058
	(-0.31)	(0.95)	(0.46)	(-0.29)	(2.37)	(1.61)
β_1	0.823	0.613	0.974	0.812	0.659	0.568
	(2.59)	(2.45)	(5.10)	(2.47)	(2.88)	(2.79)
β_2	0.060	0.683	0.603	0.071	0.363	0.643
	(0.09)	(1.58)	(1.11)	(0.10)	(0.88)	(2.71)
β_3	0.879	0.834	1.194	1.706	1.171	-0.920
	(3.53)	(0.83)	(2.63)	(3.71)	(2.80)	(-28.89)
β_4	0.293	0.915	0.609	0.315	0.430	0.100
	(0.69)	(3.65)	(2.44)	(0.76)	(1.54)	(2.74)
β_5	1.886	1.424	1.181	1.919	1.471	0.053
	(2.30)	(3.30)	(3.26)	(2.26)	(2.79)	(1.60)
β_6	0.299	0.254	0.609	0.494	-0.188	0.022
	(1.22)	(0.25)	(1.34)	(0.86)	(-0.40)	(0.68)
Panel D: Kuwait						
β_0	0.048	0.104	0.107	0.048	0.096	0.092
	(2.05)	(7.18)	(7.07)	(1.25)	(8.44)	(4.09)
β_1	0.198	0.212	0.204	0.173	0.139	0.124
	(1.91)	(2.11)	(1.55)	(1.80)	(1.63)	(1.79)
β_2	-0.075	0.059	0.117	-0.132	-0.007	0.138
	(-0.33)	(0.33)	(0.92)	(-0.60)	(-0.07)	(1.75)
β_3	0.418	0.370	0.924	0.466	0.340	-0.512
	(1.40)	(1.07)	(6.02)	(1.59)	(1.29)	(-1.89)
β_4	-0.050	0.202	0.184	-0.041	0.127	0.149
	(-0.32)	(2.02)	(0.94)	(-0.27)	(1.27)	(2.67)
β_5	-0.246	0.006	-0.221	-0.305	0.115	0.049
	(-0.80)	(0.04)	(-0.38)	(-1.08)	(0.67)	(1.87)
β_6	0.341	0.355	0.795	0.344	0.476	0.025
	(1.02)	(1.02)	(4.96)	(0.86)	(2.06)	(0.90)

Table 3.14 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel E: Oman						
β_0	0.042	0.072	0.059	0.037	0.055	0.058
	(1.63)	(5.61)	(4.55)	(1.13)	(5.18)	(3.82)
β_1	0.105	0.141	0.163	0.152	0.160	0.059
	(0.86)	(1.27)	(1.67)	(1.22)	(1.80)	(0.80)
β_2	0.168	0.111	0.117	0.333	-0.097	0.157
	(1.16)	(0.62)	(1.07)	(1.89)	(-0.90)	(1.78)
β_3	0.753	-0.024	0.107	0.642	0.123	0.563
	(1.51)	(-0.12)	(0.79)	(1.63)	(0.56)	(0.30)
β_4	0.250	0.208	0.220	0.410	0.184	-0.143
	(1.44)	(1.88)	(1.18)	(3.05)	(1.62)	(-0.22)
β_5	-0.008	0.111	0.308	0.112	0.096	0.066
	(-0.02)	(0.62)	(1.96)	(0.30)	(0.52)	(0.50)
β_6	0.831	0.103	0.159	0.635	0.104	-0.002
	(1.49)	(0.50)	(0.89)	(1.19)	(0.39)	(-0.02)
Panel F: Qatar						
β_0	0.060	0.096	0.072	0.063	0.071	0.087
	(1.60)	(4.55)	(3.67)	(1.36)	(4.80)	(3.22)
β_1	0.378	0.549	0.523	0.302	-0.321	-0.297
	(1.28)	(2.29)	(3.51)	(1.08)	(-0.73)	(-1.49)
β_2	-0.297	-0.304	-0.288	-0.245	-0.297	0.316
	(-1.19)	(-1.09)	(-1.38)	(-1.00)	(-1.38)	(1.87)
β_3	0.466	0.431	1.061	0.311	-0.090	0.880
	(1.08)	(0.59)	(3.55)	(0.95)	(-0.69)	(2.45)
β_4	0.001	0.925	0.780	-0.006	0.322	-0.255
	(0.00)	(3.86)	(2.57)	(-0.01)	(1.12)	(-2.01)
β_5	0.508	0.435	0.439	0.579	0.070	0.033
	(2.06)	(1.56)	(2.30)	(2.18)	(0.39)	(0.83)
β_6	0.777	0.741	1.775	0.751	1.629	-0.003
	(1.08)	(1.01)	(5.95)	(0.97)	(7.19)	(-0.10)

Table 3.14 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel G: Saudi Arabia						
β_0	0.023	0.143	0.118	0.020	0.110	0.120
	(0.65)	(7.39)	(6.48)	(0.47)	(5.81)	(4.55)
β_1	1.220	0.776	0.803	1.407	0.573	0.486
	(3.84)	(3.48)	(5.43)	(4.28)	(3.41)	(3.10)
β_2	-0.042	-0.145	0.021	-0.061	-0.003	0.448
	(-0.20)	(-0.36)	(0.13)	(-0.26)	(-0.04)	(1.93)
β_3	1.516	1.396	1.420	1.648	6.469	-0.497
	(43.45)	(1.40)	(7.02)	(8.62)	(1.73)	(-0.88)
β_4	0.592	0.866	0.943	0.694	0.538	0.078
	(0.92)	(3.88)	(1.05)	(1.19)	(1.89)	(1.47)
β_5	-0.760	-0.362	-0.346	-0.713	-0.390	0.045
	(-0.94)	(-0.89)	(-0.70)	(-0.94)	(-1.19)	(1.10)
β_6	3.011	2.891	2.915	2.905	3.015	0.030
	(86.32)	(2.91)	(14.42)	(19.42)	(14.91)	(0.93)

A close look at Table 3.14 reveals that religious holidays are associated with a more positive sentiment in the majority of the markets under investigation, except for the market of Abu Dhabi. Considering Panel A that contains the results for the Abu Dhabi market, we find that the post-holiday significantly high returns are largely attributable to secular holidays, as β_5 (the coefficient estimates pertaining to secular post-holiday days) is found to be positive and is statistically significant at the 1 percent level, except for Model 6. Furthermore, the coefficient β_4 estimates that pertain to religious post-holiday days is only significant when Models 2 and 3 (robust estimators) are used.

The results in Panel B, pertaining to the market of Bahrain, indicate that the negative returns on post-holiday days are concentrated on secular holidays, as the coefficient β_5 estimates are found to be negative and statistically significant across all models, except Model 6. Moreover, the coefficient β_4 estimates pertaining to religious post-holiday days are negative, but statistically insignificant, except for Model 6.

The results for the market of Dubai are shown in Panel C. The holiday seasonality in the Dubai market is strong, as it manifest in both pre and post-holiday days. The results of the refined analysis indicate that while the higher returns documented on pre-holiday days is attributed to religious holidays, the post-holiday seasonality is more pronounced for secular holidays.

The results for the market of Kuwait in Panel D offer some evidence in support of the positive sentiment associated with religious holidays, as the coefficient β_1 estimates are shown to be positive and significant across the majority of models. The coefficient β_2 estimates are, on the other hand insignificant, with the exception of Model 6.

The results in Panels E and F, which pertain to the markets of Oman and Qatar are mixed. No distinctive pattern is observed after apportioning the holidays into their religious and secular components. On the contrary, the results for the Saudi market reported in Panel G are remarkable. Holiday seasonality is clearly associated with the religious festivities which invoke market closures. The coefficient β_1 estimates are highly significant at the 1 percent level across the board. On the other hand, no other meaningful patterns are detected.

The results of estimating Eq. (3.29)—from which the post-holiday dummy variables are omitted—are reported in Table 3.15. Panels A to G provide the estimation results for the seven GCC markets obtained using the six different models.

Table 3.15: Estimated regressions for Eq. (3.29) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
β_0	0.021	0.042	0.033	0.019	0.033	0.034
	(0.72)	(2.73)	(2.26)	(0.48)	(2.20)	(1.45)
β_1	0.152	0.034	-0.040	0.125	-0.125	-0.135
	(1.10)	(0.28)	(-0.34)	(0.84)	(-0.95)	(-1.21)
β_2	0.240	0.378	0.322	0.041	-0.018	-0.145
	(0.77)	(1.99)	(1.68)	(0.16)	(-0.10)	(-0.73)
β_3	-0.360	-0.373	0.081	-0.488	-0.145	-0.205
	(-0.74)	(-0.96)	(0.26)	(-1.08)	(-0.48)	(-0.68)
Panel B: Bahrain						
β_0	0.001	0.015	0.005	0.003	0.013	-0.088
	(0.03)	(1.43)	(0.49)	(0.07)	(1.35)	(-1.30)
β_1	0.113	0.108	0.115	0.097	0.079	0.074
	(1.61)	(1.43)	(1.25)	(1.37)	(0.90)	(0.94)
β_2	0.042	0.034	-0.010	0.094	0.035	0.060
	(0.45)	(0.32)	(-0.10)	(1.01)	(0.45)	(0.77)
β_3	0.527	0.120	0.194	0.496	0.743	0.655
	(1.49)	(0.55)	(1.71)	(1.53)	(1.95)	(1.74)
Panel C: Dubai						
β_0	0.001	0.048	0.034	-0.003	0.069	0.067
	(0.01)	(1.52)	(1.02)	(-0.05)	(2.82)	(1.83)
β_1	0.808	0.594	0.956	0.797	0.616	0.474
	(2.54)	(2.35)	(5.00)	(2.42)	(2.74)	(2.06)
β_2	0.045	0.663	0.585	0.003	0.293	0.272
	(0.07)	(1.52)	(1.07)	(0.00)	(0.69)	(0.62)
β_3	0.864	0.817	1.176	1.713	1.157	1.073
	(3.47)	(0.80)	(2.60)	(3.92)	(2.86)	(2.71)

Table 3.15 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel D: Kuwait						
β_0	0.046	0.108	0.109	0.045	0.100	0.096
	(1.95)	(7.58)	(7.14)	(1.17)	(8.93)	(4.27)
β_1	0.200	0.207	0.202	0.184	0.118	0.094
	(1.95)	(2.06)	(1.54)	(1.96)	(1.43)	(1.20)
β_2	-0.073	0.055	0.115	-0.070	-0.019	-0.055
	(-0.32)	(0.30)	(0.91)	(-0.35)	(-0.18)	(-0.50)
β_3	0.420	0.366	0.923	0.396	0.321	0.374
	(1.40)	(1.05)	(5.99)	(1.25)	(1.13)	(1.24)
Panel E: Oman						
β_0	0.048	0.075	0.061	0.047	0.059	0.065
	(1.88)	(5.94)	(4.74)	(1.46)	(5.52)	(3.70)
β_1	0.106	0.145	0.161	0.057	0.150	0.074
	(0.86)	(1.31)	(1.65)	(0.48)	(1.66)	(0.81)
β_2	0.162	0.108	0.115	0.300	-0.111	-0.154
	(1.12)	(0.60)	(1.06)	(1.70)	(-1.01)	(-1.33)
β_3	0.746	-0.027	0.105	0.485	0.104	0.028
	(1.50)	(-0.13)	(0.78)	(1.64)	(0.51)	(0.17)
Panel F: Qatar						
β_0	0.064	0.105	0.076	0.067	0.075	0.095
	(1.70)	(5.03)	(3.91)	(1.48)	(5.15)	(3.89)
β_1	0.375	0.539	0.518	0.301	-0.370	-0.326
	(1.26)	(2.25)	(3.47)	(0.91)	(-0.87)	(-1.29)
β_2	-0.301	-0.314	-0.293	-0.392	-0.272	-0.467
	(-1.21)	(-1.12)	(-1.40)	(-1.55)	(-1.30)	(-2.08)
β_3	0.462	0.421	1.056	0.127	0.695	-1.040
	(1.07)	(0.57)	(3.52)	(0.27)	(0.83)	(-1.26)

Table 3.15 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel G: Saudi Arabia						
β_0	0.026	0.146	0.120	0.025	0.120	0.126
	(0.74)	(7.60)	(6.56)	(0.58)	(6.38)	(4.82)
β_1	1.216	0.773	0.802	1.356	0.485	0.518
	(3.79)	(3.46)	(5.40)	(3.90)	(2.77)	(2.70)
β_2	-0.046	-0.149	0.019	-0.034	-0.004	-0.040
	(-0.22)	(-0.37)	(0.12)	(-0.17)	(-0.04)	(-0.38)
β_3	1.512	1.392	1.419	1.475	0.248	0.130
	(42.66)	(1.40)	(6.98)	(6.66)	(0.15)	(0.07)

The findings that emerge from the analysis pertaining to pre-holiday days are as expected. In general, there is no substantial difference in the magnitude and the statistical significance of coefficient β_1 estimates that measure the difference between pre-holiday returns and returns on other days (which include the post-holiday days).

We now turn to an alternative specification that combines the dummy variables that capture the simultaneous occurrence of religious and secular holidays with religious and secular holiday dummy variables, as shown in Eq. (3.30). This specification is suitable to test the hypotheses $H_0\colon \beta_1 + \beta_2 = \beta_3$ and $H_0\colon \beta_4 + \beta_5 = \beta_6$ when Eq. (3.28) is considered. When we conducted the post-estimation test for Model 1, we found that these hypotheses largely hold.[25]

Table 3.16 contains the estimation results for Eq. (3.30). Panels A to G of Table 3.16 provide the estimation results for the seven GCC markets obtained using the six different models. A close look at Panel A that reports the results for the Abu Dhabi market reveals that seasonal patterns are more evident on post-holiday days, in particular on secular occasions, in

[25] Results are available upon request.

accordance with the results reported in Table 3.14. Indeed, it is interesting to note that the coefficient β_4 estimates are statistically insignificant when Model 3 is used, whereas in Table 3.14, β_4 is shown to be significant. This is due to the fact that the hypothesis $H_0{:}\,\beta_4+\beta_5=\beta_6$ is rejected for the Abu Dhabi market.

Table 3.16: Estimated regressions for Eq. (3.30) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
β_0	0.012	0.036	0.029	0.006	0.024	0.023
	(0.44)	(2.31)	(2.00)	(0.14)	(1.56)	(0.97)
β_1	0.084	-0.010	-0.063	0.097	-0.128	-0.108
	(0.61)	(-0.08)	(-0.57)	(0.72)	(-1.02)	(-0.93)
β_2	0.118	0.274	0.222	0.247	0.051	0.072
	(0.44)	(1.59)	(1.61)	(1.21)	(0.42)	(0.68)
β_3	0.061	0.276	0.210	0.107	0.148	0.122
	(0.22)	(2.39)	(1.52)	(0.44)	(1.28)	(1.08)
β_4	1.024	0.432	0.472	1.100	0.570	0.577
	(2.84)	(2.51)	(0.66)	(3.44)	(2.96)	(3.15)
Panel B: Bahrain						
β_0	0.004	0.018	0.006	0.004	0.017	0.015
	(0.21)	(1.70)	(0.57)	(0.14)	(1.74)	(0.70)
β_1	0.148	0.111	0.179	0.114	0.136	0.115
	(2.06)	(1.54)	(2.44)	(1.51)	(1.58)	(1.42)
β_2	0.104	0.026	0.014	0.089	0.142	0.111
	(1.00)	(0.27)	(0.16)	(0.92)	(1.29)	(1.04)
β_3	-0.028	0.001	0.020	-0.033	-0.078	-0.064
	(-0.37)	(0.01)	(0.27)	(-0.42)	(-0.93)	(-0.78)
β_4	-0.260	-0.272	-0.253	-0.238	-0.289	-0.295
	(-2.61)	(-2.83)	(-2.29)	(-2.49)	(-2.69)	(-2.78)

Table 3.16 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: Dubai						
β_0	-0.013	0.033	0.015	-0.019	0.059	0.057
	(-0.28)	(1.03)	(0.47)	(-0.28)	(2.39)	(1.53)
β_1	0.821	0.584	0.863	0.853	0.658	0.545
	(2.71)	(2.38)	(4.68)	(2.69)	(2.94)	(2.40)
β_2	0.058	0.583	0.381	0.197	0.392	0.494
	(0.10)	(1.46)	(0.89)	(0.32)	(1.03)	(1.34)
β_3	0.200	0.790	0.551	0.232	0.376	0.344
	(0.49)	(3.23)	(2.27)	(0.59)	(1.38)	(1.31)
β_4	1.610	0.922	1.160	1.675	1.270	1.245
	(2.24)	(2.31)	(2.96)	(2.29)	(2.66)	(2.49)
Panel D: Kuwait						
β_0	0.046	0.103	0.107	0.046	0.095	0.091
	(1.99)	(7.17)	(7.02)	(1.21)	(8.41)	(4.06)
β_1	0.217	0.218	0.204	0.201	0.157	0.160
	(2.26)	(2.25)	(1.49)	(2.22)	(1.90)	(2.03)
β_2	-0.015	0.079	0.117	-0.043	0.053	0.058
	(-0.08)	(0.49)	(0.82)	(-0.23)	(0.48)	(0.47)
β_3	-0.011	0.211	0.278	0.003	0.147	0.165
	(-0.07)	(2.17)	(1.96)	(0.02)	(1.55)	(1.86)
β_4	-0.119	0.055	-0.014	-0.159	0.168	0.108
	(-0.46)	(0.34)	(-0.03)	(-0.65)	(1.12)	(0.68)

Table 3.16 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel E: Oman						
β_0	0.040	0.072	0.059	0.037	0.055	0.059
	(1.54)	(5.69)	(4.57)	(1.11)	(5.24)	(3.84)
β_1	0.171	0.101	0.141	0.174	0.172	0.154
	(1.32)	(0.99)	(1.49)	(1.48)	(1.96)	(1.79)
β_2	0.347	0.019	0.114	0.391	-0.068	-0.094
	(1.59)	(0.14)	(1.04)	(1.82)	(-0.66)	(-0.89)
β_3	0.331	0.184	0.170	0.426	0.152	0.185
	(1.86)	(1.79)	(1.12)	(2.93)	(1.36)	(1.87)
β_4	0.212	0.038	0.036	0.154	0.043	0.024
	(0.67)	(0.26)	(0.18)	(0.48)	(0.27)	(0.16)
Panel F: Qatar						
β_0	0.060	0.096	0.072	0.062	0.070	0.087
	(1.59)	(4.57)	(3.67)	(1.35)	(4.79)	(3.19)
β_1	0.411	0.570	0.523	0.323	-0.284	-0.177
	(1.50)	(2.49)	(3.34)	(1.24)	(-0.69)	(-0.63)
β_2	-0.253	-0.281	-0.261	-0.216	-0.275	-0.410
	(-1.09)	(-1.07)	(-1.10)	(-0.95)	(-1.31)	(-1.75)
β_3	0.024	0.871	0.780	0.009	0.413	0.354
	(0.04)	(3.81)	(2.44)	(0.01)	(1.55)	(1.45)
β_4	0.539	0.373	0.439	0.600	0.213	0.335
	(2.20)	(1.43)	(2.15)	(2.36)	(1.19)	(1.90)
Panel G: Saudi Arabia						
β_0	0.021	0.141	0.118	0.019	0.113	0.118
	(0.62)	(7.32)	(6.47)	(0.45)	(6.04)	(4.55)
β_1	1.235	0.815	0.861	1.420	0.594	0.675
	(4.00)	(3.72)	(5.51)	(4.47)	(3.61)	(3.86)
β_2	0.005	-0.036	0.021	-0.014	0.059	-0.020
	(0.03)	(-0.10)	(0.12)	(-0.06)	(0.28)	(-0.10)
β_3	0.724	1.020	0.943	0.815	0.642	0.713
	(1.18)	(4.66)	(1.02)	(1.47)	(2.22)	(2.58)
β_4	-0.324	0.031	-0.346	-0.306	0.078	-0.011
	(-0.42)	(0.08)	(-0.65)	(-0.43)	(0.18)	(-0.03)

The results pertaining to the Bahraini market are displayed in Panel B. The thrust of the results is mainly the same as for Table 3.14. Notwithstanding the consistency of results between Tables 3.14 and 3.16, we find that the pre-holiday seasonal pattern pertaining to religious occasions becomes more pronounced, while the post-holiday market movement down becomes marginally weaker.

The results for the Dubai market which are shown in Panel C are largely in line with the findings from Table 3.14. This confirms the validity of the econometric specification employed. The results pertaining to the Kuwaiti market in Panel D are also clear. The seasonal pattern during religious pre-holiday days is more evident, in terms of both magnitude and statistical significance.

The results for the market of Oman in Panel E indicate that post-holiday seasonality is more evident during religious occasions. The results in Panel F pertaining to the market of Qatar reveal a pattern similar to that found in the market for Dubai. That is, there is a higher religious pre-holiday returns in conjunction with higher secular post-holiday returns. Finally, the results for the Saudi Arabian market in Panel G are striking, revealing strong evidence in support of higher returns during religious pre-holiday days, as the coefficient β_2 estimates are highly significant at the 1 percent level across the board.

Table 3.17 contains the estimation results for Eq. (3.31) from which the post-holiday dummies are omitted. Panels A to G provide the estimation results for the seven GCC markets obtained by using the six different models.

Table 3.17: Estimated regressions for Eq. (3.31) using six estimation techniques

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Abu Dhabi						
β_0	0.021	0.043	0.033	0.019	0.033	0.034
	(0.75)	(2.78)	(2.30)	(0.50)	(2.20)	(1.44)
β_1	0.099	-0.007	-0.067	0.082	-0.125	-0.130
	(0.74)	(-0.06)	(-0.60)	(0.57)	(-1.00)	(-1.20)
β_2	0.106	0.266	0.218	-0.074	-0.019	-0.131
	(0.40)	(1.55)	(1.59)	(-0.33)	(-0.11)	(-0.75)
Panel B: Bahrain						
β_0	0.000	0.015	0.004	0.002	0.012	0.010
	(-0.01)	(1.44)	(0.44)	(0.05)	(1.24)	(0.56)
β_1	0.146	0.106	0.116	0.124	0.142	0.116
	(2.03)	(1.47)	(1.44)	(1.74)	(1.59)	(1.47)
β_2	0.108	0.030	0.039	0.148	0.158	0.171
	(1.04)	(0.31)	(0.43)	(1.53)	(1.32)	(1.44)
Panel C: Dubai						
β_0	0.001	0.048	0.035	-0.004	0.068	0.066
	(0.01)	(1.54)	(1.06)	(-0.06)	(2.82)	(1.83)
β_1	0.808	0.567	0.844	0.842	0.624	0.485
	(2.66)	(2.31)	(4.57)	(2.65)	(2.83)	(2.16)
β_2	0.047	0.569	0.361	0.133	0.334	0.347
	(0.08)	(1.42)	(0.85)	(0.22)	(0.85)	(0.87)
Panel D: Kuwait						
β_0	0.045	0.108	0.109	0.045	0.100	0.096
	(1.93)	(7.57)	(7.13)	(1.16)	(8.92)	(4.27)
β_1	0.218	0.214	0.202	0.201	0.135	0.118
	(2.30)	(2.20)	(1.48)	(2.26)	(1.69)	(1.51)
β_2	-0.014	0.076	0.115	-0.011	0.042	0.042
	(-0.08)	(0.47)	(0.80)	(-0.06)	(0.37)	(0.33)

Table 3.17 ***(Continued)***

Market	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel E: Oman						
β_0	0.047	0.076	0.061	0.047	0.058	0.065
	(1.85)	(5.99)	(4.80)	(1.45)	(5.52)	(3.66)
β_1	0.173	0.104	0.138	0.075	0.160	0.092
	(1.33)	(1.01)	(1.47)	(0.69)	(1.87)	(1.11)
β_2	0.339	0.016	0.112	0.347	-0.082	-0.117
	(1.57)	(0.11)	(1.03)	(1.85)	(-0.83)	(-1.22)
Panel F: Qatar						
β_0	0.064	0.105	0.076	0.067	0.076	0.103
	(1.70)	(5.03)	(3.91)	(1.48)	(5.18)	(4.38)
β_1	0.408	0.561	0.518	0.319	-0.397	-0.340
	(1.48)	(2.44)	(3.30)	(1.03)	(-1.00)	(-1.36)
β_2	-0.256	-0.289	-0.266	-0.367	-0.302	-0.496
	(-1.11)	(-1.10)	(-1.12)	(-1.53)	(-1.38)	(-2.02)
Panel G: Saudi Arabia						
β_0	0.026	0.146	0.119	0.025	0.120	0.126
	(0.74)	(7.59)	(6.50)	(0.58)	(6.38)	(4.82)
β_1	1.230	0.811	0.861	1.362	0.473	0.498
	(3.94)	(3.71)	(5.50)	(4.07)	(2.53)	(2.49)
β_2	0.001	-0.040	0.020	-0.013	-0.047	-0.116
	(0.01)	(-0.11)	(0.11)	(-0.07)	(-0.14)	(-0.33)

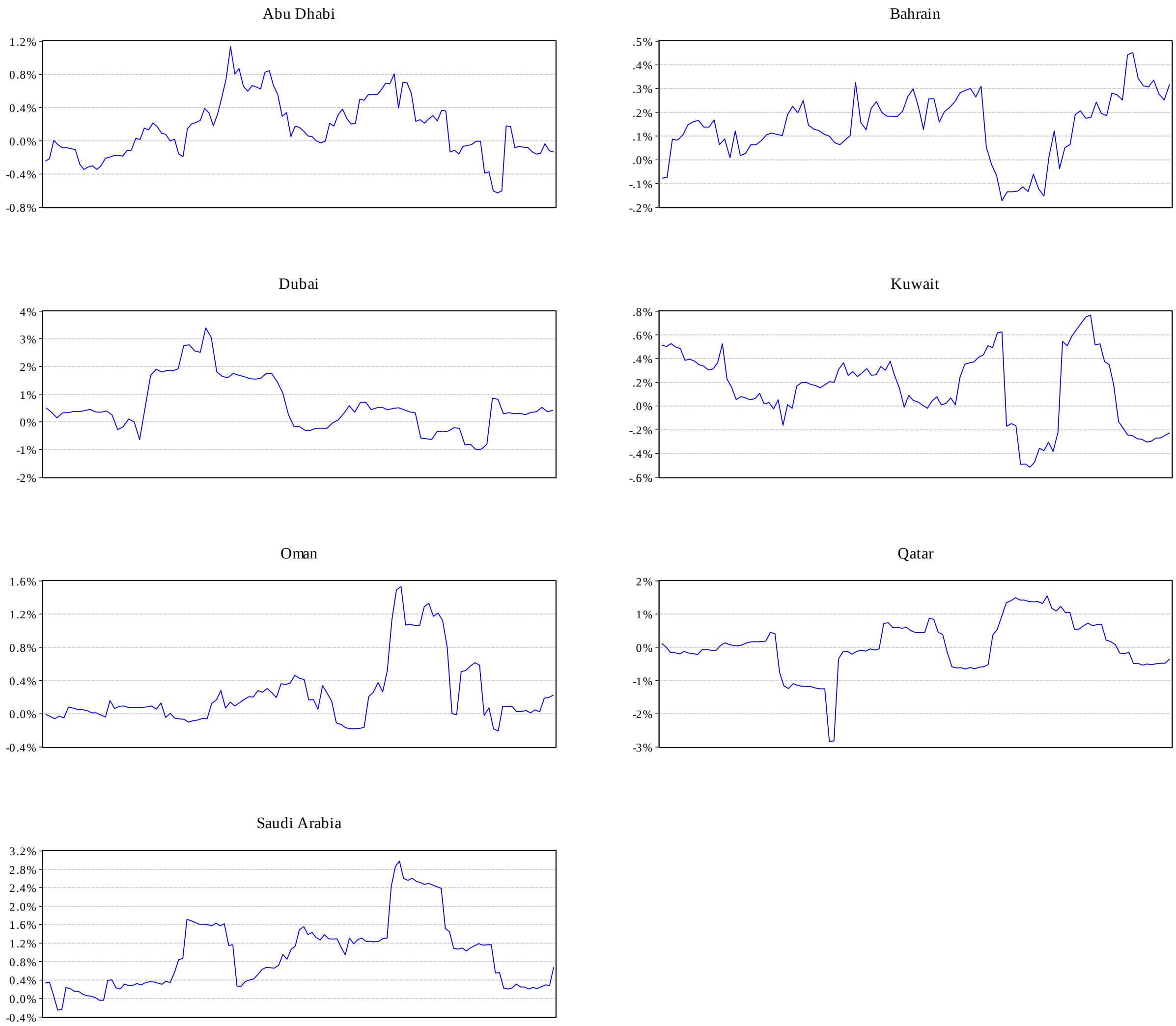
The conclusions that emerge from Table 3.17 with regard to pre-holiday seasonality are qualitatively similar to the findings from Table 3.15. Of course, post-holiday seasonality is ignored here, as the dummy variables that capture this effect are deleted.

Overall, our findings highlight several points. First, seasonal patterns for holidays are evident in the majority of the GCC markets. The seasonal patterns are not confined to pre-holiday days, as suggested by numerous studies; this highlights the importance of post-holiday days in the GCC markets, particularly the markets of Abu Dhabi and Bahrain. Second, the refined analysis conducted by categorising holidays into religious and secular unveils important aspects of the holiday effect in GCC markets. In the majority of markets, the impact of holidays is shown to be heterogeneous, which is at odds with the findings of the salient studies in the literature including, *inter alia,* Lakonishok and Smidt (1988) and Ariel (1990). Finally, the use of alternative model specifications and estimation techniques alleviates the consequences of the violation of the statistical assumptions of OLS. For instance, Models 2 and 3 (robust estimation techniques) detect a post-holiday effect in the Qatari market, whereas OLS techniques fail to do this due the presence of outliers.

We now investigate the behaviour of the holiday effect over the sample period, by providing a visual representation of its evolution in the holiday effect in Figures 3.4 and 3.5 for the seven GCC markets. A careful look at Figure 3.4 gives the impression that the first slope coefficient β_1 OLS estimate of Eq. (3.26) is time-varying.[26] The coefficient β_1 seems to be declining in the market of Kuwait, in spite of spikes around the GFC. On the other hand, no clear pattern is apparent in the remaining markets.

[26] As discussed earlier, the first slope coefficient β_1 represents the difference between mean daily return over pre-holiday days and the mean daily return during other days (that is, non-pre-holiday days and post-holiday days).

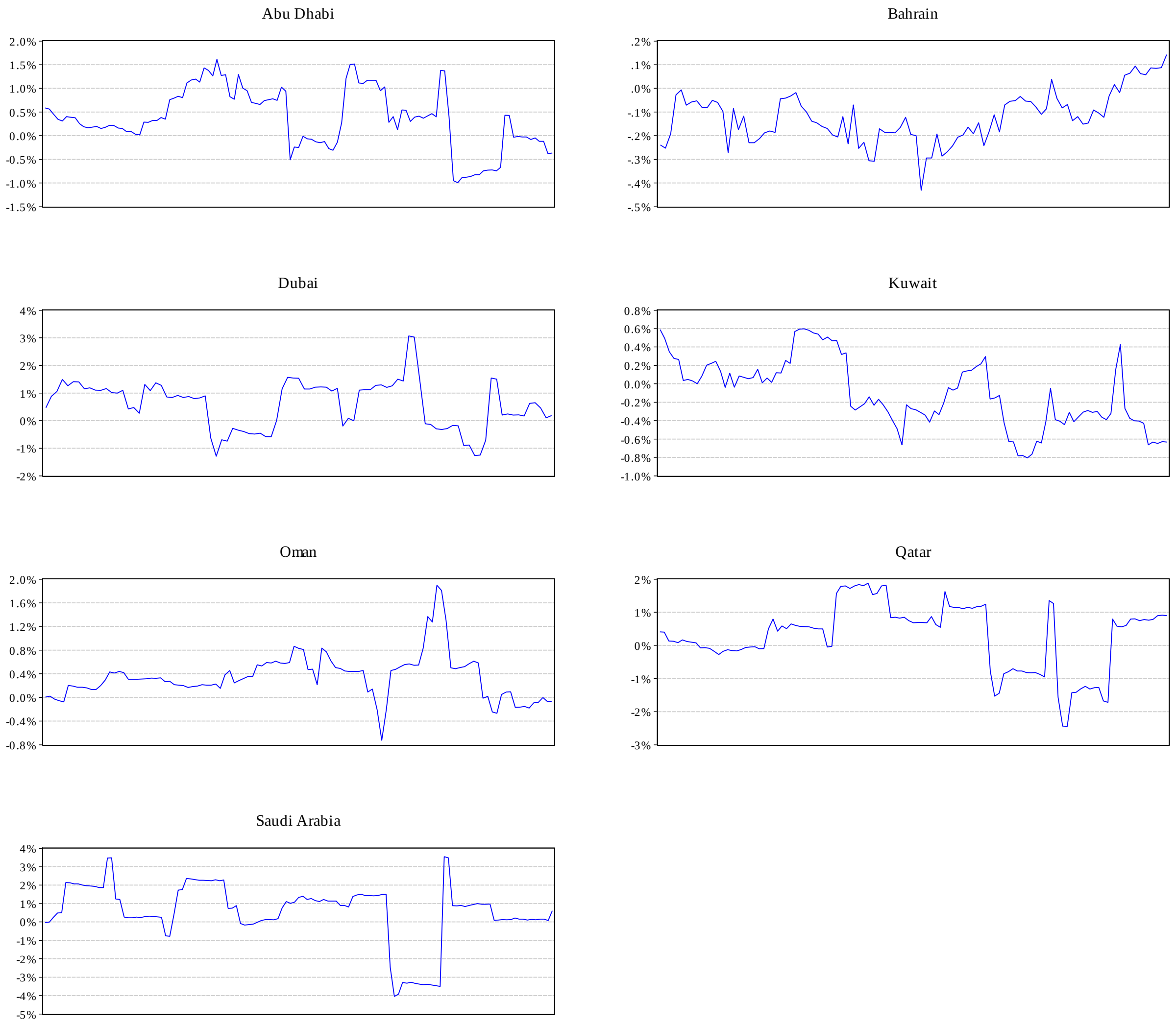
Figure 3.4: Evolution of the holiday effect—the pre-holiday coefficient (β_1)



Moreover, the OLS rolling regression coefficient estimates of the second slope coefficient β_2 of Eq. (3.26), depicted in Figure 3.5, show a similar yet less pronounced decline for the market of Kuwait.[27] Other markets, however, do not exhibit such a pattern—instead they exhibit random fluctuations.

[27] The second slope coefficient β_2 represents the difference between mean daily return over post-holiday days and the mean daily return during other days (that is, non-pre-holiday days and post-holiday days).

Figure 3.5: Evolution of the holiday effect—the post-holiday coefficient (β_2)



This casual observation is not sufficient to establish that the holiday effect is either time-varying or declining over the sample period. Therefore, to investigate this we estimate the regression in Eq. (3.32). The estimation results of Eq. (3.32) are shown in Table 3.18. We employ four estimation techniques and model specifications as robustness checks. The first column of Table 3.18 contains the OLS coefficient estimates of Eq. (3.32) and their corresponding *t*-statistics (in parentheses) calculated using the HAC standard errors of Newey and West (1987). The following three columns contain, respectively, the same set of results generated using the ARMA(20,1) with HAC standard errors of Newey and West (1987); and GARCH(1,1) and ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992). In this analysis, we are particularly interested in the sign and statistical significance of the coefficients β_3 and β_4 that capture the direction of the evolution of the holiday effect that manifested in the pre and post-holiday days, respectively, over the sample period.

Panel A of Table 3.18 reports the results for the market index of Abu Dhabi. The direction of evolution for the pre-holiday days captured by coefficient β_3 is shown to be positive and robust across techniques and model specifications; in terms of sign, it lacks statistical significance. While the post-holiday days coefficient β_4 is found to be persistently negative, the estimates are, like their pre-holiday counterparts, indistinguishable from zero. Thus, there is insufficient evidence to support the hypothesis that the holiday effect is declining over the sample period in the market of Abu Dhabi.

The results for market index of Bahrain are reported in Panel B. Both coefficients β_3 and β_4 are found to be persistently negative, but both are statistically insignificant. Indeed, the results of the market indices of Dubai shown in Panel C are mixed and lack statistical significance for both β_3 and β_4. On the other hand, the results in Panel D pertaining to the market index of Kuwait are noteworthy. Both coefficients β_3 and β_4 are found to be persistently negative and statistically significant at the 1 percent level for coefficient β_3, and at least at the 5 percent level for the coefficient β_4. Indeed, the results in Panels E to G that pertain to the market indices of Oman, Qatar, and Saudi Arabia, respectively, are largely inconclusive; the coefficient estimates are not robust to alternative techniques and model specifications.

Table 3.18: Estimated regressions for Eq. (3.32) using four estimation techniques

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Panel A: Abu Dhabi								
β_0	0.010	(0.36)	0.004	(0.09)	0.024	(1.52)	0.023	(0.98)
β_1	0.115	(0.70)	0.097	(0.59)	-0.146	(-1.08)	-0.137	(-1.01)
β_2	0.764	(3.36)	0.705	(3.39)	0.441	(3.01)	0.405	(2.77)
β_3	2.53E-05	(0.18)	8.68E-05	(0.74)	6.64E-05	(0.58)	7.35E-05	(0.70)
β_4	-2.70E-04	(-1.12)	-1.86E-04	(-0.92)	-1.14E-04	(-0.88)	-8.54E-05	(-0.71)
Panel B: Bahrain								
β_0	0.005	(0.29)	0.005	(0.20)	0.019	(1.89)	0.017	(0.91)
β_1	0.163	(1.71)	0.039	(0.38)	0.043	(0.38)	0.005	(0.05)
β_2	-0.099	(-0.79)	-0.208	(-1.67)	-0.199	(-1.54)	-0.240	(-1.97)
β_3	-3.81E-05	(-0.55)	4.59E-05	(0.66)	6.83E-05	(0.90)	8.07E-05	(1.11)
β_4	-3.41E-05	(-0.39)	6.11E-05	(0.71)	1.18E-05	(0.12)	5.58E-05	(0.57)
Panel C: Dubai								
β_0	-0.014	(-0.31)	-0.019	(-0.30)	0.058	(2.35)	0.058	(1.60)
β_1	1.226	(2.41)	0.960	(1.77)	0.692	(2.64)	0.484	(1.83)
β_2	0.998	(2.02)	0.938	(1.85)	0.616	(1.43)	0.595	(1.44)
β_3	-5.68E-04	(-1.55)	-2.83E-04	(-0.77)	-4.53E-05	(-0.15)	7.28E-05	(0.23)
β_4	-3.14E-04	(-0.61)	-2.10E-04	(-0.41)	3.63E-06	(0.01)	4.98E-05	(0.15)
Panel D: Kuwait								
β_0	0.048	(2.05)	0.047	(1.28)	0.094	(8.39)	0.093	(4.33)
β_1	0.580	(4.64)	0.499	(3.28)	0.517	(4.76)	0.528	(4.02)
β_2	0.583	(2.87)	0.382	(1.87)	0.659	(4.98)	0.508	(3.44)
β_3	-3.51E-04	(-3.15)	-2.98E-04	(-2.65)	-3.17E-04	(-4.24)	-3.16E-04	(-3.67)
β_4	-5.34E-04	(-2.95)	-3.64E-04	(-2.14)	-3.89E-04	(-3.58)	-2.87E-04	(-2.52)
Panel E: Oman								
β_0	0.042	(1.64)	0.037	(1.11)	0.055	(5.19)	0.058	(3.80)
β_1	0.067	(0.66)	0.039	(0.38)	0.046	(0.56)	-0.006	(-0.08)
β_2	0.347	(2.68)	0.248	(2.02)	0.186	(1.66)	0.159	(1.40)
β_3	1.30E-04	(1.05)	1.96E-04	(1.63)	4.14E-05	(0.50)	6.62E-05	(0.85)
β_4	-4.64E-05	(-0.30)	1.12E-04	(0.72)	-4.47E-05	(-0.45)	-5.51E-07	(-0.01)

Table 3.18 ***(Continued)***

Market	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Panel F: Qatar								
β_0	0.060	(1.60)	0.062	(1.31)	0.071	(4.86)	0.087	(3.20)
β_1	-0.015	(-0.05)	0.028	(0.09)	-0.054	(-0.27)	-0.031	(-0.17)
β_2	0.544	(1.69)	0.635	(1.96)	0.381	(1.70)	0.289	(1.36)
β_3	9.54E-05	(0.48)	4.87E-05	(0.25)	-2.30E-04	(-0.86)	-2.45E-04	(-1.29)
β_4	-2.21E-04	(-0.58)	-2.67E-04	(-0.68)	-6.33E-05	(-0.35)	3.09E-05	(0.17)
Panel G: Saudi Arabia								
β_0	0.023	(0.65)	0.020	(0.47)	0.115	(6.10)	0.120	(4.55)
β_1	0.745	(2.42)	0.753	(2.15)	0.448	(2.02)	0.474	(1.98)
β_2	1.303	(2.00)	1.320	(2.19)	0.489	(1.19)	0.572	(1.43)
β_3	1.33E-04	(0.65)	2.18E-04	(0.90)	-7.64E-06	(-0.06)	6.92E-06	(0.05)
β_4	-5.96E-04	(-1.18)	-5.46E-04	(-1.19)	-5.37E-05	(-0.22)	-8.13E-05	(-0.34)

Taking the results together, we can safely conclude that the holiday effect is diminishing over time in the market of Kuwait. However, there is insufficient evidence to establish that the holiday effect, in any form, evolves in a certain direction over the sample period for any of the remaining GCC markets—Abu Dhabi, Bahrain, Dubai, Oman, Qatar, and Saudi Arabia.

Next, we turn to the alternative specification to test for the evolution of the holiday effect, or in other words we attempt to answer the question of whether the holiday effect is time-varying over the sample period. This specification does not impose any structure as to the direction of evolution of the holiday effect, which is at odds with the previously discussed specification (represented by Eq. (3.32)). It forces the holiday effect to be either strengthening or weakening over the sample period in a linear fashion. Therefore, we estimate the regression Eq. (3.33) using the same estimation techniques and model specifications as are defined in the preceding section.[28] After the estimation of Eq. (3.33), we test the hypothesis that the holiday effect is time-varying, which amounts to a post-estimation Wald test. The test statistic has a $\chi^2(18)$ distribution for the markets of Abu Dhabi, Kuwait, Oman, Qatar, and Saudi Arabia (since there are 9 restrictions on the values of the estimated coefficients). In the cases of Bahrain and Dubai, the Wald test statistic has $\chi^2(16)$ and $\chi^2(14)$ distributions, respectively.[29]

We show the results of the post-estimation Wald test in Table 3.19. The first column contains the χ^2 test statistics with their corresponding *P-values* generated from OLS with the HAC standard errors of Newey and West (1987) estimation technique. The same set of results are respectively displayed in the following three columns for the ARMA(20,1) with the HAC standard errors of Newey and West (1987), GARCH(1,1), and ARMA(20,1) GARCH(1,1) with the robust standard errors of Bollerslev and Wooldridge (1992).

Table 3.19: Wald test results for Eq. (3.33)

	OLS		ARMA(20,1)		GARCH(1,1)		ARMA-GARCH	
Market	χ^2	*P-value*	χ^2	*P-value*	χ^2	*P-value*	χ^2	*P-value*
Abu Dhabi	20.90	0.28	21.07	0.28	20.42	0.31	18.14	0.45
Bahrain	8.64	0.93	7.92	0.95	14.53	0.56	12.57	0.70
Dubai	15.78	0.33	16.06	0.31	28.61	0.01	30.81	0.01
Kuwait	48.97	0.00	37.96	0.00	59.84	0.00	51.56	0.00
Oman	15.84	0.60	19.15	0.38	19.57	0.36	25.77	0.11
Qatar	46.72	0.00	58.10	0.00	109.20	0.00	82.24	0.00
Saudi Arabia	67.24	0.00	72.14	0.00	40.46	0.00	33.77	0.01

[28] To conserve space, the estimation results are not reported.

[29] Because the markets of Abu Dhabi, Kuwait, Oman, Qatar, and Saudi Arabia have 10 years of data, we exclude one year to avoid falling into the dummy variable trap; thus, we end up with 18 degrees of freedom. The same applies to the markets of Bahrain and Dubai.

Examining Table 3.19, it appears that there is strong support for the hypothesis that the holiday effect is time-varying in the markets of Kuwait, Qatar, and Saudi Arabia. The null hypothesis that the holiday effect is the same over all years is rejected at the 1 percent level across all estimation techniques and model specifications for these markets. On the other hand, the results pertaining to the three remaining markets (Abu Dhabi, Bahrain, and Oman) indicate that there is no evidence of a time-varying holiday effect; there is only mild evidence in support of the time-varying holiday hypothesis found for the Dubai market.

3.5 Monthly Seasonality

The January Effect

We investigate the presence of monthly seasonal patterns by using the model described by Rozeff and Kinney (1976) and employed in numerous studies (for example Agrawal and Tandon, 1994; Ariss *et al.*, 2011; Bley and Saad, 2010). This model is specified as:

$$r_t = \sum_{i=1}^{12} \beta_i D_{i,t} + \varepsilon_t \tag{3.34}$$

where r_t is the return on month t, $D_{i,t}$, are dummy variables that take the value 1 if the return in month t corresponds to month i and 0 otherwise ($D_{1,t}$ =January, $D_{2,t}$ =February … etc.), β_i is the mean return in month i and ε_t is error term assumed to be iid. To deal with the autocorrelation problem, some economists (for example Al-Saad and Moosa, 2005; Moosa, 2007, 2010) use an ARDL model, which is specified as:

$$r_t = \sum_{i=1}^{k} \alpha_i \, r_{t-i} \sum_{i=1}^{12} \beta_i D_{i,t} + \varepsilon_t \tag{3.35}$$

A significant β_i, in essence, indicates a significant seasonal factor in month i, while k is the order of the autoregressive process, which is determined using a goodness-of-fit measure.

The Halloween Effect

To test for the presence of a Halloween effect, or "a sell in May and go away" effect, we employ the basic regression model proposed by Bouman and Jacobsen (2002), which is used in subsequent studies (Maberly and Pierce, 2003; Witte, 2010). The model is specified as:

$$r_t = \alpha_0 + \alpha_1 Halloween_t + \varepsilon_t \tag{3.36}$$

where r_t is the return on month *t*, $Halloween_t$ is a dummy variable that takes the value 1 if the return in month t falls within the November to April period, and 0 otherwise; α_0 is the intercept representing the monthly mean return over the Mayto October period; the slope α_1 captures the difference between monthly mean returns over the May to October and the November to April periods; $\alpha_0 + \alpha_1$ represents the monthly mean return over the November to April period. The null hypothesis is $H_0 : \alpha_1 = 0$.

In a similar manner to that for the daily seasonal effects, we estimate Eq. (3.34) and (3.36) using five estimation techniques in addition to OLS (Model 1) to accommodate the characteristics of the data.[30] The estimation techniques that we employ to test for monthly seasonality are:

- Model 2: OLS with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)
- Model 3: AR(1) with the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)
- Model 4: ARMA(1,1) with the heteroscedasticity and autocorrelation consistent (HAC) standard errors of Newey and West (1987)
- Model 5: L-estimator

[30] As shown in Table 1.2, there exist potentially influential observations (outliers) that may undermine the accuracy of the OLS estimates. In addition, high and statistically significant first order autocorrelation is also documented.

- Model 6: M-estimator

Empirical Results

Tables 3.20-3.25 contains the regression results of Eq. (3.34) and Eq. (3.36) using the six estimation techniques for the seven GCC markets. The Table 23-28 are formatted in a similar fashion that is Panel A of Tables 3.20-3.25 display the estimation results for Eq. (3.34) and Panel B shows the results for Eq. (3.36). Each table displays the estimation results for one of the estimation techniques and each column contains estimated regression coefficients and their *t*-statistics.

Table 3.20: Estimated regression for Eq. (3.34) and (3.36) using the OLS estimation technique

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A:Months of the Year							
β_1	-0.734	1.430	-2.626	0.778	2.887	-2.997	-0.684
	(-0.30)	(1.04)	(-0.64)	(0.40)	(1.53)	(-1.03)	(-0.25)
β_2	2.785	0.018	0.526	0.557	0.168	0.346	2.328
	(1.14)	(0.01)	(0.13)	(0.29)	(0.09)	(0.12)	(0.84)
β_3	3.452	-0.313	2.006	2.119	1.611	5.521	2.296
	(1.41)	(-0.23)	(0.49)	(1.10)	(0.85)	(1.90)	(0.83)
β_4	1.386	1.122	5.114	6.067	4.634	5.022	3.363
	(0.57)	(0.82)	(1.24)	(3.15)	(2.45)	(1.73)	(1.21)
β_5	0.462	-0.268	1.339	1.885	2.338	0.790	-0.673
	(0.19)	(-0.20)	(0.33)	(0.98)	(1.24)	(0.27)	(-0.24)
β_6	0.064	-0.064	1.252	1.061	1.815	1.948	1.802
	(0.03)	(-0.05)	(0.30)	(0.55)	(0.96)	(0.67)	(0.65)
β_7	0.097	-0.279	-2.022	-0.478	0.249	2.888	-0.465
	(0.04)	(-0.20)	(-0.49)	(-0.25)	(0.13)	(0.99)	(-0.17)
β_8	1.117	1.114	3.914	1.493	-0.003	3.200	2.115
	(0.46)	(0.81)	(0.95)	(0.77)	(0.00)	(1.10)	(0.76)

Table 3.20 ***(Continued)***

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
β_9	1.102	-0.239	3.861	0.777	0.564	-1.179	0.504
	(0.45)	(-0.17)	(0.94)	(0.40)	(0.30)	(-0.41)	(0.18)
β_{10}	-0.306	0.573	-1.167	-1.094	-1.500	-1.440	-3.009
	(-0.13)	(0.42)	(-0.28)	(-0.57)	(-0.79)	(-0.50)	(-1.09)
β_{11}	-3.442	-2.213	-7.389	-1.390	-0.073	-2.531	-0.648
	(-1.41)	(-1.61)	(-1.80)	(-0.72)	(-0.04)	(-0.87)	(-0.23)
β_{12}	0.368	0.170	-1.023	0.466	0.514	4.894	2.783
	(0.15)	(0.12)	(-0.25)	(0.24)	(0.27)	(1.68)	(1.00)
N	120	108	96	120	120	120	120
Panel B:Halloween effect							
α_0	0.423	0.139	1.196	0.608	0.577	1.035	0.046
	(0.43)	(0.25)	(0.72)	(0.77)	(0.76)	(0.87)	(0.04)
α_1	0.213	-0.104	-1.761	0.825	1.047	0.675	1.527
	(0.15)	(-0.13)	(-0.75)	(0.74)	(0.97)	(0.40)	(0.98)
N	120	108	96	120	120	120	120

Table 3.21: Estimated regression for Eq. (3.34) and (3.36) using the OLS estimation techniques with Newey-West heteroscedasticity and autocorrelation Consistent Standard Errors

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A:Months of the Year							
β_1	-0.734	1.430	-2.626	0.778	2.887	-2.997	-0.684
	(-0.39)	(0.85)	(-1.10)	(0.39)	(1.48)	(-0.90)	(-0.28)
β_2	2.785	0.018	0.526	0.557	0.168	0.346	2.328
	(2.55)	(0.01)	(0.22)	(0.48)	(0.09)	(0.08)	(1.00)
β_3	3.452	-0.313	2.006	2.119	1.611	5.521	2.296
	(0.90)	(-0.35)	(0.50)	(0.78)	(0.85)	(2.20)	(0.76)
β_4	1.386	1.122	5.114	6.067	4.634	5.022	3.363
	(0.43)	(1.26)	(1.03)	(3.16)	(3.12)	(1.67)	(0.86)
β_5	0.462	-0.268	1.339	1.885	2.338	0.790	-0.673
	(0.20)	(-0.15)	(0.35)	(1.09)	(1.24)	(0.22)	(-0.27)

Table 3.21 ***(Continued)***

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
β_6	0.064	-0.064	1.252	1.061	1.815	1.948	1.802
	(0.08)	(-0.07)	(0.26)	(0.93)	(1.39)	(0.91)	(0.71)
β_7	0.097	-0.279	-2.022	-0.478	0.249	2.888	-0.465
	(0.04)	(-0.25)	(-0.83)	(-0.41)	(0.24)	(2.33)	(-0.17)
β_8	1.117	1.114	3.914	1.493	-0.003	3.200	2.115
	(0.60)	(0.81)	(0.97)	(1.23)	(0.00)	(1.30)	(1.12)
β_9	1.102	-0.239	3.861	0.777	0.564	-1.179	0.504
	(0.56)	(-0.15)	(1.07)	(0.37)	(0.34)	(-0.57)	(0.22)
β_{10}	-0.306	0.573	-1.167	-1.094	-1.500	-1.440	-3.009
	(-0.11)	(0.35)	(-0.21)	(-0.34)	(-0.41)	(-0.40)	(-0.78)
β_{11}	-3.442	-2.213	-7.389	-1.390	-0.073	-2.531	-0.648
	(-1.16)	(-1.41)	(-1.29)	(-0.76)	(-0.07)	(-0.87)	(-0.21)
β_{12}	0.368	0.170	-1.023	0.466	0.514	4.894	2.783
	(0.16)	(0.13)	(-0.26)	(0.26)	(0.29)	(2.35)	(1.47)
N	120	108	96	120	120	120	120
Panel B:Halloween effect							
α_0	0.423	0.139	1.196	0.608	0.577	1.035	0.046
	(0.43)	(0.18)	(0.65)	(0.61)	(0.49)	(0.83)	(0.04)
α_1	0.213	-0.104	-1.761	0.825	1.047	0.675	1.527
	(0.12)	(-0.11)	(-0.72)	(0.68)	(0.88)	(0.39)	(1.14)
N	120	108	96	120	120	120	120

Table 3.22: Estimated regression for Eq. (3.34) and (3.36) using an AR(1) specification

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A:Months of the Year							
β_1	-1.858	1.410	-4.312	0.542	2.741	-3.122	-0.825
	(-1.13)	(0.81)	(-2.24)	(0.28)	(1.33)	(-0.83)	(-0.30)
β_2	2.407	0.007	-0.056	0.433	0.119	0.326	2.297
	(2.06)	(0.01)	(-0.02)	(0.35)	(0.06)	(0.07)	(0.95)
β_3	3.325	-0.318	1.805	2.054	1.595	5.518	2.289
	(0.88)	(-0.31)	(0.45)	(0.75)	(0.82)	(2.19)	(0.74)

Table 3.22 ***(Continued)***

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
β_4	1.344	1.119	5.045	6.033	4.629	5.021	3.361
	(0.43)	(1.28)	(1.04)	(3.00)	(3.01)	(1.62)	(0.87)
β_5	0.447	-0.269	1.315	1.868	2.336	0.790	-0.673
	(0.18)	(-0.15)	(0.33)	(1.05)	(1.26)	(0.22)	(-0.28)
β_6	0.059	-0.064	1.243	1.052	1.814	1.948	1.802
	(0.06)	(-0.06)	(0.27)	(0.79)	(1.43)	(0.88)	(0.69)
β_7	0.095	-0.279	-2.025	-0.482	0.249	2.888	-0.465
	(0.04)	(-0.25)	(-0.67)	(-0.40)	(0.23)	(2.29)	(-0.17)
β_8	1.117	1.114	3.913	1.490	-0.003	3.200	2.115
	(0.56)	(0.78)	(0.94)	(1.22)	(0.00)	(1.30)	(1.11)
β_9	1.101	-0.239	3.861	0.776	0.564	-1.179	0.504
	(0.56)	(-0.15)	(1.07)	(0.38)	(0.36)	(-0.57)	(0.22)
β_{10}	-0.306	0.573	-1.168	-1.094	-1.500	-1.440	-3.009
	(-0.11)	(0.36)	(-0.22)	(-0.35)	(-0.42)	(-0.41)	(-0.79)
β_{11}	-3.442	-2.213	-7.390	-1.391	-0.073	-2.531	-0.648
	(-1.17)	(-1.48)	(-1.35)	(-0.72)	(-0.06)	(-0.88)	(-0.22)
β_{12}	0.368	0.170	-1.023	0.466	0.514	4.894	2.783
	(0.16)	(0.14)	(-0.28)	(0.27)	(0.30)	(2.25)	(1.47)
N	119	107	95	119	119	119	119
Panel B:Halloween effect							
α_0	0.606	0.280	1.052	0.255	0.428	0.986	-0.105
	(0.48)	(0.35)	(0.49)	(0.21)	(0.43)	(0.73)	(-0.08)
α_1	-0.382	-0.437	-1.788	1.467	1.272	0.855	1.857
	(-0.24)	(-0.49)	(-0.65)	(1.12)	(0.99)	(0.46)	(1.04)
N	119	107	95	119	119	119	119

Table 3.23: Estimated regression for Eq. (3.34) and Eq. (3.36) using an ARMA(1,1) specification

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A:Months of the Year							
β_1	-1.687	1.532	-3.909	0.536	2.783	-3.183	-0.796
	(-1.01)	(0.95)	(-1.31)	(0.27)	(1.42)	(-0.87)	(-0.29)
β_2	2.315	0.113	-0.235	0.440	0.146	0.461	2.285
	(1.81)	(0.09)	(-0.07)	(0.35)	(0.07)	(0.10)	(0.94)
β_3	3.205	-0.243	1.391	2.062	1.594	5.452	2.262
	(0.84)	(-0.20)	(0.30)	(0.75)	(0.78)	(2.00)	(0.68)
β_4	1.256	1.173	4.617	6.039	4.622	5.064	3.336
	(0.40)	(1.26)	(0.99)	(2.99)	(2.68)	(1.59)	(0.80)
β_5	0.393	-0.231	0.937	1.872	2.329	0.765	-0.695
	(0.15)	(-0.12)	(0.21)	(1.06)	(1.18)	(0.22)	(-0.26)
β_6	0.028	-0.037	0.926	1.055	1.808	1.963	1.785
	(0.03)	(-0.03)	(0.23)	(0.80)	(1.36)	(0.91)	(0.66)
β_7	0.078	-0.259	-2.285	-0.481	0.244	2.879	-0.478
	(0.03)	(-0.21)	(-0.57)	(-0.39)	(0.19)	(2.16)	(-0.18)
β_8	1.107	1.128	3.701	1.491	-0.007	3.206	2.104
	(0.55)	(0.73)	(0.90)	(1.21)	(0.00)	(1.32)	(1.08)
β_9	1.096	-0.229	3.689	0.776	0.561	-1.182	0.496
	(0.56)	(-0.14)	(0.98)	(0.38)	(0.32)	(-0.55)	(0.21)
β_{10}	-0.309	0.581	-1.307	-1.094	-1.502	-1.438	-3.016
	(-0.11)	(0.37)	(-0.23)	(-0.35)	(-0.42)	(-0.40)	(-0.79)
β_{11}	-3.443	-2.208	-7.502	-1.390	-0.075	-2.532	-0.653
	(-1.17)	(-1.43)	(-1.38)	(-0.71)	(-0.05)	(-0.86)	(-0.23)
β_{12}	0.367	0.174	-1.114	0.466	0.513	4.895	2.778
	(0.16)	(0.15)	(-0.29)	(0.27)	(0.32)	(2.28)	(1.38)
N	119	107	95	119	119	119	119
Panel B:Halloween effect							
α_0	0.552	0.247	0.843	0.240	0.472	1.109	-0.068
	(0.41)	(0.26)	(0.30)	(0.21)	(0.39)	(0.85)	(-0.04)
α_1	-0.339	-0.336	-1.907	1.505	1.158	0.576	1.711
	(-0.21)	(-0.40)	(-0.77)	(1.14)	(0.97)	(0.32)	(1.04)
N	119	107	95	119	119	119	119

Table 3.24: Estimated regression for Eq. (3.34) and (3.36) using the L-estimator

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A:Months of the Year							
β_1	0.301	1.362	-1.585	2.684	3.320	-0.999	0.313
	(0.11)	(0.66)	(-0.41)	(1.28)	(2.08)	(-0.30)	(0.12)
β_2	3.640	-0.365	1.268	1.550	0.055	-0.370	2.915
	(2.12)	(-0.21)	(0.32)	(0.87)	(0.04)	(-0.07)	(0.92)
β_3	0.189	0.081	1.478	4.560	0.405	5.761	5.493
	(0.08)	(0.06)	(0.21)	(1.76)	(0.21)	(1.80)	(1.79)
β_4	3.334	1.835	2.481	4.674	4.316	6.928	5.680
	(1.07)	(1.21)	(0.59)	(2.14)	(2.03)	(2.14)	(1.73)
β_5	-0.563	1.136	0.773	2.177	4.591	-0.975	0.378
	(-0.22)	(0.57)	(0.13)	(0.58)	(2.66)	(-0.20)	(0.12)
β_6	-0.431	-0.523	-2.795	2.899	1.816	0.568	-0.438
	(-0.31)	(-0.36)	(-0.70)	(1.46)	(0.95)	(0.21)	(-0.15)
β_7	1.257	-0.170	-0.707	1.212	1.374	3.274	3.070
	(0.45)	(-0.11)	(-0.23)	(0.63)	(0.86)	(1.49)	(1.03)
β_8	2.212	0.379	4.013	2.545	-0.601	5.093	2.101
	(1.24)	(0.23)	(0.87)	(1.30)	(-0.36)	(1.68)	(0.71)
β_9	2.428	1.644	8.401	2.675	2.275	-2.760	1.156
	(0.81)	(1.12)	(1.67)	(1.31)	(1.15)	(-0.79)	(0.48)
β_{10}	-1.052	1.215	0.296	1.472	-0.203	1.305	-0.604
	(-0.57)	(0.65)	(0.08)	(0.83)	(-0.12)	(0.52)	(-0.18)
β_{11}	-2.573	-1.426	-3.864	-1.841	0.036	-0.029	1.383
	(-1.01)	(-0.91)	(-0.84)	(-0.54)	(0.02)	(-0.01)	(0.35)
β_{12}	-0.111	1.141	-1.870	1.027	2.076	2.295	2.432
	(-0.06)	(0.74)	(-0.41)	(0.55)	(1.47)	(0.85)	(1.03)
N	120	108	96	120	120	120	120
Panel B:Halloween effect							
α_0	0.450	0.379	-0.423	1.274	1.374	1.305	0.378
	(0.50)	(0.59)	(-0.25)	(1.47)	(1.60)	(1.14)	(0.32)
α_1	-0.148	0.049	0.260	0.775	0.257	0.844	2.281
	(-0.11)	(0.06)	(0.10)	(0.62)	(0.23)	(0.46)	(1.32)
N	120	108	96	120	120	120	120

Table 3.25: Estimated regression for Eq. (3.34) and (3.36) using the M-estimator

Seasonal effect	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A:Months of the Year							
β_1	-0.618	2.193	-2.749	1.875	4.229	-1.094	-0.098
	(-0.32)	(1.68)	(-0.75)	(1.11)	(2.93)	(-0.40)	(-0.04)
β_2	2.790	-0.280	0.567	0.638	-0.045	-0.928	2.317
	(1.43)	(-0.21)	(0.16)	(0.38)	(-0.03)	(-0.34)	(0.87)
β_3	-0.174	-0.172	1.571	3.384	0.245	5.862	4.152
	(-0.09)	(-0.13)	(0.43)	(2.01)	(0.17)	(2.17)	(1.57)
β_4	1.548	1.068	1.679	5.592	4.812	6.636	6.514
	(0.80)	(0.82)	(0.46)	(3.32)	(3.33)	(2.46)	(2.46)
β_5	-0.650	-0.317	0.948	2.084	3.347	-0.331	0.177
	(-0.33)	(-0.24)	(0.26)	(1.24)	(2.32)	(-0.12)	(0.07)
β_6	0.009	-0.131	-3.291	1.080	1.681	1.602	0.759
	(0.00)	(-0.10)	(-0.90)	(0.64)	(1.16)	(0.59)	(0.29)
β_7	1.979	-0.459	-1.266	-0.444	0.280	2.879	1.019
	(1.02)	(-0.35)	(-0.35)	(-0.26)	(0.19)	(1.07)	(0.38)
β_8	1.626	0.632	2.588	1.500	0.495	3.080	1.936
	(0.84)	(0.48)	(0.71)	(0.89)	(0.34)	(1.14)	(0.73)
β_9	1.697	0.762	4.740	1.659	1.298	-1.118	1.385
	(0.87)	(0.58)	(1.30)	(0.99)	(0.90)	(-0.41)	(0.52)
β_{10}	-0.826	1.703	2.121	1.637	0.859	1.149	0.637
	(-0.42)	(1.30)	(0.58)	(0.97)	(0.59)	(0.43)	(0.24)
β_{11}	-3.879	-1.040	-3.975	-1.526	-0.090	-1.576	0.563
	(-1.99)	(-0.80)	(-1.09)	(-0.91)	(-0.06)	(-0.58)	(0.21)
β_{12}	0.767	0.506	-1.748	1.333	1.840	4.519	2.303
	(0.39)	(0.39)	(-0.48)	(0.79)	(1.27)	(1.67)	(0.87)
N	120	108	96	120	120	120	120
Panel B:Halloween effect							
α_0	0.649	0.338	0.787	1.227	1.249	1.312	1.028
	(0.85)	(0.66)	(0.55)	(1.81)	(2.02)	(1.23)	(1.01)
α_1	-0.249	0.002	-1.652	0.592	0.516	1.574	1.590
	(-0.23)	(0.00)	(-0.81)	(0.62)	(0.59)	(1.04)	(1.11)
N	108	98	86	108	108	108	108

A close look at Tables 3.20-3.25 reveals that returns over the month of April are significantly positive in the markets of Kuwait and Oman across all models while this pattern is only detected in the markets of Qatar and Saudi Arabia when robust regression models are used (the M-estimator and the L-estimator). There are some traces of the January effect in the markets of Bahrain and Oman, however, such pattern is only picked up by robust regression models. The results indicate that there is no evidence for the presence of the Halloween effect in GCC markets. Indeed, there is slight variation across estimation techniques but the results are largely consistent. These findings shed light on the fragility of monthly seasonal pattern in the GCC markets.

Indeed, it could be argued that the results of our analysis ultimately serve as a test of whether or not the returns over a certain month are different from zero and therefor, insufficient to establish the presence of monthly seasonality even if a joint hypothesis of whether or not monthly returns are equal across different calendar months is rejected. This argument, in spirit, is similar to the critique levelled by Alt *et al.* (2011), in the context of the weekend, effect against an equivalent model specification—his critique has been thoroughly discussed earlier (in section 3.3).

Several economists such as Gultekin and Gultekin (1983), Brown *et al.*, 1983 and Fountas and Segredakis (2002) elect to employ a slightly altered specification mainly to test the TLS hypothesis, which was extensively discussed in Section 2.5. This specification is given by:

$$r_t = c_0 + \sum_{i=2}^{12} \beta_i D_{i,t} + \varepsilon_t \tag{3.37}$$

where c_0 is the intercept representing the mean return over the first month of the tax year (January), β_i captures the difference in mean returns between month i and the first month of the tax year. [31]

[31] Although we are aware that some countries have a different starting month for the tax year, such as Australia and the UK, for the sake of generality we discuss the specification represented by Eq. (3.37).

The null hypotheses are $H_{0,i}: \beta_i = 0 \quad 2 \leq i \leq 12$. If each of the partial slopes is found to be negative and significantly different from zero, the presence of the January effect is supported.

While the criticism levelled against the use of the specification that we employ in our analysis (represented by Eq. (3.34)) may be valid in general, this does not necessarily apply to our case. As discussed in Section 3.5, numerous empirical studies have confirmed the presence of the January effect for several developed and emerging markets. This is not the case for the GCC markets, however. The empirical findings of the GCC-based studies are rather mixed as to the presence and form of seasonal monthly patterns, let alone the explanations for their presence. In addition, as the GCC markets are largely tax-free, the TLS hypothesis does not readily apply to these markets. Therefore, the use of the specification given by Eq. (3.37) is not warranted, because the rationale behind the selection of a reference month is obscure and unjustifiable in the case of the GCC markets.

3.6 Conclusion

Motivated by the gaps in the literature, which were identified in Chapter 2, this third chapter undertakes an empirical analysis to investigate the presence and the nature of seasonal patterns in the GCC markets using several estimation techniques and model specifications.

The main conclusion to be drawn from the results is that although we document pronounced seasonal patterns in all GCC markets, these patterns are not the same for every market. Furthermore, the bulk of these patterns appear to be fairly sensitive to estimation techniques and model specifications. Moreover, when the behaviour of the seasonal effects is investigated carefully over the sample period, we find that the majority of seasonal effects are time-varying. These findings shed light on the influences of institutional settings, financial developments, and crises on the nature of seasonality in stock returns in the GCC markets.

CHAPTER 4

SEASONALITY-BASED TRADING RULES

4.1 Introduction

Since the work of Bachelier (1900), financial economists have been fascinated by the behaviour of stock prices. This interest stems from the fact that stock prices carry important implications for the determination of stock-return dynamics and the potential profitability of trading strategies (Lo and MacKinlay, 1988; Poterba and Summers, 1988). In his review of the efficient market hypothesis (EMH), Fama (1970, p. 383) argues that "a market in which prices always 'fully reflect' available information is called 'efficient'". Thus, any attempt to predict future prices using technical or even fundamental analysis is fruitless and will not fare any better than the passive buy-and-hold strategy. Jensen (1978) further cements the EMH definition by emphasising the importance of economic profit (risk-adjusted and net of transaction costs) as a yardstick for testing whether the EMH holds.

Following the influential review of Fama (1970), the EMH enjoyed intellectual dominance among financial economists. However, by the turn of the twenty-first century, the mushrooming literature on the predictability of stock returns, as well as the failure of the EMH to predict the collapse of bubbles in asset prices started to cast serious doubts on the validity of the EMH (Brown, 2011; Malkiel, 2003). The bulk of the literature on stock-return predictability is devoted to providing empirical evidence on the departure that stock prices exhibit from the predictions of EMH. This strand of the literature encompasses empirical studies that document persistent time series patterns in stock returns.

A substantial number of empirical studies utilise statistical measures to gauge how closely stock returns follow a random-walk (RW) process. The most widely used statistical techniques to test the RW hypothesis include unit root tests, (for example Alimov *et al*., 2004; Chaudhuri and Wu, 2003; Cooray, 2004), autocorrelation-based measures (for example Claessens *et al.*, 1995; Errunza and Losq, 1985; Mookerjee and Yu, 1999; Solnik, 1973), and a battery of variance ratio tests (for example Chow and Denning, 1993; Lo and MacKinlay, 1988; Wright, 2000). Another substantial part of this literature is devoted to documenting seasonal regularities such as the January effect (for example Keim, 1983; Reinganum, 1983; Rozeff and Kinney, 1976), the holiday effect (for example Ariel, 1990; Cadsby and Ratner, 1992), the weekend effect (for example French, 1980; Jaffe and Westerfield, 1985; Lakonishok and Levi, 1982; Lakonishok and Maberly, 1990), the turn-of-the-month effect, (for example Ariel, 1987; Lakonishok and Smidt, 1988; Ogden, 1990), and the Halloween effect (for example Bouman and Jacobsen, 2002; Jacobsen and Visaltanachoti, 2009).

The common factor of these studies of the EMH is that they focus on statistical significance, rather than economic significance. In other words, statistical significance is taken as the sole evidence against the EMH, without taking into consideration transaction costs or appropriate risk adjustments. Due to these shortcomings, the focus of the literature has shifted to test the EMH using various trading rules which are concerned not only with predictability, but also with economic profitability. This literature focuses on mechanical trading rules including, among others, technical trading rules, (for example Bessembinder and Chan, 1995; Brock *et al.*, 1992; Hudson *et al.*, 1996; Ito, 1999), momentum trading strategies (for example Chan *et al*., 2000; Hameed and Kusnadi, 2002; Jegadeesh and Titman, 1993, 1999; Naughton *et al*., 2008), and contrarian trading strategies (for example Chou *et al*., 2007).

Statistical tests of the EMH often involve estimating autocorrelation and autoregression and (or) seasonal-dummy-based regression models. Under this approach, the EMH is tentatively rejected if the autocorrelation and (or) autoregression and (or) seasonal dummy coefficients are statistically significant. Groenewold *et al.* (2008) suggest that using a trading rule on the basis of a return-forecast regression is more intuitive than employing the above cited trading rules. This is because the former constitute a natural extension to predictability tests, while the latter is considered to be an alternative test to the EMH. Furthermore, this approach enables the incorporation of seasonal effects into a trading strategy.

The abundance of studies that investigate the EMH has always raised concern about data-snooping bias. This is in the sense that if a sufficient number of researchers collectively investigate a data set, predictability (and even profitability) is bound to be detected. In spite of the prevalence of studies that examine the EMH not only in developed but also in emerging markets, empirical work using GCC data is relatively scarce. The majority of GCC-based studies focus on the predictability of stock returns, while the question of whether predictability implies profitability (taking transaction costs into consideration) remains unanswered. This state of affairs motivated us to contribute to the literature by overcoming potential data-snooping bias by using the relatively fresh data set from the sparsely studied GCC markets. Furthermore, we do not sift through the data looking for interesting patterns—instead we adopt a limited number of trading rules that have been employed in prior studies. Moreover, the GCC markets are evolving rapidly and they possess interesting features that set them apart from other developed and emerging markets. Therefore, analysing these markets promises valuable insights into the EMH.

4.2 Literature Review

The majority of the GCC studies focus on the predictability of stock returns using traditional statistical techniques such as unit root tests, and autocorrelation and autoregression analysis, as well as the runs and variance ratio tests. In addition, several studies investigate seasonal patterns in stock returns.[32] Salient studies that examine the predictability of stock returns in the GCC markets in terms of how closely these markets follow a random walk include, among others, Butler and Malaikah (1992), Abraham *et al.* (2002), Al-Loughani (1995), Al-Khazali *et al.* (2007), Bley (2011), Al-Ajmi and Kim (2012), Abdmoulah (2010), Al Janabi *et al.* (2010), Niemczak and Smith (2013), Squalli (2006), Moustafa (2004), Smith (2007) and Asiri (2008).

In an early study, Butler and Malaikah (1992) investigate individual stock returns in the markets of Kuwait and Saudi Arabia over the period 1985 to 1989. In their analysis, the researchers utilise autocorrelation and runs tests. The empirical results indicate that individual stock returns in the market of Saudi Arabia exhibit a high degree of autocorrelation, as all the stocks show large negative and statistically significant autocorrelation at the first lag. On the other hand, autocorrelation in stock returns is relatively less-pronounced in the market of Kuwait. In a subsequent study, Al-Loughani (1995) examines the Kuwaiti market index using more robust statistical techniques. The results indicate that the Kuwaiti market index does not follow a random walk.

Using the variance ratio and nonparametric runs tests, Abraham *et al.* (2002) investigate broad market indices for the markets of Kuwait and Saudi Arabia and Bahrain over the period 1992 to 1998. They use weekly data and correct returns for thin trading. Their results reveal that when the raw returns series are used, the RW hypothesis and weak-form efficiency are

[32] A comprehensive updated literature review on stock-return seasonality is provided in Chapter 2.

rejected for all markets. Nonetheless, when the corrected indices are used, successive price changes are shown to be independent in all three markets. Furthermore, the markets of Bahrain and Saudi Arabia are shown to follow a random walk, while the RW hypothesis is rejected for the market of Kuwait.

Examining individual stocks in the UAE market, Moustafa (2004) finds evidence in favour of the weak form of market efficiency using the nonparametric runs test over the period 2001 to 2003. However, these findings are disputed by Squalli (2006), who studies the broad market index in addition to sectoral indices in the markets of Abu Dhabi and Dubai over the period 2000 to 2005. Using the variance ratio test in addition to the nonparametric runs test, he shows—with very few exceptions—that the RW hypothesis is strongly rejected for broad market and sectoral indices across the two UAE markets (Abu Dhabi and Dubai).

In a recent paper, Asiri (2008) examines daily data for all listed stocks in the Bahraini market over the period 1990 to 2000 using unit root tests and ARIMA models. The results that emerge from the empirical analysis support weak-form efficiency in the market of Bahrain. Nonetheless, the findings of Asiri (2008) have been refuted by subsequent studies where state-of-the-art statistical techniques are used to test for the weak-form efficiency (Al-Ajmi and Kim, 2012; Bley, 2011).

More recent studies employ a broader sample including all seven GCC markets, often as a subset of the greater MENA region stock markets. Smith (2007) investigates two GCC markets (Kuwait and Oman) in addition to three other MENA markets (Israel, Jordan, and Lebanon). The sample consists of weekly data for broad market indices over the period 1996 to 2003. By using multiple variance ratio tests, results are obtained indicating that the RW hypothesis is rejected for the Omani market and the domestic companies' index for Kuwait, while the remaining MENA markets are shown to be weak form efficient.

Another MENA-based study is conducted by Al-Khazali *et al.* (2007) who examine the GCC markets of Bahrain, Kuwait, Oman, and Saudi Arabia in addition to other MENA markets including Jordan, Morocco, Egypt, and Tunisia. They use weekly data for the period 1994 to 2003 for all markets except Egypt, where the sample is from 1996 to 2003. By utilising the rank and sign tests of Wright (2000), in addition to the runs test, they find that none of the eight markets follows a random walk process. When the returns series are corrected for thin trading, all eight markets are shown to be consistent with the RW hypothesis.

In a comprehensive paper, Bley (2011) examines the seven GCC broad market indices (Abu Dhabi, Bahrain, Dubai, Kuwait, Oman, Qatar, and Saudi Arabia) using daily, weekly, and monthly data over the period from 2000 to 2009. In order to find out if the stock returns in the GCC are predictable, he employs a wide range of statistical techniques: unit root tests, autocorrelation analysis, and several variance ratio tests. Once these tests reject the RW hypothesis, ARIMA modelling is applied to capture the patterns in the second moment by selecting from several GARCH-type models. The results for daily data provide evidence against the RW hypothesis, in spite of correcting the data for thin trading; less-consistent results are documented when weekly and monthly data are used. The results obtained from the ARIMA-GARCH modelling procedure indicate that the GARCH-type model offers the best fit for all the GCC markets, except for the market of Saudi Arabia where a simple AR(2) is found to be the best fit to the data. These results are corroborated by examining the forecasting accuracy of the selected model using several forecasting-error statistics. In subsequent research, Al-Ajmi and Kim (2012) study the same markets using variance ratio tests. The results that emerge from their analysis are in accordance with those reported by Bley (2011), in that when daily data are used the RW hypothesis is strongly rejected across the board, even after correcting for thin trading. The results derived using weekly data are more supportive of the RW hypothesis when the data are corrected for thin trading.

In a newly emerging strand of the literature, the evolving nature of market efficiency is highlighted. Recently developed statistical techniques are employed to capture changes in market efficiency over time. Studies that investigate the efficiency of GCC and MENA markets over time include Abdmoulah (2010) and Niemczak and Smith (2013). Abdmoulah (2010) investigates the GCC markets of Saudi Arabia, Kuwait, Dubai, Qatar, Abu Dhabi, Bahrain, and Oman, in addition to four MENA markets (Tunisia, Egypt, Jordan, and Morocco). He employs a GARCH-M(1,1) approach with state-space time-varying parameters. The results indicate that the majority of markets are shown to be sensitive to past shocks and are weak form inefficient. In general, the markets under examination do not exhibit improvements in efficiency towards the end of the sample period; they appear to be adversely affected by the GFC. On the other hand, the results obtained by using US data clearly show steady improvement in efficiency over the sample period.

Niemczak and Smith (2013) investigate four GCC markets (Kuwait, Oman, Saudi Arabia, and Qatar) in addition to seven MENA markets and use the US S&P 500 index. Their sample consists of daily data for broad market indices over the period 1999 to 2010. They employ several variance ratio tests and use a fixed-length rolling window of 500 days to detect changes in market efficiency over time. The results reveal that the markets undergo consecutive periods of efficiencies and inefficiencies that are associated with a number of local and global crises. Based on these results, they argue that the time-varying efficiency behaviour is in line with the adaptive market hypothesis (Lo, 2004, 2005, 2012).[33]

The general conclusion that emerges from these studies is that the GCC stock returns do not follow a random walk. These findings are taken as evidence against the EMH in its weak form. Most of the studies suggest that using trading rules to exploit the predictability in stock returns could be worthwhile. To the best of our knowledge, the question of whether the documented predictability in stock returns can be exploited profitably by using trading rules is yet to be answered.

We turn to examine studies based on trading rules. The major part of the literature on the profitability of trading rules focuses on widely used, technical trading strategies such as moving averages, trading-range break (TRB), and filter trading rules. The big picture that emerges from these studies is identified by Park and Irwin (2007). In their comprehensive review of the technical trading literature, they indicate that early studies (such as Fama and Blume,1966); Jensen and Benington, 1970) found evidence against the profitability of trading rules, as they showed that filter trading rules failed to outperform the passive buy-and-hold strategies in the US stock market. On the other hand, recent studies arrive at the opposite conclusion (for example Bessembinder and Chan, 1995; Brock *et al.*, 1992). Several studies argue that these findings are consistent with the EMH, as the profits generated from technical rules are shown to be compromised when they account for transaction costs (Bessembinder and Chan, 1998; Hudson *et al.*, 1996). Others go as far as to assert that the profits produced by technical trading are merely a manifestation of data-snooping bias (Hsu *et al.*, 2010; Hsu and Kuan, 2005; Romano and Wolf, 2005; Sullivan *et al.*, 1999). More recently, several

[33] The adaptive market hypothesis is discussed in Chapter 5.

papers have highlighted the temporal instability of the performance of technical trading rules (Neely and Weller, 2011; Neely and Weller, 2013; Neely *et al.*, 2009; Taylor, 2014).

While the literature on technical trading rules is vast, only a few studies examine the profitability of other types of trading rules. These studies include, among others, Groenewold *et al.* (2008), Chong and Lam (2010), and Chong *et al.* (2012). Groenewold *et al.* (2008) investigate daily, weekly, and monthly data from the Shanghai A share index over the period 1992 to 2001. They evaluate market efficiency by means of trading rules designed on the basis of forecasts derived from linear regressions. Several autoregressive specifications are used, augmented by seasonal dummies (the days of week and the Chinese New Year). They find that the in-sample performance of the trading rules is remarkably better than the buy-and-hold strategy. However, when a more practical out-of-sample recursive approach is used, the performance of trading rules deteriorates, albeit that they remain profitable. Furthermore, when the impact of transaction costs is measured, daily trading gains are shown to be completely eliminated, whereas weekly and monthly rules remain widely profitable.

Chong and Lam (2010) study the US market over the period that from 1951 to 2005. To avert data-snooping bias, they utilise four US broad market indices (DJIA, NASDAQ, NYSE, and S&P 500) with varying sample periods. They conduct a horse race between the profitability of trading rules formulated on the basis of three models: self-exciting threshold autoregressive (SETAR), first order linear autoregressive (AR(1)), and the widely used variable length moving average (VMA) method. The results that emerge from their analysis reveal that the performance of the models varies across markets. While the SETAR-model-based trading rules perform slightly better than the AR(1) rule for the DJIA and the S&P 500, the AR(1) rules fare slightly better for the NASDAQ. Moreover, the SETAR and AR(1) models consistently outperform the VMA method.

Chong *et al.* (2012) extend the analysis to the Chinese market and adopt the methodology used by Chong and Lam (2010). Their sample consists of daily data from the Shanghai Composite (SHC) index and the Shenzhen Composite (SZC) index over the period 1991 to 2010. The results that emerge from this study indicate that the SETAR-model rules outperform the buy-and-hold strategy, and fare better than the linear counterpart in general. Furthermore, when they split the sample period into several subsamples to investigate the impact of structural changes witnessed by the Chinese markets, the efficiency of the Chinese market is shown to improve markedly. In addition, they show that the profitability of trading rules is compromised when transaction costs are taken into consideration.

4.3 Methodology

Time Series Regression Models

In the spirit of Groenewold *et al.* (2008), Chong and Lam (2010), and Chong *et al.* (2012), the return forecast regression, under this approach, is typically expressed as autoregressive (AR) specification as:

$$r_t = \beta_0 + \sum_{i=1}^{k} \rho_i r_{t-i} + \varepsilon_t \tag{4.1}$$

where r_t is the continuously compounded return on day t, k is the order of the autoregressive process, and ε_t is error term assumed to be iid. The choice of k is essentially an empirical issue. Numerous studies select k using a goodness-of-fit measure such as the Bayes information criterion (Timmermann, 2008). Other studies, however, select k following prior studies (for example Groenewold *et al.*, 2008). In fact, the AR specifications can be easily augmented with seasonal dummies in order to investigate their incremental impact on forecasting accuracy as well as profitability. Thus the model is rewritten as:

$$r_t = \beta_0 + \sum_{i=1}^{k} \rho_i r_{t-i} + \sum_{i}^{q} \beta_i D_{i,t}^{Seasonality} + \varepsilon_t \tag{4.2}$$

where $D_{i,t}^{Seasonality}$ are dummy variables that take the value 1 on the trading days corresponding to the seasonal effect under investigation and 0 otherwise. The seasonal dummies incorporated into the model are empirically well-established. For example Groenewold *et al.* (2008) included the day-of-the-week and the Chinese New Year dummies in their models.

In the present study, we set k in Eq. (4.1) to be 1, 5, and 20 such that we are left with AR(1), AR(5), and AR(20) models. Each of these AR specifications is augmented with the weekend, holiday, and TOM dummies, one at a time. We therefore end up with 12 (4×3) models as:

M1: AR(1)	M5: AR(5)	M9: AR(20)
M2: AR(1)Weekend	M6: AR(5)Weekend	M10: AR(20)Weekend
M3: AR(1)TOM	M7: AR(5)TOM	M11: AR(20)TOM
M4: AR(1)Holiday	M8: AR(5)Holiday	M12: AR(20)Holiday

We employ a recursive-window estimation approach in which the forecast equations are estimated using an in-sample period of 250 trading days. Then, a sequence of one-step-ahead forecasts are computed, rolling the sample forward by one observation after each forecast until the end of the entire sample is reached.

Formulation Trading Rules

The trading rules on the basis of the forecasts from the predictive regression equations are formulated as:

$$I_t^b = \begin{cases} 1 \; if \; \hat{r}_{t+1} > 0 \\ 0 \; otherwse \end{cases} \tag{4.3}$$

$$I_t^s = \begin{cases} 1 \; if \; \hat{r}_{t+1} < 0 \\ 0 \; otherwse \end{cases} \tag{4.4}$$

where I_t^b and I_t^s are, respectively, the buy and the sell signals. In order to evaluate the performance of the regression-based trading rules, the return generated by these rules is calculated. To achieve that, signals generated by these trading rules are utilised in the computation of conditional unrealised daily buy and sell returns at time t (r_{t+1}^b and r_{t+1}^s). These are, respectively, written as:

$$r_{t+1}^b = [ln(p_{t+1}) - ln(p_t)] \times I_t^b \tag{4.5}$$

$$r_{t+1}^s = [ln(p_{t+1}) - ln(p_t)] \times I_t^s \tag{4.6}$$

When $I_t = I_{t-1}$, the initial position (either long or short) is maintained and no trade needs to be executed; this means that no transaction costs are incurred. If $I_t \neq I_{t-1}$, the position is unwound which gives rise to two transactions: the first is to close the existing position, and the second is to take a position in the opposite direction.

Performance Evaluation: Traditional Measures

Then, the means and variances of the conditional buy and sell as well as the unconditional passive buy-and-hold returns are computed for each trading rule. When calculating the conditional and unconditional means and variances, the sample starts at time $t = 250 + 1$, which is the first day of the out-of-sample period. The unconditional and conditional mean returns and variances are defined, respectively, as:

$$\mu = E(r) = \frac{1}{N} \sum_{t=250}^{N} r_{t+1} \tag{4.7}$$

$$\mu_b = E\left(r_t \middle| I_t^b = 1\right) = \frac{1}{N_b} \sum_{t=250}^{N_b} r_{t+1}^b \tag{4.8}$$

$$\mu_s = E(r_t | I_t^s = 1) = \frac{1}{N_s} \sum_{t=250}^{N_s} r_{t+1}^s \quad (4.9)$$

$$\sigma^2 = E[(r_t - \mu)^2] = \frac{1}{N-1} \sum_{t=250}^{N} (r_{t+1} - \mu)^2 \quad (4.10)$$

$$\sigma_b^2 = E[(r_t - \mu_b)^2 | \, I_t^b = 1] = \frac{1}{N_b - 1} \sum_{t=250}^{N_b} (r_{t+1}^b - \mu_b)^2 \quad (4.11)$$

$$\sigma_s^2 = E[(r_t - \mu_s)^2 | \, I_t^s = 1] = \frac{1}{N_s - 1} \sum_{t=250}^{N_s} (r_{t+1}^s - \mu_s)^2 \quad (4.12)$$

where μ is the unconditional mean return, μ_b and μ_s are, respectively, the mean return conditional on buy and sell signals, σ^2 the unconditional variances, σ_b^2 and σ_s^2 are, respectively, the variance conditional on the buy and the sell signals, N is total number of all trading days associated with each trading rule, and N_b and N_s are, respectively, the total number of buy and sell days.

We attempt to find out whether or not the returns conditional on the regression-based trading-rule signals are different from the unconditional return of the buy-and-hold passive strategy, and whether or not the conditional mean buy returns are different from the conditional mean sell returns. These hypotheses are specified as:

$$H_0: \mu_b - \mu = 0, \mu_s - \mu = 0, \mu_b - \mu_s = 0 \quad (4.13)$$

$$H_A: \mu_b - \mu \neq 0, \mu_s - \mu \neq 0, \mu_b - \mu_s \neq 0 \quad (4.14)$$

Following Brock *et al.* (1992), we assess the statistical significance of the mean buy and sell returns generated by each rule over the mean of the buy-and-hold strategy and the buy returns over the sell returns. In order to account for the violation of the assumption of equal variances, the Welch (1951) version of the test statistic is utilised as:

$$t = \frac{\mu_b - \mu}{\sqrt{\frac{\sigma_b^2}{N_b} + \frac{\sigma^2}{N}}} \tag{4.15}$$

$$t = \frac{\mu_s - \mu}{\sqrt{\frac{\sigma_s^2}{N_s} + \frac{\sigma^2}{N}}} \tag{4.16}$$

$$t = \frac{\mu_b - \mu_s}{\sqrt{\frac{\sigma_b^2}{N_b} + \frac{\sigma_s^2}{N_s}}} \tag{4.17}$$

Performance Evaluation: Alternative Measures

Mitra (2011) postulates that a straightforward way to gauge the performance of a trading rule is to compare the actual return with that predicted by the model. The methods used for this purpose are known as statistical criteria (forecast-accuracy measure). Basically, the performance of the forecasting model is measured based on the divergence between the forecasts generated by the forecast model and the actual data, and is formally referred to as the forecasting error. Therefore, if the realised market movement is in the same magnitude and direction as what the model predicted, the model has no forecasting error, and vice versa. The forecast error is measured as:

$$e_{t+1} = \hat{r}_{t+1} - r_{t+1} \tag{4.18}$$

where e_{t+1} is the forecast error at time $t+1$, r_{t+1} and $\hat{r}_{t+1}$ are, respectively, the actual realised and forecast returns. The statistical criteria are categorised into stand-alone and relative measures. The stand-alone measures can be calculated without any additional reference forecast or a benchmark, such that each forecast measure is associated with a certain loss function. According to Hyndman and Koehler (2006), the most widely used measures of forecasting accuracy are the mean squared error (MSE) and the root mean squared error (RMSE). They suggest that the popularity of these measures stems from their theoretical relevance in statistical modelling. Carbone and Armstrong (1982) suggest that the RMSE is the most widely employed measure of forecasting accuracy. Hyndman and Koehler (2006) argue that RMSE is often preferred to the MSE because it is on the same scale as the data. The MSE is given by:

$$MSE = \frac{\sum_{t=T_1}^{T} {e_t}^2}{T - (T_1 - 1)} \tag{4.19}$$

where T is the entire sample size encompassing in-sample and out-of-sample periods, and T_1 is the first out-of-sample forecast observation. The RMSE is simply calculated by taking the square root of the MSE.

$$RMSE = \sqrt{MSE} \tag{4.20}$$

Another stand-alone accuracy measure is the mean absolute error (MAE), which is computed as:

$$MAE = \frac{\sum_{t=T_1}^{T} |e_t|}{T - (T_1 - 1)} \tag{4.21}$$

The MSE and RMSE are associated with a quadratic loss function, while the mean absolute error is characterised by an absolute loss function. Therefore, the mean squared error measures penalise outliers more heavily than the MAE do, which is why Armstrong (2001) argues against their use. In accordance with Armstrong (2001), Chen and Yang (2004) suggest that the choice of the accuracy measures should be made on the grounds of the distribution of the errors. Chen and Yang (2004) demonstrate that the MSE is optimal when the errors are normally distributed, whereas MAE is preferred if the distribution of the errors is leptokurtic.

The MSE, RMSE, and MAE are scale-dependent and should not be utilised when comparing across data sets with different scales. There are a number of unit-free measures that can be used to compare performance across data sets with different scales. One such measure is the mean absolute percentage error (MAPE), which according to Hyndman and Koehler (2006) is recommended by the majority of forecasting textbooks. The MAPE is calculated as:

$$MAPE = \frac{\sum_{t=T_1}^{T} \frac{|e_t|}{r_t}}{T - (T_1 - 1)} \tag{4.22}$$

Notwithstanding its popularity, Gardner (1990) argues against the use of MAPE. This is because in some circumstances, it can yield meaningless results. This measure is undefined or infinite if $r_t = 0$ for any t in the sample period, and it has a skewed distribution when r_t is close to zero.

Stand-alone measures can be flawed by the bias introduced by outliers, seasonal effects, and trends (Chen and Yang, 2004). The relative measures can be used to mitigate such bias. These measures are calculated with reference to a benchmark forecast, typically a naïve forecast. One of the widely used relative accuracy measures is Theil's inequality coefficient, which is calculated as:

$$U = \frac{\sqrt{\frac{\sum_{t=T_1}^{T} {e_t}^2}{T - (T_1 - 1)}}}{\sqrt{\frac{\sum_{t=T_1}^{T} {\hat{r}_t}^2}{T - (T_1 - 1)}} + \sqrt{\frac{\sum_{t=T_1}^{T} {r_t}^2}{T - (T_1 - 1)}}} \tag{4.23}$$

Although the Theil's inequality coefficient alleviates some of the biases associated with the stand-alone measures, the choice of the benchmark forecast remains subjective.

Some economists, on the other hand, favour the use of economic criteria, which are based on profits or returns derived from the forecasts in an economic-decision framework. Despite the abundance of studies that utilise statistical criteria in evaluating forecasting models, their usefulness in practical situations is questionable (Brooks, 2008). For example Leitch and Tanner (1991) find that the correlation between statistical criteria and profitability is weak. Gerlow *et al.* (1993) show that while economic criteria are consistent with one another, they are not so with statistical criteria. In fact, Leitch and Tanner (1991) show that models that generate forecasts that can predict the sign of future returns are more useful. One measure of the ability of a model to predict the direction of changes regardless of their magnitude is the directional accuracy (DA) of a forecast. This measure is given by:

$$DA = \frac{\sum_{t=T_1}^{T} z_{t+s} \, ,}{T - (T_1 - 1)} \tag{4.24}$$

Where

$$z_t = \begin{cases} 1 \\ 0 \end{cases} if \begin{cases} \left(\hat{r}_{t,s} \; and \; r_{t+s}\right) > 0 \; or \; \left(\hat{r}_{t,s} \; and \; r_{t+s}\right) < 0 \\ otherwise \end{cases} \tag{4.25}$$

The measure yields the percentage of correctly predicted signs for some given lead time $, s$. Another economic measure is the cumulative wealth index employed by Groenewold *et al.* (2008). The cumulative wealth index for unconditional buy-and-hold and conditional buy-return series starting at time $t = 250$ until the conclusion of the sample period is calculated as:

$$CWI^b = WI_{250} \prod_{t=250}^{N} (1 + r_{t+1}^b) \tag{4.26}$$

where CWI and CWI^b are the cumulative wealth indices, and WI is the initial wealth. In the present study, we set this at \$1.

Profitability of Time Series Regression-based Trading Rules

In spite of the innovations in market microstructure in particular, the shift from the traditional outcry to an electronic-screen trading system and the introduction of ETFs enhanced market efficiency by reducing transaction costs, they remain above zero (Aitken *et al.*, 2004; Blennerhassett and Bowman, 1998; Kurov and Lasser, 2002; Park and Switzer, 1995; Switzer *et al.*, 2000). Transaction costs include the bid-ask spreads, round-trip commission fees, and taxes, as well as the market impact. For a trading rule to be profitable, it should generate profits over and above transaction costs.

Reliable transaction-cost estimates in the GCC markets are not available. Thus, instead of incorporating transaction costs into our performance-evaluation measures, we assess the possibility of earning profits using these rules via the approach taken by Bessembinder and Chan (1995, 1998). Under this approach, a "double-or-out" trading strategy is implemented, whereby a trader borrows at the risk-free rate to double their investment in the market index when a buy signal is generated. If a sell signal is issued, a trader liquidates his equity holdings and invests the proceeds in a risk-free interest-bearing security.

Following Bessembinder and Chan (1995, 1998), the interest rate is assumed to be zero. According to Yu *et al.* (2013), this is seen in the literature as acceptable practice, because of the difficulty in accounting accurately for the difference between lending and borrowing interest rates. Indeed, Bessembinder and Chan (1995, 1998) note that if the lending and borrowing rates are the same, and the buy and sell signals are equal, the assumption of a zero interest rate does not introduce bias into the calculation of returns. Nevertheless, if the number of buy (sell) signals is higher that the sell (buy) signals, the trading returns will be overstated (understated). The bias is estimated, on an annual basis, to be approximately $(w_b - w_s) \times r^f$, where w_b and w_s are, respectively, the proportions of buy and sell days and r^f is the average annual interest rate. Bessembinder and Chan (1995, 1998) conjecture that the bias is relatively small in the case of a typical interest rate—this conjecture is supported empirically by Yu *et al.* (2013).

The additional return: π, generated by a technical trading rule with reference to the buy-and-hold strategy in the absence of transaction cost is given as:

$$\pi = \sum_{t=250}^{N_b} r_{t+1}^{b} - \sum_{t=250}^{N_s} r_{t+1}^{s} \tag{4.27}$$

Dividing the additional return (π) by the number of initially generated buy and sell signals, we obtain the round-trip break-even costs (C), which is given by:

$$C = \frac{\pi}{n_b + n_s} \tag{4.28}$$

where n_b and n_s are, respectively, the number of initially generated buy and sell signals. Thus, the round-trip break-even cost (C) can be interpreted as the minimum level of transaction costs that would completely eliminate the additional return (π) from technical trading.

In a recent study, Chong and Lam (2010) argue that the buy-sell spreads (reported in Table 4.1) are a straightforward and more conservative of measure of transaction cost. The buy-sell spread will be equivalent to a beak-even cost if transaction costs are incurred on every trading day. Therefore, it is sufficient to say that transaction-cost estimates obtained using this measure (buy-sell spreads) will normally be lower than those derived using the Bessembinder and Chan (1995, 1998) measure, which as discussed above is calculated based on the initially generated buy and sell signals—almost always a fraction of all trading days.

4.4 Empirical Results

The results from the trading rules constructed on the basis of the previously specified time series regression models are reported in Table 4.1 (12 trading rules for each of the seven GCC markets). In Panels A to G of Table 4.1, for each trading rule across the seven GCC markets (84 rules in total), we report the number of buy and sell signals, the mean daily returns during buy and sell periods with their corresponding *t*-statistics (in parentheses), and the daily mean buy-sell spreads with their corresponding *t*-statistics (in parentheses). At the end of Panels A to G of Table 4.1, we present for each GCC market the averages of trading signals, mean daily returns, and buy-sell spreads and their corresponding *t*-statistics across the 12 trading rules.

From Table 4.1, we can clearly see that the number of buy signals persistently exceeds the number of sell signals for all trading rules across the seven GCC markets over the sample period. Considering the AR(1) model, we find ratios of buy to sell signals for ranges from as high as 5.5 times for the market of Saudi Arabia, to as low as 1.8 times for the market of Qatar. Interestingly, looking at the "plain vanilla" AR models, we note that the number of sell signals monotonically increases at the expense of the buy signals, as the autoregressive order increases across all GCC markets.

Table 4.1: Traditional test results for the time series regression-based trading rules

Model	N(Buy)	N(Sell)	Buy	t-stat	Sell	t-stat	Buy-Sell	t-stat	N(Buy)	N(Sell)	Buy	t-stat	Sell	t-stat	Buy-Sell	t-stat
	Panel A. Abu Dhabi								***Panel B. Bahrain***							
AR(1)	1548	847	0.203	(4.74)	-0.304	(-5.99)	0.506	(9.06)	1377	593	0.049	(2.62)	-0.142	(-4.04)	0.191	(5.64)
AR(1),Weekend	1531	864	0.210	(4.91)	-0.307	(-6.16)	0.517	(9.39)	1325	645	0.047	(2.44)	-0.121	(-3.67)	0.168	(5.24)
AR(1),TOM	1521	874	0.219	(5.12)	-0.316	(-6.39)	0.535	(9.78)	1378	592	0.050	(2.66)	-0.144	(-4.08)	0.193	(5.70)
AR(1),Holiday	1479	916	0.215	(4.94)	-0.285	(-5.98)	0.500	(9.33)	1370	600	0.046	(2.47)	-0.132	(-3.77)	0.178	(5.28)
AR(5)	1472	923	0.210	(4.77)	-0.275	(-5.90)	0.514	(9.16)	1338	632	0.058	(3.02)	-0.149	(-4.40)	0.200	(6.30)
AR(5),Weekend	1471	924	0.213	(4.83)	-0.278	(-5.99)	0.520	(9.30)	1284	686	0.054	(2.77)	-0.125	(-3.89)	0.175	(5.71)
AR(5),TOM	1475	920	0.216	(4.90)	-0.285	(-6.11)	0.532	(9.46)	1330	640	0.056	(2.92)	-0.142	(-4.21)	0.200	(6.05)
AR(5),Holiday	1442	953	0.214	(4.82)	-0.265	(-5.82)	0.499	(9.16)	1336	634	0.053	(2.75)	-0.137	(-4.03)	0.185	(5.76)
AR(20)	1364	1031	0.196	(4.33)	-0.205	(-4.69)	0.500	(7.76)	1174	796	0.055	(2.74)	-0.102	(-3.31)	0.197	(5.21)
AR(20),Weekend	1361	1034	0.199	(4.41)	-0.208	(-4.75)	0.507	(7.88)	1145	825	0.056	(2.77)	-0.098	(-3.21)	0.177	(5.15)
AR(20),TOM	1338	1057	0.213	(4.68)	-0.217	(-5.06)	0.530	(8.42)	1166	804	0.052	(2.60)	-0.096	(-3.12)	0.196	(4.93)
AR(20),Holiday	1309	1086	0.196	(4.19)	-0.185	(-4.46)	0.481	(7.49)	1169	801	0.057	(2.83)	-0.104	(-3.39)	0.189	(5.35)
Average	1442.58	952.42	0.209	(4.72)	-0.261	(-5.61)	0.512	(8.85)	1282.67	687.33	0.053	(2.71)	-0.124	(-3.76)	0.187	(5.53)
	Panel C. Dubai								***Panel D. Kuwait***							
AR(1)	1526	348	0.037	(0.82)	-0.246	(-1.45)	0.283	(1.78)	1751	454	0.126	(3.38)	-0.294	(-5.53)	0.420	(7.00)
AR(1),Weekend	1334	540	0.024	(0.57)	-0.112	(-0.88)	0.136	(1.22)	1739	466	0.124	(3.32)	-0.279	(-5.40)	0.403	(6.88)
AR(1),TOM	1387	487	0.042	(0.86)	-0.178	(-1.36)	0.220	(1.82)	1712	493	0.143	(4.08)	-0.322	(-6.34)	0.465	(8.21)
AR(1),Holiday	1342	532	0.047	(0.93)	-0.173	(-1.39)	0.220	(1.92)	1735	470	0.132	(3.62)	-0.302	(-5.77)	0.433	(7.38)
AR(5)	1240	634	0.080	(1.42)	-0.202	(-1.76)	0.326	(2.62)	1668	537	0.132	(3.67)	-0.250	(-5.18)	0.426	(6.91)
AR(5),Weekend	1171	703	0.058	(1.05)	-0.137	(-1.24)	0.170	(1.93)	1663	542	0.130	(3.55)	-0.238	(-5.05)	0.408	(6.74)
AR(5),TOM	1189	685	0.091	(1.54)	-0.199	(-1.84)	0.269	(2.83)	1637	568	0.136	(3.79)	-0.241	(-5.31)	0.459	(7.19)
AR(5),Holiday	1138	736	0.055	(0.98)	-0.124	(-1.16)	0.228	(1.82)	1657	548	0.134	(3.73)	-0.248	(-5.23)	0.436	(7.02)
AR(20)	1090	784	0.039	(0.77)	-0.090	(-0.81)	0.285	(1.33)	1543	662	0.125	(3.34)	-0.162	(-4.16)	0.420	(5.98)
AR(20),Weekend	1079	795	0.075	(1.24)	-0.137	(-1.36)	0.187	(2.22)	1525	680	0.128	(3.43)	-0.160	(-4.20)	0.407	(6.10)
AR(20),TOM	1075	799	0.050	(0.92)	-0.103	(-0.94)	0.228	(1.58)	1525	680	0.125	(3.27)	-0.153	(-4.10)	0.447	(5.94)
AR(20),Holiday	1042	832	0.033	(0.67)	-0.076	(-0.67)	0.206	(1.14)	1539	666	0.130	(3.50)	-0.170	(-4.34)	0.431	(6.25)
Average	1217.75	656.25	0.053	(0.98)	-0.148	(-1.24)	0.230	(1.85)	1641.17	563.83	0.130	(3.56)	-0.235	(-5.05)	0.430	(6.80)

Table 4.1 *(Continued)*

Model	N(Buy)	N(Sell)	Buy	t-stat	Sell	t-stat	Buy-Sell	t-stat	N(Buy)	N(Sell)	Buy	t-stat	Sell	t-stat	Buy-Sell	t-stat
	Panel E. Oman								***Panel F. Qatar***							
Model	N(Buy)	N(Sell)	Buy	t-stat	Sell	t-stat	Buy-Sell	t-stat	N(Buy)	N(Sell)	Buy	t-stat	Sell	t-stat	Buy-Sell	t-stat
AR(1)	1528	704	0.196	(4.29)	-0.271	(-5.61)	0.467	(8.15)	1455	815	0.332	(5.64)	-0.429	(-6.67)	0.761	(10.29)
AR(1),Weekend	1503	729	0.207	(4.60)	-0.278	(-5.90)	0.485	(8.69)	1446	824	0.334	(5.67)	-0.425	(-6.67)	0.759	(10.33)
AR(1),TOM	1525	707	0.199	(4.38)	-0.275	(-5.71)	0.474	(8.31)	1434	836	0.337	(5.71)	-0.419	(-6.65)	0.756	(10.37)
AR(1),Holiday	1518	714	0.194	(4.23)	-0.261	(-5.50)	0.455	(8.03)	1432	838	0.336	(5.68)	-0.414	(-6.59)	0.750	(10.29)
AR(5)	1502	730	0.191	(4.13)	-0.243	(-5.19)	0.461	(7.67)	1423	847	0.342	(5.74)	-0.418	(-6.78)	0.771	(10.59)
AR(5),Weekend	1479	753	0.202	(4.44)	-0.252	(-5.47)	0.480	(8.19)	1423	847	0.348	(5.84)	-0.427	(-6.97)	0.773	(10.86)
AR(5),TOM	1491	741	0.196	(4.30)	-0.248	(-5.32)	0.472	(7.92)	1410	860	0.344	(5.76)	-0.409	(-6.73)	0.763	(10.58)
AR(5),Holiday	1488	744	0.195	(4.24)	-0.243	(-5.25)	0.455	(7.83)	1415	855	0.343	(5.73)	-0.411	(-6.74)	0.757	(10.57)
AR(20)	1418	814	0.180	(3.73)	-0.180	(-4.40)	0.451	(6.79)	1364	906	0.300	(4.71)	-0.304	(-5.44)	0.729	(8.68)
AR(20),Weekend	1426	806	0.181	(3.77)	-0.186	(-4.49)	0.459	(6.90)	1370	900	0.301	(4.73)	-0.310	(-5.52)	0.726	(8.77)
AR(20),TOM	1426	806	0.179	(3.71)	-0.182	(-4.40)	0.454	(6.77)	1352	918	0.301	(4.72)	-0.298	(-5.39)	0.720	(8.66)
AR(20),Holiday	1419	813	0.174	(3.54)	-0.169	(-4.18)	0.434	(6.45)	1354	916	0.302	(4.73)	-0.300	(-5.42)	0.716	(8.69)
Average	1476.92	755.08	0.191	(4.11)	-0.232	(-5.12)	0.462	(7.64)	1406.5	863.50	0.327	(5.39)	-0.380	(-6.30)	0.748	(9.89)
	Panel G. Saudi Arabia															
AR(1)	2085	378	0.070	(0.66)	-0.148	(-1.46)	0.217	(1.72)								
AR(1),Weekend	2013	450	0.060	(0.47)	-0.072	(-1.06)	0.132	(1.28)								
AR(1),TOM	2035	428	0.066	(0.58)	-0.105	(-1.24)	0.170	(1.50)								
AR(1),Holiday	2017	446	0.061	(0.50)	-0.079	(-1.04)	0.140	(1.27)								
AR(5)	1808	655	0.067	(0.61)	-0.050	(-0.92)	0.215	(1.25)								
AR(5),Weekend	1770	693	0.065	(0.55)	-0.037	(-0.85)	0.137	(1.16)								
AR(5),TOM	1800	663	0.072	(0.70)	-0.062	(-1.06)	0.177	(1.44)								
AR(5),Holiday	1761	702	0.071	(0.67)	-0.051	(-0.98)	0.149	(1.36)								
AR(20)	1622	841	0.047	(0.20)	0.015	(-0.28)	0.195	(0.41)								
AR(20),Weekend	1614	849	0.064	(0.50)	-0.016	(-0.71)	0.136	(1.03)								
AR(20),TOM	1613	850	0.061	(0.45)	-0.011	(-0.62)	0.165	(0.91)								
AR(20),Holiday	1583	880	0.049	(0.23)	0.014	(-0.30)	0.127	(0.45)								
Average	1810.08	652.92	0.063	(0.51)	-0.050	(-0.88)	0.163	(1.15)								

For a trading rule to have predictive power, the average returns during buy (sell) periods should be positive (negative) and significantly different from the placebo of unconditional buy-and-hold returns. The approach that we take in judging the success of a trading rule is more conservative than in prior studies. Instead of relying on the statistical significance of the buy-sell spreads, we consider the statistical significance of the buy (sell) return separately—for a trading rule to be successful both buy (sell) returns should be statistically significantly different from the buy-and-hold returns.

Table 4.1 reveals that mean returns during buy (sell) periods have the expected sign across the seven GCC markets with only a few exceptions, namely the AR(20) and the AR(20)Holiday results for Saudi Arabia. Out of the 84 rules tested across the seven GCC markets, 60 rules (or about 71 percent of the rules) exhibit more statistically significant positive (negative) buy (sell) returns than those earned by the passive buy-and-hold strategy, at a 5 percent significance level using a two-tailed test. Table 4.1 also shows that at the 5 percent statistical significance level, essentially all trading rules produce statistically significant results in five of the seven GCC markets (Abu Dhabi, Bahrain, Kuwait, Oman, and Qatar), while none of the trading rules produce statistical significant results in the markets of Dubai and Saudi Arabia. In terms of the magnitude of the buy (sell) returns, and of the statistical significance across trading rules, the most potentially profitable markets are Abu Dhabi, Oman, and Qatar.

The bottom parts of Panels A to G show that the average buy (sell) returns across the 12 trading rules are 0.209 percent (-0.261 percent) for Abu Dhabi, 0.053 percent (-0.124 percent) for Bahrain, 0.130 percent (-0.235 percent) for Kuwait, 0.191 percent (-0.232 percent) for Oman, and 0.327 percent (-0.380 percent) for Qatar—they all reject the null of equality to the buy-and-hold returns at a significance level of 1 percent. On the other hand, the null hypothesis that the average buy return is equal to the buy-and-hold return cannot be rejected in the markets of Dubai and Saudi Arabia.

We turn to the results of alternative performance-evaluation measures that are displayed in Table 4.2. For each GCC market in Panels A to G we report the RMSE, MAE, Theil, DA, and CWI for each trading rule.

Table 4.2: Alternative performance measures results for the time series regression-based trading rules

Model	RMSE	MAE	Theil	DA	CWI	RMSE	MAE	Theil	DA	CWI
	Panel A. Abu Dhabi					***Panel B. Bahrain***				
AR(1)	1.199	0.769	0.743	0.584	20.87	0.642	0.442	0.803	0.529	1.92
AR(1),Weekend	1.198	0.769	0.741	0.587	22.64	0.644	0.444	0.799	0.530	1.81
AR(1),TOM	1.199	0.769	0.741	0.593	25.28	0.642	0.442	0.802	0.527	1.94
AR(1),Holiday	1.203	0.773	0.740	0.589	21.74	0.643	0.444	0.797	0.521	1.83
AR(5)	1.202	0.773	0.725	0.578	20.04	0.644	0.443	0.800	0.537	2.13
AR(5),Weekend	1.202	0.772	0.724	0.577	20.79	0.646	0.445	0.797	0.537	1.96
AR(5),TOM	1.202	0.772	0.723	0.583	21.78	0.644	0.443	0.800	0.528	2.06
AR(5),Holiday	1.206	0.776	0.723	0.577	19.88	0.645	0.445	0.795	0.531	1.97
AR(20)	1.215	0.784	0.718	0.554	13.29	0.648	0.450	0.771	0.537	1.87
AR(20),Weekend	1.215	0.784	0.717	0.550	13.77	0.650	0.452	0.769	0.533	1.86
AR(20),TOM	1.215	0.784	0.716	0.557	15.82	0.648	0.451	0.770	0.531	1.80
AR(20),Holiday	1.219	0.788	0.716	0.552	11.88	0.649	0.452	0.768	0.539	1.91
	Panel C. Dubai					***Panel D. Kuwait***				
AR(1)	2.002	1.379	0.873	0.507	1.40	0.848	0.593	0.772	0.590	8.58
AR(1),Weekend	2.005	1.384	0.867	0.509	1.10	0.847	0.591	0.769	0.590	8.26
AR(1),TOM	2.003	1.377	0.868	0.521	1.43	0.848	0.593	0.767	0.595	11.07
AR(1),Holiday	2.007	1.380	0.860	0.519	1.52	0.851	0.594	0.768	0.592	9.33
AR(5)	2.010	1.377	0.838	0.534	2.25	0.850	0.593	0.762	0.595	8.68
AR(5),Weekend	2.012	1.382	0.835	0.522	1.63	0.849	0.591	0.760	0.595	8.25
AR(5),TOM	2.011	1.376	0.833	0.541	2.44	0.850	0.593	0.756	0.594	8.92
AR(5),Holiday	2.014	1.378	0.829	0.535	1.54	0.853	0.594	0.759	0.594	8.80
AR(20)	2.036	1.416	0.797	0.516	1.29	0.855	0.599	0.736	0.576	6.66
AR(20),Weekend	2.038	1.419	0.795	0.514	1.87	0.854	0.598	0.734	0.573	6.77
AR(20),TOM	2.038	1.414	0.794	0.521	1.45	0.855	0.598	0.730	0.577	6.43
AR(20),Holiday	2.040	1.418	0.792	0.515	1.19	0.859	0.601	0.732	0.574	7.05

Table 4.2 ***(Continued)***

Model	RMSE	MAE	Theil	DA	CWI	RMSE	MAE	Theil	DA	CWI
	Panel E. Oman					***Panel F. Qatar***				
AR(1)	1.099	0.638	0.749	0.606	18.54	1.542	0.998	0.708	0.611	109.36
AR(1),Weekend	1.099	0.638	0.747	0.608	20.95	1.542	0.999	0.708	0.611	109.66
AR(1),TOM	1.099	0.637	0.749	0.609	19.30	1.543	0.998	0.708	0.611	109.57
AR(1),Holiday	1.101	0.639	0.749	0.605	17.76	1.544	1.000	0.708	0.611	106.54
AR(5)	1.110	0.641	0.748	0.605	16.29	1.553	1.003	0.690	0.611	113.29
AR(5),Weekend	1.110	0.641	0.746	0.608	18.40	1.553	1.004	0.689	0.613	122.47
AR(5),TOM	1.110	0.641	0.748	0.609	17.42	1.553	1.003	0.690	0.607	111.14
AR(5),Holiday	1.111	0.642	0.747	0.608	16.86	1.555	1.004	0.690	0.608	111.02
AR(20)	1.119	0.656	0.719	0.597	12.02	1.577	1.019	0.691	0.598	51.46
AR(20),Weekend	1.119	0.657	0.718	0.595	12.39	1.577	1.019	0.690	0.600	53.18
AR(20),TOM	1.120	0.657	0.719	0.595	12.02	1.578	1.020	0.691	0.593	50.64
AR(20),Holiday	1.121	0.658	0.719	0.592	10.94	1.579	1.021	0.690	0.597	51.30
	Panel G. Saudi Arabia									
AR(1)	1.763	1.095	0.928	0.572	3.22					
AR(1),Weekend	1.762	1.093	0.924	0.564	2.51					
AR(1),TOM	1.763	1.096	0.925	0.569	2.88					
AR(1),Holiday	1.768	1.100	0.909	0.567	2.62					
AR(5)	1.771	1.100	0.881	0.556	2.71					
AR(5),Weekend	1.770	1.098	0.878	0.561	2.49					
AR(5),TOM	1.772	1.101	0.879	0.558	2.92					
AR(5),Holiday	1.776	1.105	0.870	0.552	2.79					
AR(20)	1.800	1.124	0.837	0.534	1.72					
AR(20),Weekend	1.799	1.122	0.835	0.536	2.21					
AR(20),TOM	1.800	1.126	0.836	0.539	2.13					
AR(20),Holiday	1.804	1.128	0.831	0.529	1.74					

Examining Table 4.2, it appears that the results for the statistical measures are fairly similar across trading rules for each market. On the other hand, the results for the economic criteria do vary markedly across both markets and trading rules. In general, the rankings generated using the statistical measures are largely inconsistent with those produced using the economic criteria. This is in line with the cited studies.

With respect to the measurement of profitability, the results of the break-even cost for the "double or out" strategy are shown in Table 4.3, where we present the break-even cost for each trading rule across the seven GCC markets. The average of break-even cost for each market is also reported at the bottom of the table. Looking at Table 4.3, we can see that the Qatari market is the most likely to be profitable with the break-even cost averaging 0.83 percent; the least likely to be profitable is the Saudi market with an average break-even cost of 0.18 percent. However, we cannot reach a conclusion on whether or not the trading rules are profitable without a reasonably accurate estimate of transaction costs in these markets.

Table 4.3: Break-even cost for the "double or out" strategy

Rules	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
AR(1)	0.68	0.22	0.32	0.65	0.65	1.02	0.39
AR(1),Weekend	0.69	0.19	0.17	0.63	0.64	1.01	0.24
AR(1),TOM	0.77	0.22	0.32	0.74	0.67	1.02	0.31
AR(1),Holiday	0.67	0.20	0.31	0.67	0.63	1.00	0.26
AR(5)	0.50	0.24	0.41	0.61	0.55	0.85	0.17
AR(5),Weekend	0.50	0.21	0.26	0.59	0.57	0.86	0.14
AR(5),TOM	0.54	0.22	0.46	0.61	0.57	0.84	0.19
AR(5),Holiday	0.49	0.21	0.27	0.61	0.56	0.83	0.17
AR(20)	0.42	0.20	0.15	0.45	0.45	0.63	0.06
AR(20),Weekend	0.42	0.19	0.24	0.45	0.45	0.64	0.11
AR(20),TOM	0.46	0.19	0.20	0.44	0.45	0.62	0.11
AR(20),Holiday	0.39	0.20	0.14	0.46	0.42	0.62	0.06
Average break-even cost	0.54	0.21	0.27	0.57	0.55	0.83	0.18

4.5 Robustness Checks: Jensen's Alpha

Since high returns could potentially be a consequence of high risk, risk-adjusted returns are estimated utilising the CAPM to evaluate the performance of technical trading rules. This is motivated by Brown *et al.* (1998) who argue that investors who employ technical trading rules are frequently out of the market. This means that adjustment for systematic risk when evaluating the performance of these rules is warranted. The empirical evidence supports their conjecture. In the spirit of Brown *et al.* (1998) and Fang *et al.* (2014), we regress the buy and sell returns as well as the buy-sell spreads in excess of the risk-free rate on an intercept and the market risk premium in the usual manner as:

$$r_t^b - r_t^f = \alpha^b + \beta^b\left(r_t - r_t^f\right) + \varepsilon_t^b \tag{4.29}$$

$$r_t^s - r_t^f = \alpha^s + \beta^s\left(r_t - r_t^f\right) + \varepsilon_t^s \tag{4.30}$$

$$\left(r_t^b - r_t^s\right) - r_t^f = \alpha^{b-s} + \beta^{b-s}\left(r_t - r_t^f\right) + \varepsilon_t^{b-s} \tag{4.31}$$

where α is Jensen's alpha, which represents the differential between the return on the trading rule in excess of the risk-free rate and the return explained by the CAPM, β captures the systematic risk of the trading rule, and ε_t is an error term assumed to be independently and identically distributed (iid). In order to mitigate the potential size distortion of the *t*-test that arises due to the autocorrelation of the residuals, we calculate the *t*-statistics from the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987) via the Andrews (1991) automatic-selection procedure.

The results obtained by fitting the CAPM to each of the time series regression-based trading rules are reported in Table 4.4. Jensen's alpha (α) captures the differential superior or inferior performance of the trading rule in relation to that predicted by the CAPM, given a risk level of β. If Jensen's alpha is positive and statistically significant, it is concluded that the trading rule delivers a superior performance, which can be attributed to its market-timing ability. Table 4.4 contains the estimation results of the CAPM for the 12 trading rules across the seven GCC markets. For each trading rule, we report the Jensen's alpha estimates (α^b) and the beta estimates (β^b) during the periods in which buy signals are generated. We also report Jensen's alpha estimates (α^s) and the beta estimates (β^s) during the periods in which sell signals are generated, as well as the Jensen's alpha (α^{b-s}) and beta (β^{b-s}) estimates for buy-sell spreads, all with their corresponding *t*-statistics (in parentheses).

Table 4.4: The CAPM estimation results for the time series regression-based trading rules

Rules		**Abu Dhabi**	**Bahrain**	**Dubai**	**Kuwait**	**Oman**	**Qatar**	**Saudi Arabia**
AR(1)	α^b	0.115	0.037	0.037	0.074	0.105	0.181	0.031
		(9.21)	(4.91)	(1.67)	(7.80)	(7.78)	(10.64)	(1.92)
	β^b	0.52	0.61	0.62	0.57	0.51	0.48	0.72
		(16.26)	(16.72)	(17.84)	(18.84)	(9.30)	(15.10)	(23.27)
	α^s	-0.123	-0.044	-0.045	-0.081	-0.114	-0.188	-0.037
		(-9.82)	(-5.86)	(-2.08)	(-8.51)	(-8.48)	(-11.06)	(-2.32)
	β^s	0.48	0.39	0.38	0.43	0.49	0.52	0.28
		(14.79)	(10.49)	(10.95)	(14.12)	(8.84)	(16.44)	(8.83)
	α^{b-s}	0.230	0.073	0.073	0.149	0.209	0.362	0.062
		(9.21)	(4.91)	(1.67)	(7.80)	(7.78)	(10.64)	(1.92)
	β^{b-s}	0.05	0.23	0.24	0.14	0.02	-0.04	0.45
		(0.75)	(3.11)	(3.45)	(2.36)	(0.23)	(-0.67)	(7.22)
AR(1),Weekend	α^b	0.118	0.034	0.023	0.073	0.110	0.181	0.020
		(9.49)	(4.80)	(1.03)	(7.63)	(8.24)	(10.61)	(1.31)
	β^b	0.53	0.62	0.61	0.57	0.51	0.48	0.76
		(16.33)	(19.41)	(18.52)	(19.38)	(9.53)	(15.04)	(26.10)
	α^s	-0.126	-0.041	-0.032	-0.080	-0.120	-0.188	-0.027
		(-10.11)	(-5.81)	(-1.42)	(-8.36)	(-8.94)	(-11.03)	(-1.74)
	β^s	0.48	0.38	0.39	0.43	0.49	0.52	0.24
		(14.77)	(11.70)	(11.67)	(14.38)	(9.20)	(16.37)	(8.43)
	α^{b-s}	0.237	0.068	0.046	0.145	0.220	0.362	0.041
		(9.49)	(4.80)	(1.03)	(7.63)	(8.24)	(10.61)	(1.31)
	β^{b-s}	0.05	0.25	0.23	0.15	0.02	-0.04	0.51
		(0.78)	(3.85)	(3.42)	(2.50)	(0.17)	(-0.66)	(8.84)
AR(1),TOM	α^b	0.123	0.037	0.037	0.087	0.106	0.181	0.026
		(9.92)	(5.03)	(1.64)	(9.01)	(7.91)	(10.66)	(1.64)
	β^b	0.52	0.61	0.61	0.55	0.51	0.48	0.72
		(15.66)	(16.83)	(18.49)	(17.44)	(9.29)	(15.16)	(23.09)
	α^s	-0.131	-0.044	-0.046	-0.094	-0.116	-0.188	-0.033
		(-10.54)	(-6.00)	(-2.04)	(-9.71)	(-8.61)	(-11.07)	(-2.05)
	β^s	0.48	0.39	0.39	0.45	0.49	0.52	0.28
		(14.29)	(10.66)	(11.93)	(14.45)	(8.87)	(16.52)	(8.94)
	α^{b-s}	0.246	0.074	0.074	0.173	0.213	0.362	0.053
		(9.92)	(5.03)	(1.64)	(9.01)	(7.91)	(10.66)	(1.64)
	β^{b-s}	0.05	0.22	0.22	0.09	0.02	-0.04	0.44
		(0.70)	(3.08)	(3.28)	(1.48)	(0.21)	(-0.68)	(7.08)

Table 4.4 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
AR(1),Holiday	α^b	0.117	0.034	0.039	0.079	0.103	0.180	0.023
		(9.35)	(4.57)	(1.73)	(8.28)	(7.62)	(10.57)	(1.39)
	β^b	0.52	0.61	0.59	0.56	0.51	0.48	0.72
		(16.18)	(16.62)	(17.90)	(19.09)	(9.30)	(15.06)	(23.01)
	α^s	-0.124	-0.041	-0.048	-0.085	-0.112	-0.187	-0.029
		(-9.97)	(-5.53)	(-2.12)	(-9.00)	(-8.32)	(-10.99)	(-1.79)
	β^s	0.48	0.39	0.41	0.44	0.49	0.52	0.28
		(14.91)	(10.52)	(12.51)	(15.03)	(8.82)	(16.53)	(9.06)
	α^{b-s}	0.233	0.069	0.079	0.157	0.205	0.360	0.045
		(9.35)	(4.57)	(1.73)	(8.28)	(7.62)	(10.57)	(1.39)
	β^{b-s}	0.04	0.22	0.18	0.12	0.03	-0.05	0.43
		(0.64)	(3.05)	(2.70)	(2.02)	(0.24)	(-0.74)	(6.97)
AR(5)	α^b	0.113	0.042	0.056	0.077	0.099	0.182	0.026
		(8.60)	(5.73)	(2.45)	(8.07)	(6.83)	(10.76)	(1.42)
	β^b	0.54	0.59	0.50	0.50	0.50	0.49	0.58
		(16.19)	(16.66)	(15.82)	(16.17)	(8.92)	(16.22)	(17.29)
	α^s	-0.121	-0.049	-0.065	-0.084	-0.109	-0.189	-0.032
		(-9.15)	(-6.71)	(-2.84)	(-8.78)	(-7.48)	(-11.18)	(-1.78)
	β^s	0.46	0.41	0.50	0.50	0.50	0.51	0.42
		(13.85)	(11.35)	(15.84)	(15.89)	(9.05)	(16.72)	(12.62)
	α^{b-s}	0.226	0.083	0.113	0.154	0.199	0.364	0.052
		(8.60)	(5.73)	(2.45)	(8.07)	(6.83)	(10.76)	(1.42)
	β^{b-s}	0.08	0.19	0.00	0.01	-0.01	-0.01	0.16
		(1.16)	(2.65)	(-0.01)	(0.13)	(-0.07)	(-0.25)	(2.34)
AR(5),Weekend	α^b	0.115	0.037	0.040	0.074	0.105	0.185	0.022
		(8.74)	(5.17)	(1.74)	(7.64)	(7.40)	(10.86)	(1.19)
	β^b	0.54	0.60	0.50	0.51	0.49	0.50	0.61
		(16.28)	(18.11)	(14.76)	(15.74)	(8.84)	(16.43)	(18.45)
	α^s	-0.122	-0.045	-0.048	-0.081	-0.114	-0.192	-0.029
		(-9.29)	(-6.14)	(-2.13)	(-8.33)	(-8.06)	(-11.27)	(-1.54)
	β^s	0.46	0.40	0.50	0.49	0.51	0.50	0.39
		(13.80)	(12.24)	(14.67)	(14.99)	(9.14)	(16.44)	(11.88)
	α^{b-s}	0.229	0.075	0.079	0.149	0.210	0.370	0.044
		(8.74)	(5.17)	(1.74)	(7.64)	(7.40)	(10.86)	(1.19)
	β^{b-s}	0.08	0.19	0.00	0.02	-0.02	0.00	0.22
		(1.24)	(2.92)	(0.05)	(0.36)	(-0.15)	(0.00)	(3.29)

Table 4.4 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
AR(5),TOM	α^{b}	0.117	0.040	0.061	0.078	0.103	0.181	0.029
		(8.87)	(5.44)	(2.68)	(8.18)	(7.15)	(10.72)	(1.58)
	β^{b}	0.54	0.59	0.50	0.51	0.49	0.49	0.58
		(16.36)	(16.29)	(14.88)	(16.55)	(8.82)	(16.18)	(17.49)
	α^{s}	-0.124	-0.047	-0.070	-0.085	-0.112	-0.188	-0.036
		(-9.43)	(-6.40)	(-3.06)	(-8.89)	(-7.80)	(-11.14)	(-1.93)
	β^{s}	0.46	0.41	0.50	0.49	0.51	0.51	0.42
		(13.74)	(11.25)	(14.80)	(15.95)	(9.19)	(16.79)	(12.47)
	α^{b-s}	0.233	0.080	0.122	0.156	0.205	0.362	0.058
		(8.87)	(5.44)	(2.68)	(8.18)	(7.15)	(10.72)	(1.58)
	β^{b-s}	0.09	0.18	0.00	0.02	-0.02	-0.02	0.17
		(1.30)	(2.51)	(0.04)	(0.29)	(-0.19)	(-0.30)	(2.51)
AR(5),Holiday	α^{b}	0.113	0.038	0.037	0.078	0.101	0.181	0.027
		(8.55)	(5.22)	(1.61)	(8.07)	(7.05)	(10.70)	(1.52)
	β^{b}	0.53	0.60	0.52	0.50	0.49	0.49	0.57
		(16.09)	(16.70)	(16.27)	(15.81)	(8.83)	(16.24)	(17.23)
	α^{s}	-0.121	-0.045	-0.046	-0.084	-0.110	-0.188	-0.034
		(-9.10)	(-6.20)	(-1.99)	(-8.77)	(-7.70)	(-11.12)	(-1.88)
	β^{s}	0.47	0.40	0.48	0.50	0.51	0.51	0.43
		(14.00)	(11.16)	(15.05)	(15.53)	(9.11)	(16.69)	(12.82)
	α^{b-s}	0.226	0.076	0.074	0.155	0.202	0.362	0.054
		(8.55)	(5.22)	(1.61)	(8.07)	(7.05)	(10.70)	(1.52)
	β^{b-s}	0.07	0.20	0.04	0.01	-0.02	-0.01	0.15
		(1.04)	(2.76)	(0.61)	(0.13)	(-0.14)	(-0.23)	(2.20)
AR(20)	α^{b}	0.096	0.034	0.025	0.066	0.086	0.147	0.008
		(7.39)	(4.52)	(1.08)	(6.48)	(5.99)	(8.83)	(0.42)
	β^{b}	0.49	0.54	0.46	0.47	0.49	0.51	0.57
		(14.75)	(15.19)	(14.60)	(13.92)	(9.91)	(16.63)	(18.19)
	α^{s}	-0.104	-0.041	-0.034	-0.073	-0.095	-0.154	-0.014
		(-7.96)	(-5.46)	(-1.46)	(-7.14)	(-6.65)	(-9.26)	(-0.79)
	β^{s}	0.51	0.46	0.54	0.53	0.51	0.49	0.43
		(15.39)	(12.82)	(17.40)	(15.79)	(10.43)	(16.24)	(13.51)
	α^{b-s}	0.193	0.068	0.050	0.132	0.172	0.293	0.015
		(7.39)	(4.52)	(1.08)	(6.48)	(5.99)	(8.83)	(0.42)
	β^{b-s}	-0.02	0.08	-0.09	-0.06	-0.03	0.01	0.15
		(-0.33)	(1.17)	(-1.40)	(-0.94)	(-0.26)	(0.20)	(2.34)

Table 4.4 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
AR(20),Weekend	α^{b}	0.098	0.034	0.046	0.067	0.087	0.148	0.017
		(7.55)	(4.35)	(2.00)	(6.63)	(6.03)	(8.91)	(0.97)
	β^{b}	0.49	0.53	0.49	0.46	0.49	0.51	0.60
		(14.72)	(14.17)	(15.55)	(14.14)	(9.94)	(16.77)	(19.17)
	α^{s}	-0.106	-0.041	-0.055	-0.074	-0.097	-0.155	-0.024
		(-8.12)	(-5.26)	(-2.38)	(-7.31)	(-6.69)	(-9.34)	(-1.33)
	β^{s}	0.51	0.47	0.51	0.54	0.51	0.49	0.40
		(15.48)	(12.67)	(16.27)	(16.35)	(10.26)	(16.10)	(12.78)
	α^{b-s}	0.196	0.067	0.092	0.134	0.174	0.296	0.035
		(7.55)	(4.35)	(2.00)	(6.63)	(6.03)	(8.91)	(0.97)
	β^{b-s}	-0.03	0.06	-0.02	-0.07	-0.02	0.02	0.20
		(-0.39)	(0.74)	(-0.36)	(-1.12)	(-0.16)	(0.34)	(3.20)
AR(20),TOM	α^{b}	0.104	0.032	0.030	0.064	0.086	0.146	0.016
		(8.13)	(4.27)	(1.34)	(6.05)	(5.99)	(8.80)	(0.90)
	β^{b}	0.50	0.54	0.44	0.48	0.49	0.50	0.58
		(15.04)	(15.14)	(13.89)	(13.56)	(9.92)	(16.53)	(18.33)
	α^{s}	-0.111	-0.039	-0.039	-0.071	-0.095	-0.153	-0.023
		(-8.71)	(-5.21)	(-1.73)	(-6.68)	(-6.65)	(-9.22)	(-1.27)
	β^{s}	0.50	0.46	0.56	0.52	0.51	0.50	0.42
		(15.18)	(12.83)	(17.36)	(14.68)	(10.40)	(16.34)	(13.37)
	α^{b-s}	0.207	0.064	0.061	0.128	0.172	0.292	0.032
		(8.13)	(4.27)	(1.34)	(6.05)	(5.99)	(8.80)	(0.90)
	β^{b-s}	-0.01	0.08	-0.11	-0.04	-0.02	0.01	0.16
		(-0.08)	(1.14)	(-1.73)	(-0.57)	(-0.24)	(0.10)	(2.48)
AR(20),Holiday	α^{b}	0.092	0.035	0.020	0.069	0.082	0.147	0.008
		(7.13)	(4.75)	(0.88)	(6.80)	(5.71)	(8.82)	(0.44)
	β^{b}	0.50	0.54	0.45	0.47	0.49	0.50	0.56
		(15.31)	(15.41)	(14.34)	(13.96)	(9.92)	(16.60)	(17.92)
	α^{s}	-0.099	-0.042	-0.029	-0.075	-0.091	-0.154	-0.015
		(-7.71)	(-5.71)	(-1.27)	(-7.47)	(-6.37)	(-9.25)	(-0.81)
	β^{s}	0.50	0.46	0.55	0.53	0.51	0.50	0.44
		(15.32)	(13.18)	(17.73)	(15.98)	(10.33)	(16.27)	(13.81)
	α^{b-s}	0.183	0.070	0.041	0.137	0.163	0.293	0.016
		(7.13)	(4.75)	(0.88)	(6.80)	(5.71)	(8.82)	(0.44)
	β^{b-s}	0.000	0.077	-0.106	-0.068	-0.020	0.010	0.130
		(-0.01)	(1.11)	(-1.70)	(-1.02)	(-0.20)	(0.16)	(2.06)

The results in Table 4.4 are striking. For all trading rules across the seven GCC markets, all of the estimated coefficients are correctly signed. Moreover, in five out of the seven GCC markets (Abu Dhabi, Bahrain, Kuwait, Oman, and Qatar) the estimated Jensen's alpha coefficients are statistically significant at the 1 percent level, which is consistent with the results reported in Table 4.4. Interestingly, the performance of trading rules for the markets of Dubai and Saudi Arabia improves slightly when the risk dimension is taken into consideration, as few trading rules generated positive and statistically significant alphas. For instance the AR(1) rule for Dubai and Saudi in addition to the AR(1)Holiday and AR(5)Weekend rules for Dubai are found to be statistically significant, albeit at the marginal level of 10 percent. Moreover, in the market of Dubai, we find that the AR(5) and AR(20)Weekend rules are statistically significant at the 5 percent level while the AR(5) TOM turned out to be highly significant at the 1 percent level.

4.6 Conclusion

For this chapter, we conducted an empirical investigation to find out if the widely documented departures from the weak-form EMH in the GCC markets can be exploited profitably. Our motivation stems from the findings of several recent GCC-based studies, which observe deviations from the weak-form EMH in addition to the documented seasonal effects in Chapter 3.

This is achieved by examining the profitability of time series regression-based trading rules. Furthermore, we expand on Chapter 3 by investigating whether or not the inclusion of the seasonal dummies, which are shown to be statistically significant (in Chapter 3) in the regression-based trading rules, improves the profitability of these rules.

The results that emerge from the traditional analysis indicate that regression-based trading rules substantially outperform the passive buy-and-hold strategy in the majority of the GCC markets (Abu Dhabi, Bahrain, Kuwait, Oman, and Qatar). However, these rules fail to outperform the buy-and-hold strategy in the remaining market (Dubai and Saudi Arabia). Indeed, the inclusion of seasonal dummies seems to have a limited impact on the performance of trading rules.

We have subjected these findings to a number of robustness checks. The main results hold when the CAPM model is used and trading rules appears to be potentially profitable, even when transaction costs are taken into consideration. However, this should be viewed with caution because a reasonably accurate estimate of transaction costs is not available for the GCC markets.

CHAPTER 5

TECHNICAL TRADING STRATEGIES

5.1 Introduction

Technical analysis encompasses a broad range of techniques (chart-pattern analysis, cycle analysis, and computerised algorithmic trading systems) that attempt to predict the direction of future price changes by relying on past price and volume data. These techniques ultimately provide their users with a signal of when to buy or sell a tradable asset. Since the emergence of the Dow theory in the early twentieth century, technical analysis has enjoyed eminence among traders and finance professionals. Technical indicators and charts are widely featured in the financial media, popular finance websites, and online retail brokers.

Survey evidence shows that at least 90 percent of major Forex dealers in London place at least some weight on technical analysis, particularly for short-horizon investment decisions (Taylor and Allen, 1992). Likewise, Menkhoff (2010) reports that the usage of technical analysis is widespread among professional fund managers in five countries, particularly for predicting short-term market movements. Despite its prevalence among practitioners, economists have long been sceptical about the validity of technical analysis as a tool for predicting future price movements. Moreover, the widely accepted position among economists is that if the efficient market hypothesis (EMH) in its weak form holds, trading signals generated on the basis of technical analysis should be redundant.

In the endeavour to resolve this conflict of opinions, numerous empirical studies have been conducted in order to evaluate the performance of technical trading rules. In a pioneering empirical study, Cowles (1933) shows that the trading rule constructed on the basis of Dow theory fails to outperform the naïve buy-and-hold strategy when applied to the DJIA. The findings of subsequent studies (which were carried out using the constituents of the DJIA during the 1950s, 1960s, and 1970s) are essentially consistent with the conclusion of Cowles (1933) (Alexander, 1961; Fama and Blume, 1966; Roberts, 1959). These findings are viewed in favour of the EMH in its weak form.

More recent studies, however, tell a different story. Several empirical studies have found evidence in favour of the ability of technical trading rules to deliver superior returns in stock markets (Brock *et al.*, 1992; Brown *et al.*, 1998; Lo *et al.*, 2000; Neftci, 1991; Sullivan *et al.*, 1999). A small but vocal minority of researchers, however, maintain that once transaction costs and data-snooping bias are carefully controlled for, the gains obtained from technical trading rules are mostly eliminated (Allen and Karjalainen, 1999; Bajgrowicz and Scaillet, 2012; Bessembinder and Chan, 1998; Ready, 2002).[34] Furthermore, Shintani *et al.* (2012) cast doubt on the validity of the statistical Procedures routinely used to assess the performance of technical trading rules, particularly in relatively long horizons. Neely *et al.* (2009) and Taylor (2014) show that the performance of technical trading rules is time-varying with extended periods of success and failure. Moreover, Neely *et al.* (2009) show that once a trading rule becomes widely known, its profitability gradually declines and that more sophisticated rules remain viable relative to simpler ones. This new strand of literature

[34] Sullivan *et al.* (1999, p. 1647-1648) state that "data-snooping occurs when a given set of data is used more than once for purposes of inference or model selection [and they argue that] when such data reuse occurs, there is always the possibility that any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results".

postulates that these findings are consistent with the adaptive market hypothesis (AMH) (Lo, 2004, 2005, 2012) instead of the EMH.[35]

The majority of papers in the extant literature focus on US broad market indices, in particular the DJIA and the S&P 500, which amplifies the likelihood of biases of various sorts. Jensen and Benington (1970) posit that the superior performance of trading rules is often induced by selection bias.[36] Merton (1985) highlights the danger of selection bias and cognitive bias that can potentially influence the results when examining the behaviour of stock returns.[37] Lo and MacKinlay (1990) maintain that the degree of data-snooping bias rises with the number of published papers on the topic. Many studies, in addition, warn of the threat of statistical biases (Black, 1993; Denton, 1985; Ferson *et al.*, 2003; Shintani *et al.*, 2012).[38] Two major techniques have been developed to mitigate data-snooping bias: White's bootstrap reality check (BRC) test (White, 2000), and the false discovery-rate (FDR) test proposed by Barras *et al.* (2010). While these techniques deal with data-snooping bias, it is difficult to account for other biases that could potentially affect the results. Indeed, the best remedy against these

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[35] The AMH suggests that traders change their strategies in response to the changing market conditions in order to survive. However, because traders are subject to cognitive biases, their response to the changes in market conditions is rather slow. On the other hand, the EMH, which rests on the assumption that traders are rational utility-maximisers, implies that traders arbitrage away such opportunities.

[36] In their critique of the Levy (1967) paper, where he reports evidence in favour of the profitability of trading rules, Jensen and Benington (1970, p. 420) emphasise the danger of selection bias by arguing that "given enough computer time, we are sure that we can find a mechanical trading rule which works on a table of random numbers provided of course that we are allowed to test the rule on the same table of numbers which we used to discover the rule. [they add] we realize of course that the rule would prove useless on any other table of random numbers, and this is exactly the issue with Levy's results".

[37] Merton (1985) argues that economists tend to focus on empirical results which are unusual and appear to be inconsistent with the widely accepted theories of asset pricing. He points out that this behaviour is in accordance with the "cogitative biases" documented by Tversky and Kahneman (1974). Cognitive bias stems from "bounded rationality"; that is, the limited capacity for information-processing. In addition, Merton (1985) emphasises the fact that such anomalous results are more likely to be published in peer-reviewed journals compared to those that merely confirm a widely accepted theory. Taken altogether, Merton (1985, p. 20) posits that having "little control over the number of tests performed, creates a fertile environment for both unintended selection bias and for attaching greater significance to otherwise unbiased estimates than is justified".

[38] Shintani *et al.* (2012) provide theoretical and empirical evidence suggesting that the apparent success of technical trading rules using a relatively long time series of stock prices is likely to be spurious. This is because the regressions used to evaluate the performance of technical trading rules have similar features to those highlighted by Granger and Newbold (1974) and Phillips (1986).

biases is to conduct out-of-sample testing using an independent data set (Fama, 1991; Lakonishok and Smidt, 1988). The empirical evidence shows that emerging stock markets are weakly correlated with their developed counterparts (Harvey, 1995). Therefore, it is postulated that investigating the profitability of technical trading rules in emerging markets serves as a validation test on a sample that is characterised by relatively low correlation with the data used in previous research (Hameed and Kusnadi, 2002; Rouwenhorst, 1999).

The general flavour of non-US studies is that technical trading rules beat the buy-and-hold trading strategy, even after transaction costs are considered, particularly in small and medium-size markets. Nonetheless, these gains are diminished in larger markets (Bessembinder and Chan, 1995; McKenzie, 2007; Metghalchi *et al.*, 2012; Yu *et al.*, 2013). Despite the abundance of studies that examine the profitability of technical trading in developed and emerging markets, the empirical evidence on the profitability of these rules in GCC markets is sparse.

The bulk of GCC-based studies are centred on finding out whether or not the EMH holds in these markets using a battery of statistical measures, namely autocorrelations, runs tests, and variance ratios (for example Abraham *et al.*, 2002; Al-Ajmi and Kim, 2012; Al-Loughani, 1995; Al-Khazali *et al.*, 2007; Bley, 2011; Butler and Malaikah, 1992). The empirical evidence offered by Bley (2011) and Butler and Malaikah (1992) shows that the GCC stock returns exhibit significant positive autocorrelation. Using a number of variance ratio tests, Al-Ajmi and Kim (2012) and Bley (2011) conclude that GCC markets are inefficient in the weak form, particularly when daily frequency is considered.

In a similar vein, Abdmoulah (2010) and Niemczak and Smith (2013) examine evolving efficiency in MENA stock markets. Their empirical findings suggest that these markets witness prolonged departures from market efficiency, which is consistent with the AMH proposed by Lo (2004, 2005, 2012). Other studies focus on the financial integration of GCC markets. The thrust of these studies is that GCC markets are segmented from their developed counterparts (Bley and Chen, 2006; Cheng *et al.*, 2010; Hammoudeh and Choi, 2006; Yu and Hassan, 2008). The weak correlation of GCC stock returns with developed markets (particularly the US market), and their positive correlation with oil prices, offer diversification benefits (Bley and Chen, 2006; Cheng *et al.*, 2010; Hammoudeh and Choi, 2006; Yu and Hassan, 2008) and provide a valuable hedge against the oil-price risk faced by oil-importing economies (Abraham *et al.*, 2001; Hammoudeh and Choi, 2006).

The survey evidence provided by Al-Abdulqader *et al.* (2007) reveals that the use of technical analysis is widespread among investors in the Saudi stock market. Almujamed *et al.* (2013) reach a similar conclusion in the case of Kuwait. The results of these studies are in line with those of Menkhoff (2010) and Taylor and Allen (1992). Despite the reported prevalence of technical analysis among Saudi and Kuwaiti investors, the studies that empirically examine the profitability of technical trading rules in the GCC markets are scarce. To the best of our knowledge, only two studies do that: Al-Loughani and Moosa (1997) for Kuwait and, more recently, Metghalchi and Garza-Gomez (2011), who examine the Abu Dhabi market. These gaps in the literature offer a valuable setting in which to confirm, reject, or expand upon the conclusions of existing research in the profitability of technical trading strategies literature in the following three ways:

- Guarding against data-snooping bias, sample-selection bias, and other potential biases that may affect the results by conducting a true out-of-sample validity test that applies the same set of trading rules examined by Brock *et al.* (1992) to an independent fresh data set.

- Maintaining continuity with prior studies by using the trading rules tested by Brock *et al.* (1992). While these trading rules are not the most sophisticated and advanced techniques available to predict price movements, they are certainly known to the traders throughout the sample period. This procedure provides insulation from the threat of rule snooping.[39]
- Examining the evolution of the profitability of the trading rules over time and the possible effects of the developments in market microstructure, market integration, and the financial and political crises on the performance of these rules.

5.2 Literature Review

The literature on trading rules profitability is very extensive. The history of technical analysis can be traced back to the work of Charles H Dow, the founder of the *Wall Street Journal* and the co-founder of Dow Jones and Company. Attempting to beat the market, Dow developed a number of principles that describe the market's behaviour. These principles are nowadays referred to as the "Dow theory", which is considered to be the underpinning of the technical analysis. The concepts put forward by Dow were further developed and popularised by Hamilton (1922) and Rhea (1932). The main thrust of technical analysis is elegantly summarised by Roberts (1959, p. 1) as:

> While financial analysts agree that underlying economic facts and relationships are important, many also believe that the history of the market itself contains "patterns" that give clues to the future, if only these patterns can be properly understood. The Dow theory and its many offspring are evidence of this conviction. In the extreme form, such theories maintain that only the patterns of the past need to be studied, since the effect of everything else is reflected "on the tape".

[39] In their definition of the EMH, Timmermann and Granger (2004) posit that investors are faced with uncertainty when choosing a forecasting model from a theoretically unlimited universe of available forecasting models; this results in short-lived episodes of predictability. Therefore, instead of the classic definition of market efficiency, they introduce the concept of a market being "efficient locally in time" with respect to information set Ω_t, as well as the forecasting model $m_{it}(z_t, \hat{\theta}_t)$ selected from available M_t if $E\left[f_t\left(R^*_{t+1}, m_{it}\left(z_t, \hat{\theta}_t\right), c_t\right)\right] = 0$. Moreover, they highlight the importance of the availability of the forecasting model at time t (the beginning of the sample period) as Timmermann and Granger (2004, p. 20) write: "We can imagine that some models had predictive power before their discovery (e.g. neural networks may have worked well during, say, the 1960s). [they add that] this would not constitute a violation of the EMH defined [above] since such models would not be elements in the relevant set, M_t".

The behaviour of speculative prices, however, is perceived differently by economists and statisticians. In the pioneering empirical study of the forecasting ability of the Dow theory, Cowles (1933) evaluated the Dow theory as applied by its principal practitioner, William Peter Hamilton, over the period 1902 to 1929. Utilising Hamilton's editorials that were published in the *Wall Street Journal*, Cowles (1933) constructed a trading rule on the basis of the Hamilton's predictions of market moves. He showed that the naïve buy-and-hold strategy generated higher returns than the trading rule formulated on the basis of Dow theory.

The debate about the forecasting ability of technical trading rules has attracted the attention of statisticians. In a landmark paper, Kendall (1953) showed empirically that past price changes have no bearing on future price changes. His finding was reached by calculating serial correlations of the first differences of the 22 time series representing speculative prices. Across 19 out of the 22 time series under examination, no significant autocorrelation was found of any order up to the 29^{th} lag. These findings are at odds with the position long held by professional traders and analysts that the speculative price changes follow trends. Moreover, Kendall (1953) concluded that speculative prices resemble a random walk.

In a subsequent study, Roberts (1959) simulated an artificial price series which showed a striking resemblance to the actual price series. Indeed, the classic patterns of technical analysis such as "head-and-shoulders" are found in both the actual and the simulated series. Moreover, Fama (1965) provided empirical evidence in favour of the RW hypothesis using statistical tests of independence (serial correlation and runs tests), in addition to investigating the profitability of technical trading directly by using the filter trading rule advanced by Alexander (1961). Indeed, the findings of Alexander (1961) are mostly in accordance with Fama (1965) and prior studies. Alexander (1961, p. 26) concludes with following statement:

> The findings surveyed in this paper can be summarized by the statement that, in speculative markets, price changes appear to follow a random walk over time, but a move, once initiated, tends to persist. In particular, if the stock markets has moved up x percent it is likely to move up more than x percent further before it moves down by x percent.

As can be gleaned from previous research, while price changes resemble a random walk, episodes of predictability cannot be ruled out. Fama (1965) posits that while the studies that examine the behaviour of stock-price changes using a statistical approach are abundant, testing technical theories directly would constitute a valuable contribution to the literature. Therefore, there has been a proliferation in the number of studies that test directly the profitability of technical trading rules in stock, foreign exchange, and commodity markets over the last 50 years. These studies examine a plethora of technical trading strategies.

The most extensively studied trading strategies are technical trading systems, namely the moving averages and trade range breakouts trading rules (for example Bessembinder and Chan, 1995; Brock *et al.*, 1992; Hudson *et al.*, 1996; Mills, 1997), the relative-strength index (Chong and Ng, 2008; Wilder, 1986), and the filter rule (Alexander, 1961; Fama and Blume, 1966). This is, in part, because these rules can be easily expressed in quantitative terms. On the other hand, testing the usefulness of charting heuristics is more challenging, as these techniques are subject to the researcher's prejudices. Indeed, advances in computing power have led to an increasing number of studies that investigate the forecasting power of various chart patterns via pattern-recognition algorithms (Lo *et al.*, 2000; Osler and Chang, 1995; Savin *et al.*, 2007), and Japanese candle sticks (Lu and Shiu, 2012; Marshall *et al.*, 2006).

In a comprehensive review of this literature, Park and Irwin (2007) survey 137 papers on technical trading strategies and divide the empirical literature chronologically into early studies that span the period 1960 to 1987, and the more modern studies that began with

Lukac *et al.* (1988a). The early studies concluded that technical trading strategies are profitable in foreign exchange markets and futures markets, but not in stock markets. However, the more modern studies predominantly show that technical trading strategies consistently generated economic profits in stock markets as well as in foreign exchange and futures markets, at least until the early 1990s.

Park and Irwin (2007) report that about half of the published empirical work on technical trading strategies was done over the period 1995 to 2004. Early studies, in general, examined few trading rules with little attention given to transaction costs, risk adjustment, and statistical procedures. However, the more modern studies use more sophisticated statistical techniques and examine a large set of trading rules in order to control for data-snooping biases. Moreover, they tend more often than their early counterparts to account for transaction costs and to consider carefully the risk-return trade-off when evaluating the profitability of trading rules.

Among the noteworthy modern studies is the influential paper of Brock *et al.* (1992) who evaluated the performance of widely used technical trading systems, moving averages, and trade-range breakouts, as applied to the DJIA. Their sample spans the period from 1897 to 1986. To guard against data-snooping bias, Brock *et al.* (1992) tested 26 trading rules without optimisation and reported their performance. Their empirical results indicate that the majority of the technical trading rules outperform the buy-and-hold strategy. In fact, a shortcoming of the Brock *et al.* (1992) study is that transaction costs are not considered.

Another prime example of modern studies is the research conducted by Sullivan *et al.* (1999); they expand the universe of trading rules tested in Brock *et al.* (1992) to 7846. They examine the out-of-sample validity of the Brock *et al.* (1992) findings by updating the sample period by 10 years (1987 to 1996). While the Bonferroni correction is considered to be a remedy for data-snooping bias, it is far too conservative, especially when the number of investigated trading rules is large.[40] To alleviate data-snooping bias, Sullivan *et al.* (1999) use White's BRC methodology (White, 2000) to investigate the concern raised by Brock *et al.* (1992) as to the need for a joint test across all trading rules, taking into consideration the dependency between the performance of trading rules.

The BRC methodology is primarily a joint test that enables explicit adjustment for data-snooping bias by considering the entire universe from which a rule is selected. Specifically, this method is used to find out whether the profitability of the best-performing trading rule is genuine, and is not simply due to chance, by reducing the statistical significance of profitable trading rules for data-snooping bias. This is achieved by testing the null hypothesis that the best trading rule from the universe of M rules does not outperform a benchmark strategy, $H_0: max_{k=1,\dots,M}\,\varphi_k \leq 0$, where φ_k is the performance metric of the rule k relative to the benchmark.

Sullivan *et al.* (1999) show that the results of Brock *et al.* (1992) are robust to data-snooping bias, as they find trading rules that perform better than those considered by Brock *et al.* (1992) across all subsamples. Nonetheless, the results reveal that technical trading rules failed to outperform the buy-and-hold strategy over the 10-year out-of-sample period. A recent study reached the same conclusion by analysing a longer out-of-sample period (Fang *et al.*, 2014).

Many extensions to White's BRC methodology have been suggested. While the BRC test only considers the best-performing trading rule and is unable to identify further trading rules

[40] The Bonferroni correction is applied by adjusting down the significance level, α, by the number of trading rules under examination (M). The individual tests are evaluated at the α/M level.

that produce a genuine performance, in practice investors consider more than one trading rule to diversify model risk. Romano and Wolf (2005) (RW) deal with this shortcoming by developing a stepwise multiple-testing method that not only utilises a different version of BRC as a first step to identify the best-performing trading rule, but it also detects further trading rules with true performance in subsequent steps.

In a similar vein, Bajgrowicz and Scaillet (2012) utilise a newer approach to alleviate data-snooping bias, which is the FDR method proposed by Barras *et al.* (2010). Compared to the BRC methodology, the FDR approach selects more out-performing rules which enables diversification against model risk, instead of just selecting the best trading rule from the universe of M rules, as in the case of the BRC test. Bajgrowicz and Scaillet (2012) use Monte Carlo simulations and empirical analysis to show that the FDR approach is more powerful and that it allows for selecting more rules when compared to the RW method.

With respect to the diversification of model risk, Bajgrowicz and Scaillet (2012) argue that investors tend to examine the performance of trading rules on a monthly basis, such that they retain the profitable rules and discard those that perform poorly. In response to this issue, Bajgrowicz and Scaillet (2012) employ a novel approach to evaluate the performance of technical rules out-of-sample in a similar manner to what an investor would do in practice. They apply the persistence analysis approach proposed by Carhart (1997) to technical trading rules' performance appraisal. This analysis is conducted monthly by forming four portfolios of the best-performing trading rules using price data for the past month. These rules are selected on the basis of the FDR, RW, and BRC (the best trading rule) approaches, as well as the best-performing 50 rules. Then, the out-of-sample performance of the previously selected rules is evaluated over the subsequent month. The process is repeated every month by rebalancing the portfolio of rules until the end of the sample period is reached.

Bajgrowicz and Scaillet (2012) note that some of the best-performing trading rules generate a large number of trading signals which could offset their profitability once they account for transaction costs. Thus, they expanded persistence analysis in a way that incorporates transaction costs into the best-performing-rules selection process. In the empirical section of their paper, they use the DJIA data over the period from 1897 to 2011 and reveal that the turnover of trading rules in the four portfolios is very high. Therefore, they rightly argue that while it is possible to find trading rules with predictive power *ex post*, the future best-performing trading rules would never have been selected *ex ante*. In addition, even the usual in-sample results show that the profitability of trading rules is eliminated upon the introduction of low transaction costs.

The methodological innovations introduced in modern studies have refuted the conclusion of the earlier studies. For instance, Brown *et al.* (1998) replicate the study of Cowles (1933) and find that the buy-and-hold strategy outperforms the trading rule constructed on the basis of Dow theory when focusing only on the return dimension. On the other hand, when measures of risk-adjusted returns (Jensen's alpha and the Sharpe ratio) are used, the trading rule constructed on the basis of Dow theory outperforms the buy-and-hold strategy. Brown *et al.* (1998) argue that these findings cast doubt on the empirical foundations of the EMH.

Several studies provide empirical evidence in support of the notion of differing levels of predictability between markets. Siegel (1998) maintains that weak-form efficiency is more likely to be rejected in young markets. Thus, the less-investigated small cap indices, such as the S&P 600 and the Russell 2000 have recently attracted the attention of researchers. This interest stems from empirical evidence indicating that the momentum effect and autocorrelation are more pronounced in small cap stocks (Hong *et al.*, 2000; Knez and Ready, 1996; Lo and MacKinlay, 1990). The persistence in small cap stocks is thought be potentially exploitable via trend-chasing trading rules. Hsu and Kuan (2005) examine the profitability of technical trading rules when applied to the DJIA, S&P 500, the NASDAQ composite, and Russell 2000 over the period 1989 to 2002. Their empirical results reveal that while technical trading rules fail to generate profits for the DJIA and S&P 500, significantly profitable trading rules are found when data from the NASDQ and Russell 2000 are utilised. In a later study, Hsu *et al.* (2010) show that the profitability of technical trading rules was eliminated following the introduction Exchange Traded Funds (ETF).

In a recent study, Shynkevich (2012) evaluates the profitability of a large universe of technical trading rules. The data set comprises several technology-industry and small cap sector portfolios throughout the 1995 to 2010 period. The empirical findings of this paper are that for the first half of the sample period, technical trading rules are able to deliver statistically significant profits for a number of portfolios, even when transaction costs are taken into consideration. For the second half of the sample, however, no statistically significant profits are found for any of the portfolios under examination. He links the profitability of technical trading rules to the presence of positive autocorrelation in stock returns during the first half of the sample period, which becomes negative in the second half. He interprets the findings as an improvement in market efficiency, which could be attributed to developments in equity-market microstructure, such as the introduction of ETF and decimalisation of quotes.

While the majority of studies focus on the US markets, Metghalchi *et al.* (2012) examine the performance of technical trading rules using a sample of 16 European stock markets of different market capitalisations and maturity, over the period from 1990 to 2006. Although Metghalchi *et al.* (2012) use different trading rules from those used by Brock *et al.* (1992), they use the White (2000) BRC test to account for data-snooping bias. Their results indicate that buy (sell) signals generated by technical trading rules are able to discriminate between positive (negative) market movements, as the majority of buy-sell spreads are shown to be statistically significant. In addition, they find evidence in support of the hypothesis that the returns produced by technical trading rules are higher than those offered by the buy-and-hold strategy, even after taking transaction costs into consideration. Consistent with the conjecture of Siegel (1998), that young markets are more likely to be less efficient than developed markets, as well as the empirical findings of Shynkevich (2012), Metghalchi *et al.* (2012) conclude that the gains from technical rules are more pronounced in small and medium markets.

Another strand of this literature focuses on emerging markets, which serve as an out-of-sample validity test. Bessembinder and Chan (1995) examine the profitability of the set of trading rules initially used by Brock *et al.* (1992). Their sample comprises six Asian stock markets (Hong Kong, Japan, Korea, Malaysia, Thailand, and Taiwan) over the period 1975 to 1991. Their empirical results show that technical trading rules possess predictive power in all of the markets, but with varying degrees of success. The gains from employing technical trading remain largely robust, even after taking into consideration transaction costs and thin trading. The trading rules perform better in the emerging markets of Malaysia, Thailand, and Taiwan. Furthermore, it is shown that trading signals generated by the US market have forecasting power for Asian markets. Bessembinder and Chan (1995) conclude that technical rules are able to exploit the period of temporary departure from market efficiency.

Evidence on the performance of technical trading in South Asia is provided by Gunasekarage and Power (2001) who examine the profitability of moving average trading rules in the stock markets of Pakistan, India, Sri Lanka, and Bangladesh over the period from 1990 to 2000. Their results are that the trading rules they examine can discern positive from negative market movements, as buy (sell) signals are followed by positive (negative) returns. Gunasekarage and Power (2001) show that these trading rules outperform the buy-and-hold strategy. Evidence from the Chilean market, using the same set of rules as Brock *et al.* (1992) over the period from 1987 to 1998 tells a similar story (Parisi and Vasquez, 2000). However, Parisi and Vasquez (2000) indicate that when transaction costs are accounted for, the profitability of the trading rules is largely compromised.

McKenzie (2007) analyses the performance of the Brock *et al.* (1992) trading rules using a broad sample of 17 Asian and South American emerging markets, in addition to the US market, as a proxy for developed markets over the period from 1986 to 2003. His sample includes the period of the Asian financial crisis. He finds that some trading rules produce statistically significant returns in emerging markets, but not in the developed market of the US. Nonetheless, no trading rule is found to produce a persistently superior performance. Instead, economic conditions and market depth appear to influence the forecasting power of these rules. This is evident, as the forecasting power of these rules declines during the post-crisis period.

Cheung *et al.* (2011) focus on the effect of market integration on information efficiency through the profitability of technical trading rules. They utilise a sample that spans the period from 1972 to 2006 for the Hong Kong stock exchange. The researchers use the Brock *et al.* (1992) trading rules and conduct a recursive optimisation procedure whereby they select the best-performing technical rule over the in-sample period and then apply it out-of-sample to mitigate data-snooping bias. Their empirical results show that while the VMA (1, 50) rule outperforms the market before market integration, it fails to do so after 1986. This finding led them to conclude that market integration could enhance informational efficiency.

In a recent study, Yu *et al.* (2013) examine the performance of the Brock *et al.* (1992) trading rules in the markets of Malaysia, Thailand, Indonesia, the Philippines, and Singapore over the period from 1991 to 2008. In accordance with previous studies, they find that trading rules with shorter moving average windows performed better than those with longer windows. Furthermore, technical trading rules fare better in the emerging markets of Malaysia, Thailand, Indonesia, and the Philippines than in the more developed market of Singapore. Contrary to previous studies, it is shown that the gains from technical trading are largely offset by transaction costs, suggesting that market efficiency has improved over time in the markets under investigation.

In the majority of studies in the existing literature, various technical trading strategies are applied on the full sample or a few subsamples. These studies make the restrictive assumption that market efficiency is constant over time, in spite of changing market conditions.[41] The question addressed by these studies is whether a particular market is or is not weak-form efficient over the sample period in the absolute sense. The results in favour of the profitability of the technical analysis reported in these studies have long been interpreted as evidence against the EMH in its weak form. Several plausible explanations for the so-called "technical trading puzzle" have been put forward.

[41] In a recent paper, Taylor (2014) uses a smooth transition regression to allow for the possibility of time-varying returns. Other researchers deal with this issue by employing rolling window to track the evolution in the performance of trading rules (for example Neely *et al*., 2009).

In their review paper, Park and Irwin (2007) divide these explanations into theoretical and empirical. The theoretical models that offer justifications for the gains from technical trading include the noisy rational expectation models (Blume *et al.*, 1994; Brown and Jennings, 1989; Grossman and Stiglitz, 1976, 1980; Grundy and McNichols, 1989; Hellwig, 1982). While the EMH posits that new information is instantaneously incorporated into the price, the noisy rational expectations models conjecture that noise as well as the high cost of obtaining information contribute to the price not being fully revealing. The sluggish adjustment of stock prices in response to new information is evident by prolonged trends that can be exploited by technical traders.

Another plausible explanation is offered in behavioural models (Black, 1986; DeLong *et al.*, 1988, 1990; Shleifer and Summers, 1990). The thrust of behavioural models is that noise traders (that is, irrational investors who trade on sentiment rather than fundamental factors) are, as with technical traders, likely to follow positive feedback strategies (buy when prices rise). This leads to price surges due to increased demand for the underlying asset, which are not justified by fundamentals. On the other hand, arbitragers who trade only on the basis of information, and who are not subjected to sentiment, recognise that the asset is overpriced. However, fundamental risk (that is, the possibility of the asset being even more overpriced due to the overconfidence of irrational noise traders) limits arbitrage. Instead, it is optimal for arbitragers to "jump on the bandwagon" by buying the asset that noise traders have purchased and selling it later at a higher price. While arbitragers eventually drive prices back to their fundamentals, they exacerbate the effect of noise traders in the short run. Similarly, the herding model proposed by Froot *et al.* (1992) suggests that the prevalence of technical trading among a large number of investors may be sufficient to generate profits for those who employ technical trading rules. They argue further that it is optimal for speculators to use technical trading rules when such techniques are popular.

As elaborate data sets become available, novel insights are gained as to the reasons behind the profitability of trading rules. A prominent source of such data is limit-order books, which list outstanding limit orders according to price and (or) time priorities and constitute an essential source of liquidity. In fact, limit-order books are akin to demand and supply schedules. Kavajecz (1999) shows that limit orders tend to cluster at a few price limits, rather than being equally spread over a wider range, creating distinctive “peaks” of liquidity. Thus, the price levels at which limit orders cluster serve as an obstacle to reaching higher or lower price levels. In an interesting study, Osler (2003) uses data on stop-loss and take-profit orders (that are basically limit orders) for three foreign exchange pairs (USD/JPY, USD/GPB, and EUR/USD) and finds that order flows cluster at round numbers. She shows that these “peaks” of liquidity coincide with the support and resistance level. Another study by Kavajecz and Odders-White (2004) arrives at a similar conclusion by estimating limit-order books for 110 NYSE stocks. Their empirical analysis reveals that support and resistance levels are cointegrated with limit-order prices that have high cumulative depth (clusters of limit orders at a few prices). In addition, buy (sell) signals generated by moving average trading rules are in line with shifts in quoted prices towards buy-side (sell-side) liquidity levels and away from sell-side (buy-side) levels.

Another factor that can drive the profitability of technical trading is temporary market inefficiencies. Several studies document that temporary market inefficiencies coincide with the temporal profitability of trading rules (for example Bajgrowicz and Scaillet, 2012; Fang *et al.*, 2014; Olson, 2004; Sullivan *et al.*, 1999; Taylor, 2014). These studies show that the profitability of trading rules vanished over recent periods. Two potential explanations for this phenomenon are offered. The first is that the trading rules that are widely investigated in the literature become obsolete, as more investors become aware of their merits. This is evident from the documented short-lived episodes of profitability that could have been exploited by the first users of these rules (Timmermann and Granger, 2004). The second is structural changes such as the introduction of electronic trading and ETF, which enhanced market efficiency by reducing transaction costs and increasing the speed of adjustment to new information. The empirical evidence offered by Hsu *et al.* (2010) demonstrates that the profitability of technical trading rules is eliminated after the introduction of ETFs.

Brock *et al.* (1992) note that predictable variations in stock returns can be attributed to market inefficiency or, alternatively, it can be explained by the proposition that the market may be efficient, but the apparent predictability is due to time-varying risk premiums. Several performance-evaluation metrics have been used to judge the profitability of technical trading rules. These include the Sharpe ratio, the CAPM, and more recently the conditional CAPM. Both the CAPM and the Sharpe ratio—widely used in the technical trading literature—have a number of drawbacks. The Sharpe ratio is criticised for penalising the variability of gains and losses at exactly the same rate, although investors are more concerned about downside volatility. The CAPM, on the other hand, is subject to the Roll critique (Roll, 1977). Besides, the CAPM and other multi-factor pricing models are prone to misspecification (Fama, 1998). Therefore, one is not able to ascertain whether the rejection of the CAPM (when the intercept is statistically significant) is due to market inefficiency or model misspecification.[42] Indeed, the studies that utilised the CAPM—which assumes that risk premiums are constant over time—fail to explain the gains from technical trading (Levich and Thomas, 1993; Lukac *et*

[42] This is formally referred to as the "joint hypothesis".

al., 1988b; Neely *et al.*, 1997; Sweeney, 1986). The conditional CAPM alleviate some of the limitations that are associated with the CAPM by allowing for time-variation in the expected return. However, the results obtained using the conditional CAPM are far from conclusive. While Kho (1996) and Sapp (2004) show that a large fraction of the gains from technical trading are explained by time-varying risk premiums estimated using conditional CAPM, others document the failure of the same technique to account for the returns of technical trading rules (McCurdy and Morgan, 1987; Okunev and White, 2003).

Although market microstructure deficiencies are largely dismissed by Brock *et al.* (1992) as an explanation for the profitability of trading rules, they have received considerable attention. Among the suggested microstructural explanations for the apparent success of technical trading rules in outperforming the buy-and-hold strategy is their lack of attention to transaction costs (Greer *et al.*, 1992), and non-synchronous trading (Day and Wang, 2002). Indeed, both of these limitations can potentially overstate the profits realised by using technical trading rules; but it may be data-snooping bias (Bajgrowicz and Scaillet, 2012; Brock *et al.*, 1992; Jensen and Benington, 1970; Ready, 2002; Sullivan *et al.*, 1999).

In a review paper, Subrahmanyam (2008) articulates that behavioural models have long been criticised by the proponents of the EMH on three grounds. The first is that behavioural finance models tend to offer *ad hoc* and somewhat tailor-made explanations for specific stylised facts. The second is that the documented empirical support for behavioural models is routinely dismissed by the proponents of the EMH as merely a manifestation of data-snooping bias. Finally, the absence of a unified theoretical framework for behavioural finance, akin to utility maximisation using rational expectations, has long been a weakness of behavioural finance models. Subrahmanyam (2008) suggests that while the first two criticisms are debatable, the last objection is valid.

A common feature of these explanations is that the profit opportunities are relatively short-lived and hard to exploit. In an effort to construct a cohesive theoretical framework for behavioural finance, Lo (2004, 2005, 2012) puts forward the AMH, which is an alternative to the EMH and couples evolutionary principles and the bounded-rationality notion of Simon (1955). Under the AMH, individual agents are no longer assumed to be hyper-rational but rather mere "satisficers" in the terminology of Simon (1955). Thus, they arrive at their decision using rules of thumb that are adapted through trial and error, while being incapable of any elaborate optimisation. The predictions that can be derived from the AMH with respect to the profitability of technical trading are:

- Profit opportunities arise in financial markets in general.
- Profit opportunities will become gradually obsolete due to the forces of learning and completion.
- More sophisticated trading strategies will persist for longer than simple ones.

Empirical evidence in support of the AMH has accumulated over the past few years. The empirical regularities of booms and busts in the profitability of technical rules were found not only to be confined to the recent period, but are also strongly present in earlier time periods and across asset classes. The main thrust of these studies is that while the reported abnormal performance of technical trading rules is not simply a consequence of data snooping, it is highly temporal. However, the slow deterioration of the performance of these trading rules is seen to be consistent with the AMH rather than the EMH.

In a leading paper, Neely *et al.* (2009) investigate the profitability of previously used technical trading rules utilising a sample of 12 currency pairs from developed markets over the period from 1973 to 2005. In order to ascertain whether the performance of technical trading rules is genuine or merely driven by data snooping, they carefully examine the out-of-sample performance of several previously studied trading rules in the foreign exchange market. Neely *et al.* (2009) replicate five well-cited papers (Dueker and Neely, 2007; Levich and Thomas, 1993; Neely *et al.*, 1997; Sweeney, 1986; Taylor, 1994). For each of these considered studies, the data set is divided into the in-sample period that the original paper used and an out-of-sample period for verification purposes. Their empirical findings suggest that the performance of the technical trading rules originally documented in previous studies is genuine and is not simply due to data snooping. However, the out-of-sample results indicate that the performance of the technical trading rules under investigation has gradually deteriorated and that returns to the more-sophisticated or less-studied trading rules have also declined, but at a much slower pace. Neely *et al.* (2009) conclude that the gradual decline in the performance of the technical trading rules reflects the sluggish response of market participants to profit opportunities, which is consistent with the AMH view of markets as adaptive systems driven by evolutionary selection pressures.

Neely and Weller (2013) consider an important yet overlooked prediction of the AMH, which states that adaptive trading rules outperform their fixed counterparts. This is because traders under the AMH respond to change in market conditions by altering their trading strategies. To this end, Neely and Weller (2013) use a novel empirical approach wherein they simulate the behaviour of a hypothetical trader who adapts to changing market conditions by using simple rules of thumb in order to maximise his welfare. They apply 17 commonly used trading rules to a sample of 40 foreign-exchange pairs from developed as well as emerging markets. Their adaptive strategy is implemented after an initial period of 500 days, on a monthly basis, at which the performance of the 17 trading rules as applied to the 40 currency pairs (a total maximum of 680 rules) is ranked according to the Sharpe ratio. Ten portfolios are formed on the basis of the Sharpe ratio where this first portfolio comprises the rules with the highest Sharpe ratios and the tenth portfolio includes those with the lowest ratios. In the subsequent month, the constructed portfolios are tested out-of-sample. This process continues on a monthly basis where portfolios are rebalanced until the end of the sample period is reached. The results show that the adaptive strategy outperforms its fixed counterparts, as the rules with high Sharpe ratios in-sample tend perform well out-of-sample. These findings are shown to be robust to different selection windows and subsamples. They also suggest that the reason behind the switch from developed to emerging currencies is that market participants in developed currencies became widely aware of the profitability of these rules, which eventually led to the deterioration in their performance in recent periods. Neely and Weller (2013) conclude that these findings are in line with the predictions of the AMH.

In a recent study, Taylor (2014) investigates the performance of a large universe of technical trading rules as applied to the constituents of the DJIA over the period 1928 to 2011. To gauge the performance of the large universe of trading rules, Taylor (2014) employs an elaborate methodology. The analysis is carried out for every month at which the returns of the pool of technical trading rules, net of transaction costs, is calculated; then, the best-performing rule is tested out-of-sample over the following month using several out-of-sample updating methods. The performance of the selected trading rules is evaluated using stochastic-dominance tests and factor-based tests which are estimated via a smooth transition regression in order to relax the assumption that the performance of technical trading rules is fixed over the sample period. The empirical findings reveal that the performance of the technical trading rules is time-varying (in particular, profit opportunities are clustered around extreme market conditions) and they are only accessible via short selling.

5.3 Research Design

In order to mitigate potential data-snooping bias, and to be able to compare our results with prior studies, we do not search for profitable rules on an *ex-post* basis. Instead, we employ the trading rules tested by Brock *et al.* (1992).

Technical Indicators Used in the Study

The majority of empirical work focuses on the techniques that can be expressed mathematically, particularly trading systems based on moving averages, channels, and momentum oscillators (for example Bessembinder and Chan, 1995; Brock *et al.*, 1992; Hudson *et al.*, 1996; Ito, 1999). Nonetheless, there is a growing literature on visual patterns (Lo *et al.*, 2000; Marshall *et al.*, 2006), as well as computerised trading systems (for example Allen and Karjalainen, 1999). In this study, we focus on trading systems based on moving averages and channels for the following two reasons. First, trading decisions based on observing chart patterns may be subjected to the analyst's biases, as these patterns cannot be easily reformulated to be quantitative indicators. Second, some of these advanced techniques were not available or accessible during the early periods in our sample. Therefore, we use these trading rules to be able to compare our empirical results with the majority of prior studies, and to mitigate data-snooping bias that could manifest when the advanced methods are used. The technical trading rules we employ include moving average oscillator rules, as well as the trading-range break rules. Each rule is tested using a variable, as well as a fixed holding-period of 10 days, with and without a 1 percent filter. Thus, we end up with four pairs of trading rules: (i) variable moving average (VMA) with no filter, and a 1 percent filter; (ii) fixed moving average (FMA) with no filter, and a 1 percent filter; (iii) variable trading-range break (VTRB) with no filter, and a 1 percent filter; and (iv) fixed trading-range break (FTRB) with no filter, and a 1 percent filter.

The first form of trading rules that we analyse is the moving average oscillator rule. This rule is one of the most popular trend-determining techniques. It is constructed by calculating two moving averages (MA_t) of the raw index level at time t ($p_{i,t}$), a short moving average of window length S, and a long moving average of window length $L(L > S)$. These moving averages are expressed, respectively, as:

$$MA_t(S) = \frac{1}{S}\sum_{j=0}^{S-1} p_{t-j} \tag{5.1}$$

$$MA_t(L) = \frac{1}{L}\sum_{j=0}^{L-1} p_{t-j} \tag{5.2}$$

Basically, this rule generates a buy (sell) signal when the short moving average $MA_t(S)$ penetrates the long moving average $MA_t(L)$ from below (above). Once the two moving averages intersect, a trend is said to be initiated. More formally, the buy and sell signals are generated, respectively, according to the following rules:

$$I_t^b = \begin{cases} 1 \text{ if } MA_t(S) > MA_t(L) \\ 0 \ otherwise \end{cases} \tag{5.3}$$

$$I_t^s = \begin{cases} 1 \text{ if } MA_t(S) < MA_t(L) \\ 0 \ otherwise \end{cases} \tag{5.4}$$

The length of the moving average windows is important, as it is essential to select the window length that not only filters out noise from the data, but also remains sufficiently sensitive to capture trends early in their onset. In order to avoid excessive transaction costs from false trading signals, a variation on this rule employs an additional filter. For a trading signal to be generated, the $MA_t(S)$ must rise above or fall below the $MA_t(L)$ by some pre-determined amount or filter of size T. Augmenting the trading rule with a filter minimises spurious trading signals that are generated when the two moving averages fluctuate closely together and intersect frequently.

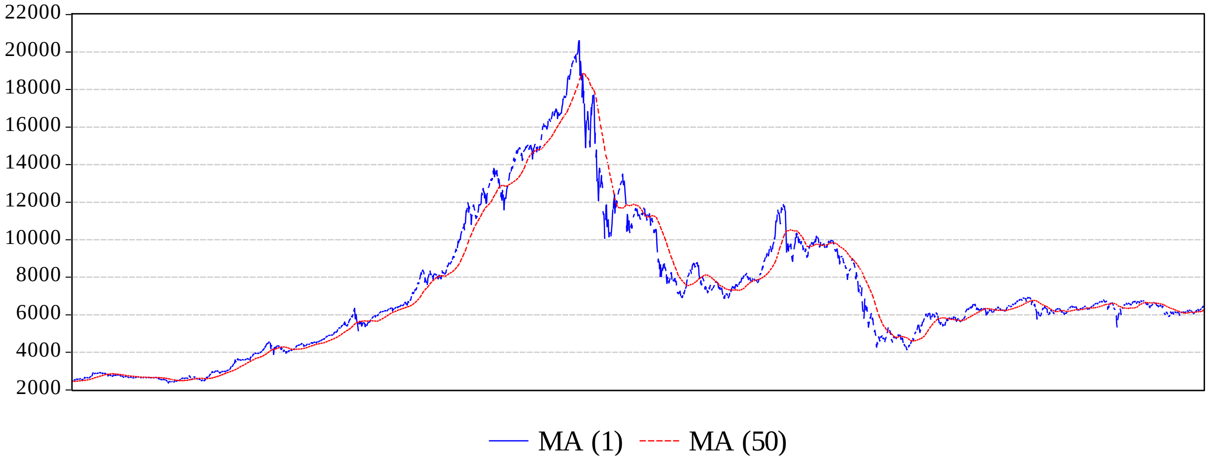
There exist an enormous number of moving average oscillator rule specifications that can be formulated by varying the window-length parameters S and L and the size of the filter T. In a remarkable paper, Sullivan *et al.* (1999) tested 2049 moving average oscillator rules selected from a theoretically infinite universe of trading rules. The conventional way of expressing these rules is *(S,L,T)* for example (5,150,1); it means that the short moving average $MA_t(S)$ is five days, the long moving average $MA_t(L)$ is 150 days, and the filter is 1 percent of the returns. Brock *et al.* (1992) argue that the most common moving average oscillator rules are (1,50), (1,150), (5,150), (1,200) and (2,200) with a trading filter of zero and 1 percent of the returns. When a trading filter is imposed, the rule that generates buy and sell signals is, therefore, rewritten as:

$$I_t^b = \begin{cases} 1 \; if \; MA_t(S) > \; MA_t(L) \times (1+T) \\ 0 \; otherwise \end{cases} \tag{5.5}$$

$$I_t^s = \begin{cases} 1 \text{ if } MA_t(S) < \; MA_t(L) \times (1+T) \\ 0 \; otherwise \end{cases} \tag{5.6}$$

A graphical depiction of a moving average oscillator rule is shown in Figure 5.1. It displays a trading rule of long and short moving averages of window lengths of 1 and 50, respectively, as applied to the Saudi raw market index level over the entire sample period.

Figure 5.1: Signals generated by the VMA (1,50,0) trading rule using the raw index level of the Saudi stock-market index



The second form of trading rule that we analyse is the trading-range break trading rule. This rule is constructed by finding a resistance level of window length L: $Res(L)_t$, defined as a local maximum of the raw index level of the market at time t: p_t, and a support level of the same window length L: $Sup(L)_t$, defined as a local minimum of the same series. The resistance and support levels are respectively given by:

$$Res(L)_t = max\ (p_t, \dots, p_{t-L}) \tag{5.7}$$

$$Sup(L)_t = min\ (p_t, \dots, p_{t-L}) \tag{5.8}$$

Once the current price breaches the support level Sup_{t-1}, a sell signal is generated. By the same token, if the current price breaches the resistance level, a buy signal is generated. If the price remains in the intermediate range then one maintains the original position. This rule can be mathematically defined as:

$$I_t^b = \begin{cases} 1 \text{ if } p_t > Res_{t-1} \\ 0 \text{ if } p_t < Sup_{t-1} \\ I_{t-1}^b\ otherwise, \end{cases} \tag{5.9}$$

$$I_t^s = \begin{cases} 1 \text{ if } p_t < Sup_{t-1} \\ 0 \text{ if } p_t > Res_{t-1} \\ I_{t-1}^s\ otherwise \end{cases} \tag{5.10}$$

As with the moving average oscillator rules, there exist an enormous number of TRBs. Sullivan *et al.* (1999) test 1220 formulations of this trading rule. In the present study, we follow Brock *et al.* (1992), L is set at 50, 150, and 200 days, and the filter is at 1 percent to limit the occurrence of spurious signals. Thus, the rule that generates buy and sell signals is rewritten as:

$$I_t^b = \begin{cases} 1 \text{ if } p_t > Res_{t-1} \times (1+T) \\ 0 \text{ if } p_t < Sup_{t-1} \times (1+T) \\ \quad I_{t-1}^b \; otherwise \end{cases} \tag{5.11}$$

$$I_t^s = \begin{cases} 1 \text{ if } p_t < Sup_{t-1} \times (1+T) \\ 0 \text{ if } p_t > Res_{t-1} \times (1+T) \\ \quad I_{t-1}^b \; otherwise \end{cases} \tag{5.12}$$

In a similar fashion to Figure 5.1, the behaviour of a TRB (50,0) is displayed in Figure 5.2 over the entire sample of the raw index level of the Saudi stock market.

Figure 5.2: Signals generated by the VTRB (50,0) trading rule using the raw index level of the Saudi stock-market index

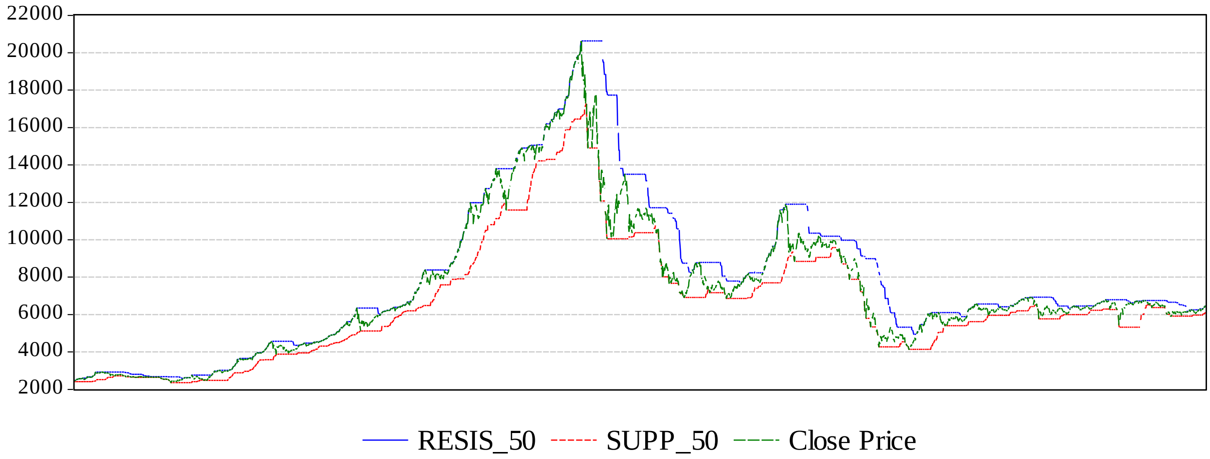


Figure 5.2 shows that the close price fluctuates between its local maximum and minimum. In our case, the maximum and minimum close-price levels are calculated over the previous 50

days. The shorter is the window selected for the local maximum and minimum, the more frequently are trading signals generated.

Holding Time

Trading rules can be employed using either a variable or a fixed holding-period. Under the variable holding-period, when a trading signal is generated, a position is held until the opposite signal is generated. Hence, the holding period varies on the basis of the time elapsing between signals. The fixed holding-period, however, requires investors to maintain their position in the market for an arbitrarily determined fixed period of time. During this pre-determined period of time, all the subsequent signals are ignored until the fixed-length period elapses. At the end of this period, the investor unwinds their position and re-enters the market, contingent upon the next trading signal. The premise behind the fixed holding-period is that the returns are particularly different for a few days subsequent to a trading signal. In the spirit of Brock *et al.* (1992), we apply a variable holding-period to the moving average oscillator and to TRB rules, in addition to a fixed holding-period of 10 days.[43]

Measuring the Performance of Trading Rules

In order to evaluate the performance of technical trading rules, the return generated by these rules is calculated. To achieve that, the signals generated by these trading rules are utilised in the computation of conditional unrealised daily buy and sell returns at time t (r_t^b and r_t^s), which are written, respectively, as:

$$r_t^b = [ln(p_t) - ln(p_{t-1})] \times I_{t-1}^b \tag{5.13}$$

$$r_t^s = [ln(p_t) - ln(p_{t-1})] \times I_{t-1}^s \tag{5.14}$$

[43] Brock *et al.* (1992) only use a fixed holding-period for the TRB. Tabak and Lima (2009) use a variable holding-period for the respective trading rule. Therefore, we elect to use both a fixed and a variable holding-period as a robustness check.

In the case of a variable holding-period, when $I_t = I_{t-1}$, the initial position (either long or short) is maintained and no trade needs to be executed. In this case, no transaction costs are incurred. If $I_t \neq I_{t-1}$, the position is unwound, and it gives rise to two transactions: the first is to close the existing position, and the second is to take a position in the opposite direction. However, the calculation of daily returns is slightly different when the holding period is fixed. The initial position is held for a pre-specified period (10 days in the present study) and any signals arising during this period are ignored. In the last day of the fixed holding-period (the tenth day in the present study), the position is liquidated and cash is held until another signal is generated. This still gives rise to two transitions, albeit not necessarily at the same time.

The means and variances of the conditional buy and sell as well as the unconditional passive buy-and-hold returns are estimated for each trading rule. When calculating the conditional and unconditional means and variances, the sample starts at time $t = L + 1$ (L is the length of the long window of the respective trading rule). Obviously, the sample period varies, depending on L, across the trading rules under investigation. The unconditional means and variances associated with every trading rule are computed at the start of the sample of the respective trading rule, such that the unconditional and conditional mean and variance sample starting points for each trading rules are the same. The unconditional and conditional means and variances are defined respectively as:

$$\mu = E(r) = \frac{1}{N} \sum_{t=L+1}^{N} r_t \tag{5.15}$$

$$\mu_b = E\left(r_t \middle| I_{t-1}^b = 1\right) = \frac{1}{N_b} \sum_{t=L+1}^{N_b} r_t^b \tag{5.16}$$

$$\mu_s = E(r_t | I_{t-1}^s = 1) = \frac{1}{N_s} \sum_{t=L+1}^{N_s} r_t^s \tag{5.17}$$

$$\sigma^2 = E[(r_t - \mu)^2] = \frac{1}{N-1}\sum_{t=L+1}^{N}(r_t - \mu)^2 \tag{5.18}$$

$$\sigma_b^2 = E[(r_t - \mu_b)^2 |\, I_{t-1}^b = 1] = \frac{1}{N_b - 1}\sum_{t=L+1}^{N_b}(r_t^b - \mu_b)^2 \tag{5.19}$$

$$\sigma_s^2 = E[(r_t - \mu_s)^2 |\, I_{t-1}^s = 1] = \frac{1}{N_s - 1}\sum_{t=L+1}^{N_s}(r_t^s - \mu_s)^2 \tag{5.20}$$

where μ is the unconditional mean return, μ_b and μ_s are, respectively, the mean return conditional on buy and sell signals; σ^2, the unconditional variances, σ_b^2 and σ_s^2 are, respectively, the variance conditional on buy and sell signals; N is total number of all trading days associated with each trading rule; and N_b and N_s are, respectively, the total number of buy and sell days.

We test whether the returns conditional on the VMA, FMA, VTRB, and FTRB rules are higher than the unconditional return of the buy-and-hold passive strategy, and whether the conditional mean buy returns are different to the conditional mean sell returns. These hypotheses are formulated as:

$$H_0: \mu_b - \mu = 0, \mu_s - \mu = 0, \mu_b - \mu_s = 0 \tag{5.21}$$

$$H_A: \mu_b - \mu \neq 0, \mu_s - \mu \neq 0, \mu_b - \mu_s \neq 0 \tag{5.22}$$

Following Brock *et al.* (1992), the statistical significance of the mean buy and sell returns generated by each technical rule over the mean of the buy-and-hold strategy, and the buy returns over the sell returns are, respectively, assessed. In order to account for the violation of the assumption of equal variance, the Welch (1951) version of the test statistic is utilised:

$$t = \frac{\mu_b - \mu}{\sqrt{\frac{\sigma_b^2}{N_b} + \frac{\sigma^2}{N}}} \tag{5.23}$$

$$t = \frac{\mu_s - \mu}{\sqrt{\frac{\sigma_s^2}{N_s} + \frac{\sigma^2}{N}}} \tag{5.24}$$

$$t = \frac{\mu_b - \mu_s}{\sqrt{\frac{\sigma_b^2}{N_b} + \frac{\sigma_s^2}{N_s}}} \tag{5.25}$$

In spite of innovations in the market microstructure, the shift from the traditional outcry to the electronic-screen trading system and the introduction of ETFs have enhanced market efficiency by reducing transaction costs (for example Aitken *et al.*, 2004; Blennerhassett and Bowman, 1998; Kurov and Lasser, 2002; Park and Switzer, 1995; Switzer *et al.*, 2000); however, transaction costs remain positive. Transaction costs include the bid-ask spreads, round-trip commission fees, and taxes, as well as the market impact. For a trading rule to be profitable, it should generate profits over and above transaction costs.

Instead of incorporating transaction costs into our performance-evaluation measures, we assess the possibility of earning profits using these rules via the approach taken by Bessembinder and Chan (1995, 1998). Under this approach, a "double or out" trading strategy is implemented, whereby a trader borrows at the risk-free rate to double his investment in the market index when a buy signal is generated. If a sell signal is issued, a trader liquidates his equity holdings and invests the proceeds in a risk-free interest-bearing security.

Following Bessembinder and Chan (1995, 1998), the interest rate is assumed to be zero. Yu *et al.* (2013) argue that this is acceptable due to differences between the lending and the borrowing interest rates, which are difficult to account for accurately. Bessembinder and Chan (1995, 1998) note that if the lending and borrowing rates are the same, and the buy and sell signals are equal, the assumption of a zero interest rate introduces no bias into the calculation of returns. Nevertheless, if the number of buy (sell) signals is higher that the sell (buy) signals, the trading returns will be overstated (understated). The bias is estimated, on an annual basis, to be approximately: $(w_b - w_s) \times r^f$, where w_b and w_s are, respectively, the proportions of buy and sell days, and r^f is the average annual interest rate. Bessembinder and Chan (1995, 1998) argue that the bias is relatively small in the case of a typical interest rate, and Yu *et al.* (2013) empirically support this conjecture.

The additional return (π) generated by the technical trading rule with reference to the buy-and-hold strategy in the absence of transaction costs is given as:

$$\pi = \sum_{t=L+1}^{N_b} r_t^b - \sum_{j=L+1}^{N_s} r_t^s \tag{5.26}$$

Dividing the additional return (π) by the number of initially generated buy and sell signals, we obtain the round-trip break-even cost (C), which is given by:

$$C = \frac{\pi}{n_b + n_s} \tag{5.27}$$

where n_b and n_s are, respectively, the number of initially generated buy and sell signals. Thus, the round-trip break-even cost (C) can be interpreted as the minimum level of transaction costs that would completely eliminate the additional return obtained (π) from technical trading.[44]

5.4 Empirical Results

Variable Moving Average Trading Rules (VMA)

The results of the trading strategies constructed on the basis of the previously defined VMA rules without a filter are reported in Table 5.1, and the results for the same set of rules with a filter of 1 percent are shown in Table 5.2 (that is, five trading rules in each table, 10 rules in total). For each trading rule across the seven GCC markets (70 rules in total), we report the

[44] As discussed in Section 4.3 of Chapter 4, the buy-sell spreads can be utilised as a more conservative estimator for transaction costs.

number of buy and sell signals, the mean daily returns during buy and sell periods and their corresponding *t*-statistics (in parentheses), the fraction of buy and sell returns greater than zero, and the daily mean buy-sell spreads with their corresponding *t*-statistics (in parentheses). For each GCC market, we report the averages of trading signals, mean daily returns, and buy-sell spreads and their corresponding *t*-statistics, as well as the fraction of daily returns greater than zero across trading rules.

Table 5.1: Traditional test results for the variable moving average (VMA) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0)	N(Buy)	1461	1238	1020	1503	1576	1512	1595
	N(Sell)	1135	933	1055	903	857	959	1069
	Buy	0.124	0.083	0.179	0.149	0.159	0.175	0.123
		(2.90)	(3.53)	(2.57)	(3.95)	(3.58)	(2.43)	(1.91)
	Sell	-0.111	-0.096	-0.154	-0.120	-0.144	-0.102	-0.093
		(-2.76)	(-3.99)	(-2.06)	(-4.26)	(-3.61)	(-2.43)	(-1.71)
	Buy > 0	0.56	0.56	0.56	0.63	0.60	0.59	0.61
	Sell > 0	0.47	0.43	0.46	0.48	0.46	0.49	0.52
	Buy -Sell	0.235	0.178	0.332	0.269	0.303	0.277	0.215
		(4.76)	(6.49)	(3.97)	(6.77)	(5.65)	(3.96)	(2.88)
(1,150,0)	N(Buy)	1439	1147	982	1458	1660	1635	1565
	N(Sell)	1057	924	993	848	673	736	999
	Buy	0.103	0.072	0.167	0.121	0.104	0.130	0.117
		(2.13)	(3.19)	(2.44)	(2.84)	(1.89)	(1.60)	(1.74)
	Sell	-0.084	-0.088	-0.175	-0.089	-0.092	-0.104	-0.099
		(-2.17)	(-3.29)	(-2.09)	(-3.40)	(-2.07)	(-1.97)	(-1.70)
	Buy > 0	0.56	0.54	0.56	0.61	0.57	0.55	0.60
	Sell > 0	0.47	0.45	0.46	0.51	0.50	0.52	0.52
	Buy-Sell	0.187	0.160	0.343	0.210	0.196	0.234	0.216
		(3.63)	(5.57)	(3.90)	(5.24)	(2.96)	(2.86)	(2.79)

Table 5.1 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(5,150,0)	N(Buy)	1441	1156	989	1462	1660	1638	1573
	N(Sell)	1055	915	986	844	673	733	991
	Buy	0.095	0.063	0.132	0.119	0.101	0.128	0.108
		(1.91)	(2.79)	(1.89)	(2.74)	(1.77)	(1.56)	(1.56)
	Sell	-0.074	-0.079	-0.143	-0.086	-0.084	-0.102	-0.087
		(-1.98)	(-2.94)	(-1.72)	(-3.34)	(-1.97)	(-1.94)	(-1.55)
	Buy > 0	0.56	0.54	0.55	0.60	0.56	0.55	0.60
	Sell > 0	0.47	0.45	0.46	0.52	0.51	0.52	0.53
	Buy -Sell	0.170	0.142	0.275	0.205	0.185	0.230	0.195
		(3.30)	(4.92)	(3.12)	(5.12)	(2.81)	(2.82)	(2.53)
(1,200,0)	N(Buy)	1447	1090	858	1348	1658	1617	1571
	N(Sell)	999	931	1067	908	625	704	943
	Buy	0.111	0.055	0.165	0.127	0.107	0.116	0.112
		(2.28)	(2.65)	(2.28)	(2.88)	(1.86)	(1.28)	(1.59)
	Sell	-0.099	-0.078	-0.147	-0.075	-0.099	-0.075	-0.094
		(-2.43)	(-2.68)	(-1.76)	(-3.28)	(-2.07)	(-1.54)	(-1.59)
	Buy > 0	0.56	0.52	0.55	0.61	0.57	0.55	0.60
	Sell > 0	0.46	0.46	0.46	0.52	0.50	0.52	0.53
	Buy -Sell	0.210	0.133	0.313	0.202	0.206	0.191	0.206
		(3.97)	(4.60)	(3.51)	(5.24)	(2.90)	(2.23)	(2.55)
(2,200,0)	N(Buy)	1451	1087	851	1346	1658	1619	1577
	N(Sell)	995	934	1074	910	625	702	937
	Buy	0.106	0.056	0.174	0.127	0.103	0.114	0.103
		(2.14)	(2.69)	(2.38)	(2.87)	(1.73)	(1.22)	(1.39)
	Sell	-0.093	-0.079	-0.152	-0.074	-0.089	-0.069	-0.079
		(-2.31)	(-2.72)	(-1.83)	(-3.28)	(-1.95)	(-1.49)	(-1.40)
	Buy > 0	0.56	0.53	0.56	0.61	0.57	0.55	0.60
	Sell > 0	0.46	0.45	0.46	0.52	0.50	0.52	0.53
	Buy-Sell	0.199	0.135	0.326	0.201	0.192	0.183	0.182
		(3.76)	(4.66)	(3.67)	(5.24)	(2.72)	(2.15)	(2.24)

Table 5.1 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Average	N(Buy)	1447.8	1143.6	940	1423.4	1642.4	1604.2	1576.2
	N(Sell)	1048.2	927.4	1035	882.6	690.6	766.8	987.8
	Buy	0.108	0.066	0.164	0.128	0.115	0.133	0.112
		(2.27)	(2.97)	(2.31)	(3.05)	(2.16)	(1.62)	(1.64)
	Sell	-0.092	-0.084	-0.154	-0.089	-0.101	-0.090	-0.090
		(-2.33)	(-3.12)	(-1.90)	(-3.51)	(-2.33)	(-1.87)	(-1.59)
	Buy > 0	0.56	0.54	0.56	0.61	0.57	0.56	0.60
	Sell > 0	0.47	0.45	0.46	0.51	0.49	0.52	0.53
	Buy-Sell	0.200	0.149	0.318	0.217	0.216	0.223	0.203
		(3.88)	(5.25)	(3.63)	(5.52)	(3.41)	(2.80)	(2.60)

Table 5.1 indicates that the number of buy signals is more than sell signals, on average, across six out of the seven GCC stock markets (the exception is the Dubai market). The average number of buy signals ranges from more than double the average number of sells signals for the Omani stock market (1642.4/690.6 = 2.37) to nearly 10 percent less than the sell signals in the Dubai stock market (940/1035 = 0.908).

Table 5.2: Traditional test results for the variable moving average (VMA) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0.01)	N(Buy)	1193	987	923	1344	1388	1366	1431
	N(Sell)	1403	1184	1152	1062	1045	1105	1233
	Buy	0.152	0.090	0.226	0.172	0.162	0.184	0.150
		(3.38)	(3.58)	(3.19)	(4.74)	(3.52)	(2.56)	(2.49)
	Sell	-0.090	-0.064	-0.164	-0.109	-0.093	-0.077	-0.096
		(-2.66)	(-3.05)	(-2.29)	(-4.34)	(-3.08)	(-2.27)	(-1.91)
	Buy > 0	0.57	0.57	0.57	0.65	0.59	0.59	0.62
	Sell > 0	0.48	0.45	0.46	0.48	0.49	0.50	0.52
	Buy-Sell	0.243	0.155	0.389	0.280	0.255	0.261	0.246
		(5.23)	(5.76)	(4.74)	(7.61)	(5.41)	(4.03)	(3.58)

Table 5.2 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,150,0.01)	N(Buy)	1360	1052	931	1371	1601	1561	1499
	N(Sell)	1136	1019	1044	935	732	810	1065
	Buy	0.115	0.077	0.172	0.128	0.106	0.133	0.117
		(2.41)	(3.31)	(2.43)	(3.02)	(1.95)	(1.65)	(1.72)
	Sell	-0.086	-0.079	-0.162	-0.080	-0.081	-0.089	-0.086
		(-2.29)	(-3.10)	(-2.00)	(-3.34)	(-2.04)	(-1.91)	(-1.60)
	Buy > 0	0.57	0.55	0.56	0.61	0.57	0.55	0.60
	Sell > 0	0.47	0.45	0.46	0.51	0.51	0.52	0.52
	Buy -Sell	0.200	0.156	0.334	0.207	0.187	0.222	0.203
		(4.00)	(5.54)	(3.83)	(5.40)	(3.03)	(2.89)	(2.72)
(5,150,0.01)	N(Buy)	1364	1056	925	1381	1604	1561	1502
	N(Sell)	1132	1015	1050	925	729	810	1062
	Buy	0.107	0.074	0.134	0.122	0.102	0.135	0.113
		(2.21)	(3.19)	(1.89)	(2.80)	(1.78)	(1.68)	(1.63)
	Sell	-0.078	-0.077	-0.127	-0.073	-0.072	-0.093	-0.081
		(-2.12)	(-3.02)	(-1.56)	(-3.16)	(-1.91)	(-1.97)	(-1.54)
	Buy > 0	0.56	0.54	0.55	0.61	0.57	0.55	0.61
	Sell > 0	0.47	0.45	0.47	0.52	0.50	0.52	0.52
	Buy -Sell	0.185	0.151	0.261	0.194	0.173	0.228	0.194
		(3.69)	(5.37)	(2.98)	(5.06)	(2.82)	(2.98)	(2.61)
(1,200,0.01)	N(Buy)	1370	1020	826	1284	1597	1577	1508
	N(Sell)	1076	1001	1099	972	686	744	1006
	Buy	0.118	0.058	0.174	0.137	0.112	0.123	0.114
		(2.41)	(2.73)	(2.38)	(3.17)	(2.01)	(1.42)	(1.58)
	Sell	-0.094	-0.071	-0.145	-0.075	-0.093	-0.079	-0.082
		(-2.43)	(-2.51)	(-1.75)	(-3.41)	(-2.15)	(-1.66)	(-1.52)
	Buy > 0	0.56	0.53	0.56	0.62	0.57	0.56	0.61
	Sell > 0	0.47	0.46	0.46	0.52	0.50	0.52	0.53
	Buy-Sell	0.211	0.129	0.319	0.212	0.205	0.202	0.196
		(4.12)	(4.52)	(3.59)	(5.65)	(3.13)	(2.45)	(2.53)

Table 5.2 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0.01)	N(Buy)	1371	1025	829	1282	1593	1573	1506
	N(Sell)	1075	996	1096	974	690	748	1008
	Buy	0.113	0.057	0.181	0.134	0.108	0.116	0.112
		(2.27)	(2.67)	(2.44)	(3.05)	(1.87)	(1.27)	(1.54)
	Sell	-0.087	-0.070	-0.151	-0.070	-0.082	-0.063	-0.079
		(-2.31)	(-2.46)	(-1.83)	(-3.28)	(-1.99)	(-1.48)	(-1.49)
	Buy > 0	0.56	0.53	0.56	0.61	0.57	0.55	0.61
	Sell > 0	0.47	0.45	0.46	0.52	0.50	0.52	0.53
	Buy -Sell	0.200	0.127	0.331	0.203	0.190	0.180	0.191
		(3.91)	(4.43)	(3.71)	(5.43)	(2.90)	(2.19)	(2.47)
Average	N(Buy)	1331.6	1028	886.8	1332.4	1556.6	1527.6	1489.2
	N(Sell)	1164.4	1043	1088.2	973.6	776.4	843.4	1074.8
	Buy	0.121	0.071	0.177	0.138	0.118	0.138	0.121
		(2.54)	(3.09)	(2.46)	(3.36)	(2.23)	(1.72)	(1.79)
	Sell	-0.087	-0.072	-0.150	-0.081	-0.084	-0.080	-0.085
		(-2.36)	(-2.83)	(-1.89)	(-3.50)	(-2.23)	(-1.86)	(-1.61)
	Buy > 0	0.57	0.54	0.56	0.62	0.57	0.56	0.61
	Sell > 0	0.47	0.45	0.46	0.51	0.50	0.52	0.52
	Buy-Sell	0.208	0.143	0.327	0.219	0.202	0.218	0.206
		(4.19)	(5.12)	(3.77)	(5.83)	(3.46)	(2.91)	(2.78)

Table 5.2 shows, in every case, that the introduction of the 1 percent filter leads to a decline in the number of buy signals across trading rules in all markets and, hence, predominantly diminished the ratio of buy to sell signals to range from (1556.6/776.4 = 2.00) for Oman, and to (886.8/1088.2 = 0.814) for Dubai. The results are mostly consistent with the upward trend in the GCC markets during the sample period and the results presented in previous studies.

To reiterate, for a trading rule to have predictive power, the average returns during buy (sell) periods should be positive (negative) and significantly different from the placebo of the unconditional buy-and-hold return. The approach that we take in judging the success of a trading rule is more conservative than the findings in prior studies. Instead of relying on the statistical significance of the buy-sell spreads, we consider the statistical significance of buy (sell) returns separately—that is, for a trading rule to successful both buy (sell) returns should be statistically significantly different from the buy-and-hold returns.

Tables 5.1 and 5.2 show that the mean returns during buy (sell) periods have the expected sign across all seven GCC markets. Out of the 70 VMA rules tested across the seven GCC markets, 38 VMA rules (or about 54 percent of these rules) exhibit statistically significant positive (negative) buy (sell) returns compared to those earned by the passive buy-and-hold strategy at the 5 percent significance level, using a two-tailed test; 56 out of 70 rules (or 80 percent of the VMA rules) become statistically significant at the marginal significance level of 10 percent. By comparing the results in Tables 5.1 and 5.2, it becomes evident that the introduction of the 1 percent filter boosts the statistical significance of the buy and sell returns, as the null hypothesis that the average buy and sell returns across trading rules are equal to the buy-and-hold returns is rejected more often in Table 5.2, albeit marginally.

Tables 5.1 and 5.2 show that at the 10 percent statistical significance level, essentially all trading rules produce statistically significant results in five of the seven GCC markets (Abu Dhabi, Bahrain, Dubai, Kuwait, and Oman); on average, only three out of the 10 trading rules produce statistical significance in the larger markets of Qatar and Saudi Arabia. In terms of the magnitude of the buy (sell) returns and their statistical significance across trading rules, the most potentially profitable markets are Dubai, Kuwait, and Oman. The bottom part of Table 5.1 shows that the average buy (sell) returns across the five VMA trading rules without a filter are 0.164 percent (-0.154 percent) for Dubai, 0.128 percent (-0.089 percent) for Kuwait, 0.115 percent (-0.101 percent) for Oman, 0.108 percent (-0.092 percent) for Abu Dhabi, and 0.066 percent (-0.084 percent) for Bahrain. They all reject the null of equality with the buy-and-hold returns at a significance level of 5 percent, except for average sell returns in the Dubai market, which is only marginally significant at the 10 percent level. On the other hand, the null hypothesis that the average buy return is equal to the buy-and-hold return cannot be rejected for the markets of Qatar and Saudi Arabia.

The results reported in the bottom part of Table 5.2 paint a similar picture and, furthermore, they indicate that average buy returns persistently increase when the 1 percent filter is introduced across the seven GCC markets, albeit slightly. Moreover, the average buy return becomes significantly different from the passive buy-and-hold return at a significance level of 10 percent in every case, except for the sell return in the Saudi market. Comparing the results in Tables 5.1 and 5.2 with those in Panel A of Table 1.2 that contains summary statistics (in Chapter 1), one can clearly see that the VMA trading rule can deliver superior returns compared to the passive buy-and-hold strategy. The average buy returns earned by the VMA trading rules range from a factor as high as 16.5 times the buy-and-hold returns in the Bahraini stock market, to a factor as low as 2.0 times the buy-and-hold returns in the Qatari stock market. These factors consistently increase across all markets upon the introduction of the 1 percent filter, albeit mildly, to range from 17.75 times the buy-and-hold returns for Bahrain to 2.1 times the buy-and-hold returns for Qatar.

The fractions of buy and sell returns greater than zero are shown in Tables 5.1 and 5.2. Buy signals are followed by a higher proportion of positive returns compared to sell signals across trading rules for all seven GCC markets. The bottom part of Table 5.1 reports the average of the fraction of positive buy (sell) returns. When ranked on the basis of the difference between fractions of positive buy (sell) returns, they range from 56 percent (46 percent) for Dubai to 57 percent (49 percent) for Oman. The results after the introduction of the 1 percent filter in Table 5.2 are essentially similar.

The buy-sell spreads reported in Tables 5.1 and 5.2 are uniformly significant at the 5 percent level across trading rules for all seven GCC markets, thus leading us to reject the null hypothesis that buy returns are equal to sell returns. Furthermore, the averages of the buy-sell spreads across trading rules in the bottom parts of Tables 5.1 and 5.2 are highly significant at the 1 percent significance level. The averages of buy-sell spreads in Table 5.1 range from 0.318 percent for Dubai, to 0.149 percent for Bahrain; in Table 5.2 with a 1 percent filter they range from 0.327 percent for Dubai to 0.143 percent for Bahrain.

A casual comparison between the various VMA rules across the seven GCC markets in Tables 5.1 and 5.2 reveals that the (1,50,0) and (1,50,0.01) rules are the most profitable for all seven GCC markets, being the only rules that generate statistically significant buy returns across all seven GCC markets at the 5 percent level. The exception is the (1,50,0) rule, which is marginally significant for the Saudi market. Comparing Table 5.1 with Table 5.2 reveals that the (1,50,0.01) rule is the best-performing rule, being the only rule that produces a significant buy return at the 5 percent level across all of these markets.

A closer look at Table 5.1 reveals that there is a pervasive negative association between the length of the long moving average and the profitability of the trading rule, holding the short moving average the constant. Table 5.1 shows that as the long moving average increases from 50 to 200 in (1,50,0) and (1,200,0), the buy return falls across all seven GCC markets. The percentage decline in buy return as we move from (1,50,0) to the (1,200,0) rule ranges from 33.7 percent ((0.175-0.116)/0.175)*100) for Qatar to 7.8 percent ((0.179-0.165)/ 0.179)*100) for Dubai. Table 5.2 shows a larger percentage decline as we move from (1,50,0.01) to the (1,200,0.01) rule ranging from 35.5 percent ((0.090-0.058)/ 0.090)*100) for Bahrain to 20.30 percent ((0.172-0.137)/ 0.172)*100) for Kuwait.

Likewise, a negative association, albeit weaker, is present between the length of the short moving average and the profitability of the trading rule, holding the long moving average constant. Table 5.1 shows that as the short moving average increases from 1 to 5 in (1,150,0) and (5,150,0), and the buy return falls across all markets. The drop in buy return ranges from about 21 percent ((0.167-0.132)/ 0.167)*100) for Dubai to 1.5 percent ((0.13-0.128)/ 0.13)*100) for Qatar. The results in Table 5.2 are, in essence, similar for all GCC markets except Qatar, where a trivial increase in buy return is documented instead of a decline. These findings reinforce the conclusion that the VMA trading rules possess forecasting power.

Fixed Moving Average Trading Rules (FMA)

Table 5.3 shows the results for FMA trading rules with a fixed holding-period of 10 days without a filter, while Table 5.4 reports the results for the same set of trading rules with a 1 percent filter. We end up with five trading rules in each table and 10 trading rules in total for each market (70 trading rules across the seven GCC markets).

Table 5.3: Traditional test results for the fixed moving average (FMA) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0)	N(Buy)	290	169	210	220	180	260	250
	N(Sell)	280	210	200	220	150	250	350
	Buy	0.029	0.084	0.059	0.154	0.185	0.039	0.061
		(0.13)	(1.60)	(0.42)	(2.25)	(1.89)	(-0.29)	(0.26)
	Sell	0.027	-0.031	-0.001	-0.035	-0.121	-0.226	-0.140
		(0.08)	(-0.92)	(-0.07)	(-1.14)	(-1.91)	(-2.84)	(-1.67)
	Buy > 0	0.54	0.56	0.51	0.60	0.63	0.57	0.57
	Sell > 0	0.53	0.45	0.50	0.49	0.48	0.44	0.51
	Buy-Sell	0.002	0.114	0.060	0.189	0.307	0.265	0.201
		(0.02)	(1.92)	(0.33)	(2.29)	(2.77)	(1.96)	(1.51)

Table 5.3 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,150,0)	N(Buy)	90	80	70	90	70	100	116
	N(Sell)	130	90	120	110	100	130	140
	Buy	0.248	0.118	0.379	0.243	0.250	0.286	-0.056
		(2.43)	(2.17)	(1.94)	(2.73)	(2.32)	(1.90)	(-0.61)
	Sell	-0.046	-0.166	0.006	-0.173	-0.035	0.286	0.134
		(-0.50)	(-2.15)	(0.05)	(-1.93)	(-0.60)	(1.59)	(0.62)
	Buy > 0	0.61	0.63	0.61	0.69	0.69	0.63	0.53
	Sell > 0	0.53	0.44	0.50	0.42	0.51	0.54	0.60
	Buy-Sell	0.294	0.284	0.373	0.415	0.285	0.000	-0.189
		(1.79)	(3.07)	(1.22)	(3.16)	(1.78)	(0.00)	(-0.89)
(5,150,0)	N(Buy)	90	80	70	90	70	100	94
	N(Sell)	100	70	100	90	90	80	110
	Buy	0.058	0.108	0.260	0.267	0.185	0.280	-0.160
		(0.36)	(1.93)	(1.27)	(3.17)	(1.47)	(1.90)	(-0.92)
	Sell	0.045	-0.131	0.241	-0.273	-0.058	0.072	0.009
		(0.13)	(-1.45)	(1.03)	(-2.29)	(-0.74)	(0.08)	(-0.13)
	Buy > 0	0.58	0.63	0.60	0.70	0.54	0.64	0.56
	Sell > 0	0.52	0.47	0.46	0.39	0.51	0.48	0.55
	Buy-Sell	0.013	0.239	0.019	0.540	0.242	0.208	-0.169
		(0.07)	(2.29)	(0.06)	(3.53)	(1.45)	(0.99)	(-0.61)
(1,200,0)	N(Buy)	90	110	80	90	50	120	125
	N(Sell)	100	80	90	80	80	100	90
	Buy	0.063	0.022	-0.211	0.040	0.423	0.091	-0.073
		(0.41)	(0.47)	(-1.05)	(-0.09)	(3.19)	(0.27)	(-0.83)
	Sell	-0.061	-0.076	0.157	-0.346	-0.161	0.110	-0.132
		(-0.57)	(-0.81)	(0.63)	(-2.85)	(-1.16)	(0.29)	(-0.74)
	Buy > 0	0.61	0.45	0.48	0.56	0.68	0.51	0.53
	Sell > 0	0.52	0.43	0.49	0.39	0.54	0.53	0.56
	Buy-Sell	0.125	0.097	-0.367	0.386	0.584	-0.018	0.059
		(0.71)	(0.95)	(-1.16)	(2.54)	(2.73)	(-0.09)	(0.23)

Table 5.3 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0)	N(Buy)	90	100	60	90	50	90	125
	N(Sell)	110	80	80	80	70	90	90
	Buy	0.126	0.045	0.054	0.032	0.408	0.245	-0.084
		(1.06)	(0.87)	(0.31)	(-0.20)	(3.07)	(1.23)	(-0.93)
	Sell	0.032	-0.051	0.035	-0.358	-0.128	0.178	-0.095
		(0.06)	(-0.53)	(0.15)	(-2.94)	(-0.91)	(0.67)	(-0.59)
	Buy > 0	0.64	0.44	0.53	0.54	0.68	0.62	0.54
	Sell > 0	0.55	0.41	0.45	0.39	0.54	0.57	0.54
	Buy-Sell	0.093	0.095	0.019	0.390	0.536	0.067	0.011
		(0.59)	(0.95)	(0.06)	(2.57)	(2.38)	(0.29)	(0.04)
Average	N(Buy)	130	107.8	98	116	84	134	142
	N(Sell)	144	106	118	116	98	130	156
	Buy	0.105	0.075	0.108	0.147	0.290	0.188	-0.062
		(0.88)	(1.41)	(0.58)	(1.57)	(2.39)	(1.00)	(-0.60)
	Sell	-0.001	-0.091	0.087	-0.237	-0.101	0.084	-0.045
		(-0.16)	(-1.17)	(0.36)	(-2.23)	(-1.06)	(-0.04)	(-0.50)
	Buy > 0	0.60	0.54	0.55	0.62	0.64	0.59	0.55
	Sell > 0	0.53	0.44	0.48	0.41	0.52	0.51	0.55
	Buy-Sell	0.105	0.166	0.021	0.384	0.391	0.104	-0.017
		(0.64)	(1.83)	(0.10)	(2.82)	(2.22)	(0.63)	(0.06)

Table 5.4: Traditional test results for the fixed moving average (FMA) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0.01)	N(Buy)	300	220	210	180	170	250	250
	N(Sell)	310	250	190	220	260	270	300
	Buy	0.095	0.133	0.176	0.201	0.257	0.149	0.184
		(1.31)	(3.09)	(1.45)	(2.85)	(2.74)	(0.92)	(1.85)
	Sell	0.085	0.000	0.051	0.000	0.097	-0.046	-0.138
		(1.03)	(-0.14)	(0.28)	(-0.66)	(0.78)	(-1.33)	(-1.49)
	Buy > 0	0.58	0.61	0.53	0.62	0.68	0.58	0.59
	Sell > 0	0.51	0.48	0.51	0.54	0.57	0.49	0.51
	Buy-Sell	0.010	0.132	0.125	0.201	0.159	0.195	0.322
		(0.13)	(2.48)	(0.71)	(2.32)	(1.79)	(1.69)	(2.42)

Table 5.4 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,150,0.01)	N(Buy)	90	80	70	100	80	120	105
	N(Sell)	120	80	120	120	120	120	140
	Buy	0.143	0.126	0.337	0.182	0.270	0.236	0.047
		(1.17)	(1.76)	(1.74)	(2.06)	(2.47)	(1.61)	(0.09)
	Sell	-0.061	-0.210	-0.025	-0.073	0.087	0.252	0.112
		(-0.55)	(-2.74)	(-0.08)	(-1.11)	(0.31)	(1.12)	(0.48)
	Buy > 0	0.62	0.58	0.60	0.65	0.65	0.61	0.53
	Sell > 0	0.51	0.36	0.48	0.48	0.56	0.54	0.56
	Buy-Sell	0.204	0.335	0.363	0.255	0.183	-0.016	-0.065
		(1.13)	(3.27)	(1.20)	(2.10)	(1.20)	(-0.08)	(-0.29)
(5,150,0.01)	N(Buy)	90	80	70	100	80	70	112
	N(Sell)	110	70	110	100	80	100	100
	Buy	0.102	0.107	0.117	0.119	0.186	0.405	-0.109
		(0.76)	(1.50)	(0.65)	(1.09)	(1.57)	(2.44)	(-0.75)
	Sell	-0.072	-0.249	0.151	-0.169	-0.035	-0.059	-0.098
		(-0.58)	(-2.91)	(0.63)	(-1.76)	(-0.54)	(-0.75)	(-0.62)
	Buy > 0	0.61	0.53	0.54	0.59	0.63	0.70	0.56
	Sell > 0	0.54	0.36	0.47	0.42	0.48	0.46	0.49
	Buy-Sell	0.174	0.355	-0.034	0.288	0.221	0.465	-0.011
		(0.90)	(3.26)	(-0.11)	(2.10)	(1.28)	(2.26)	(-0.04)
(1,200,0.01)	N(Buy)	90	80	60	110	70	80	120
	N(Sell)	130	90	110	40	90	80	80
	Buy	0.056	0.070	-0.046	-0.150	0.259	0.326	-0.153
		(0.29)	(1.05)	(-0.19)	(-2.99)	(1.82)	(2.10)	(-1.43)
	Sell	-0.035	-0.067	0.080	-0.497	-0.161	0.121	-0.130
		(-0.50)	(-0.78)	(0.36)	(-2.38)	(-1.29)	(0.28)	(-0.65)
	Buy > 0	0.60	0.45	0.50	0.42	0.63	0.64	0.53
	Sell > 0	0.52	0.46	0.45	0.33	0.51	0.49	0.55
	Buy-Sell	0.091	0.137	-0.126	0.348	0.420	0.206	-0.023
		(0.58)	(1.31)	(-0.41)	(1.47)	(2.13)	(0.82)	(-0.08)

Table 5.4 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0.01)	N(Buy)	90	80	60	110	70	70	90
	N(Sell)	110	80	90	40	90	80	90
	Buy	0.043	0.066	-0.048	-0.154	0.155	0.321	-0.109
		(0.17)	(1.03)	(-0.20)	(-3.07)	(0.92)	(1.94)	(-0.86)
	Sell	-0.004	-0.107	0.042	-0.448	-0.135	0.112	-0.112
		(-0.23)	(-1.15)	(0.20)	(-2.16)	(-1.13)	(0.25)	(-0.65)
	Buy > 0	0.60	0.48	0.52	0.41	0.60	0.63	0.57
	Sell > 0	0.51	0.46	0.46	0.38	0.52	0.49	0.58
	Buy-Sell	0.047	0.173	-0.090	0.294	0.291	0.208	0.003
		(0.29)	(1.57)	(-0.29)	(1.24)	(1.47)	(0.82)	(0.01)
Average	N(Buy)	132	108	94	120	94	118	135.4
	N(Sell)	156	114	124	104	128	130	142
	Buy	0.088	0.100	0.107	0.040	0.225	0.287	-0.028
		(0.74)	(1.69)	(0.69)	(-0.01)	(1.90)	(1.80)	(-0.22)
	Sell	-0.017	-0.126	0.060	-0.237	-0.029	0.076	-0.073
		(-0.17)	(-1.55)	(0.28)	(-1.61)	(-0.38)	(-0.09)	(-0.59)
	Buy > 0	0.60	0.53	0.54	0.54	0.64	0.63	0.56
	Sell > 0	0.52	0.42	0.47	0.43	0.53	0.49	0.54
	Buy-Sell	0.105	0.226	0.048	0.277	0.255	0.212	0.045
		(0.61)	(2.38)	(0.22)	(1.85)	(1.57)	(1.10)	(0.40)

Tables 5.3 and 5.4 indicate that the FMA rules generate far fewer buy and sell signals compared to their variable holding-period counterparts. The buy (sell) signals are on average 8.74 percent (13.44 percent) of their VMA counterparts. The average number of buy signals is quite similar to the sell signals in the bottom parts of Tables 5.3 and 5.4, but it seems that sell signals slightly exceed their buy counterparts more often—collectively considering Tables 5.3 and 5.4, buy signals are more than the sell signals in only three out of 14 instances, on average. Tables 5.3 and 5.4 reveal that the performance of the FMA rules is far less impressive than of the VMA rules. Only five FMA rules out of the 70 FMA rules tested across the seven GCC markets yield significantly different positive (negative) buy (sell) returns to those earned by the passive buy-and-hold strategy at the marginal significance level

of 10 percent. The averages of buy (sell) returns across the five FMA rules without a filter (reported in the bottom part of Table 5.3) range from as high as 0.29 percent (-0.10 percent) for Oman to as low as -0.062 percent (-0.045 percent) for Saudi. In Table 5.4 the averages of the five FMA rules with a 1 percent filter range from 0.287 percent (0.076 percent) for Qatar to -0.028 percent (-0.073 percent) for Saudi.

The fractions of positive returns that follow buy signals are generally greater than those that follow sell signals, which is in line with their variable holding-period counterparts. Nonetheless, while the VMA rule buy-sell spreads are, on average, significant at the 1 percent level across all markets, both without and with a 1 percent filter, this is not the case for the FMA rules. In fact, the bottom parts of Tables 5.3 and 5.4 indicate that, on average, buy returns significantly exceed sell returns in only three out of the seven GCC markets. In Table 5.3 the difference is significant at the 5 percent level in Kuwait and Oman, while being marginally significant in Bahrain at the 10 percent level. Table 5.4 shows that the difference is found to be significant in the Bahraini and Kuwaiti markets at the 5 and 10 percent levels, respectively. These results demonstrate that the performance of the FMA is highly erratic, which implies the failure of the FMA in offering better returns than the passive buy-and-hold strategy, which is in accordance with the findings of McKenzie (2007).

Variable Trading Range Breakout Rules (VTRB)

The VTRB results are tabulated in the same way as the moving averages rules. Table 5.5 reports the results of the previously described three VTRB rules without a trading filter and with window lengths of 50,150, and 200. Table 5.6 shows the results of the same set of trading rules with a filter of 1 percent. We end up with six trading rules in total (42 across the seven GCC markets).

Table 5.5: Traditional test results for the variable trading range breakout (VTRB) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0)	N(Buy)	1416	1266	1015	1417	1648	1494	1635
	N(Sell)	1179	904	1059	988	784	976	1028
	Buy	0.114	0.070	0.212	0.142	0.125	0.158	0.099
		(2.54)	(2.98)	(2.95)	(3.47)	(2.43)	(2.04)	(1.32)
	Sell	-0.090	-0.083	-0.184	-0.087	-0.099	-0.071	-0.065
		(-2.40)	(-3.41)	(-2.53)	(-3.75)	(-2.61)	(-1.92)	(-1.38)
	Buy > 0	0.56	0.55	0.57	0.63	0.57	0.57	0.61
	Sell > 0	0.48	0.44	0.46	0.50	0.50	0.51	0.52
	Buy-Sell	0.203	0.153	0.396	0.229	0.224	0.229	0.164
		(4.20)	(5.49)	(4.73)	(6.12)	(3.90)	(3.31)	(2.22)
(150,0)	N(Buy)	1286	1033	830	1178	1832	1791	1352
	N(Sell)	1209	1037	1144	1127	500	579	1211
	Buy	0.084	0.055	0.141	0.143	0.080	0.103	0.110
		(1.51)	(2.30)	(1.87)	(3.25)	(1.08)	(1.05)	(1.43)
	Sell	-0.042	-0.055	-0.112	-0.061	-0.071	-0.084	-0.053
		(-1.48)	(-2.21)	(-1.44)	(-3.25)	(-1.42)	(-1.41)	(-1.31)
	Buy > 0	0.55	0.54	0.56	0.62	0.56	0.55	0.61
	Sell > 0	0.49	0.45	0.47	0.52	0.52	0.53	0.53
	Buy-Sell	0.126	0.110	0.254	0.204	0.151	0.187	0.162
		(2.58)	(3.91)	(2.87)	(5.64)	(1.83)	(1.88)	(2.34)
(200,0)	N(Buy)	1654	962	836	1256	1802	1645	1464
	N(Sell)	791	1058	1088	999	480	675	1049
	Buy	0.068	0.057	0.101	0.120	0.068	0.094	0.094
		(1.17)	(2.60)	(1.29)	(2.42)	(0.56)	(0.78)	(1.13)
	Sell	-0.065	-0.063	-0.092	-0.048	-0.014	-0.028	-0.048
		(-1.55)	(-2.27)	(-1.14)	(-2.91)	(-0.76)	(-0.99)	(-1.14)
	Buy > 0	0.54	0.54	0.54	0.61	0.55	0.55	0.60
	Sell > 0	0.49	0.45	0.48	0.52	0.54	0.54	0.54
	Buy-Sell	0.133	0.120	0.193	0.169	0.082	0.122	0.142
		(2.26)	(4.22)	(2.10)	(4.63)	(0.97)	(1.41)	(1.91)

Table 5.5 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Average	N(Buy)	1452	1087	893.7	1283.7	1760.7	1643.3	1483.7
	N(Sell)	1059.7	999.7	1097	1038	588	743.3	1096
	Buy	0.088	0.061	0.151	0.135	0.091	0.118	0.101
		(1.74)	(2.63)	(2.04)	(3.05)	(1.36)	(1.29)	(1.29)
	Sell	-0.066	-0.067	-0.129	-0.065	-0.062	-0.061	-0.055
		(-1.81)	(-2.63)	(-1.70)	(-3.30)	(-1.60)	(-1.44)	(-1.28)
	Buy > 0	0.55	0.54	0.55	0.62	0.56	0.56	0.60
	Sell > 0	0.49	0.45	0.47	0.51	0.52	0.53	0.53
	Buy-Sell	0.154	0.128	0.281	0.200	0.152	0.179	0.156
		(3.01)	(4.54)	(3.23)	(5.47)	(2.23)	(2.20)	(2.15)

Table 5.5 indicates that across all GCC markets, except Dubai, there are more buy signals than sell signals. The bottom part of Table 5.5 exhibits the averages of buy and sell signals. The average buy signals range from about triple (1760.7/588) the sell signals for Oman, to about 20 percent (893.7/1097) lower than the sell signals in Dubai.

Table 5.6: Traditional test results for the variable trading range breakout (VTRB) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0.01)	N(Buy)	1169	850	953	1041	1194	1195	1165
	N(Sell)	1426	1320	1121	1364	1238	1275	1498
	Buy	0.114	0.091	0.193	0.148	0.136	0.175	0.119
		(2.34)	(3.44)	(2.63)	(3.22)	(2.49)	(2.20)	(1.55)
	Sell	-0.055	-0.049	-0.146	-0.028	-0.028	-0.033	-0.028
		(-1.85)	(-2.47)	(-2.08)	(-2.53)	(-1.92)	(-1.66)	(-1.09)
	Buy > 0	0.55	0.58	0.56	0.62	0.56	0.57	0.61
	Sell > 0	0.50	0.46	0.47	0.54	0.54	0.53	0.54
	Buy-Sell	0.170	0.140	0.340	0.176	0.164	0.208	0.147
		(3.64)	(5.15)	(4.08)	(5.00)	(3.75)	(3.38)	(2.29)

Table 5.6 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(150,0.01)	N(Buy)	1130	901	722	1119	1492	1767	1288
	N(Sell)	1365	1169	1252	1186	840	603	1275
	Buy	0.100	0.068	0.162	0.137	0.088	0.103	0.117
		(1.77)	(2.75)	(1.96)	(2.97)	(1.27)	(1.06)	(1.56)
	Sell	-0.041	-0.052	-0.102	-0.045	-0.024	-0.078	-0.052
		(-1.56)	(-2.15)	(-1.37)	(-2.83)	(-1.30)	(-1.39)	(-1.34)
	Buy > 0	0.55	0.54	0.57	0.62	0.56	0.55	0.61
	Sell > 0	0.50	0.46	0.47	0.53	0.53	0.52	0.53
	Buy-Sell	0.141	0.119	0.264	0.182	0.112	0.181	0.170
		(2.88)	(4.26)	(2.88)	(5.03)	(2.05)	(1.88)	(2.49)
(200,0.01)	N(Buy)	1286	905	812	1197	1649	1610	1443
	N(Sell)	1159	1115	1112	1058	633	710	1070
	Buy	0.080	0.048	0.100	0.115	0.065	0.095	0.088
		(1.32)	(2.17)	(1.26)	(2.17)	(0.46)	(0.79)	(1.01)
	Sell	-0.036	-0.049	-0.087	-0.032	0.012	-0.024	-0.037
		(-1.37)	(-1.76)	(-1.08)	(-2.49)	(-0.57)	(-0.98)	(-1.01)
	Buy > 0	0.54	0.53	0.54	0.61	0.55	0.55	0.60
	Sell > 0	0.51	0.46	0.48	0.53	0.54	0.54	0.54
	Buy-Sell	0.116	0.097	0.186	0.147	0.053	0.119	0.125
		(2.33)	(3.41)	(2.01)	(4.04)	(0.79)	(1.42)	(1.71)
Average	N(Buy)	1195	885.3	829	1119	1445	1524	1298.7
	N(Sell)	1316.7	1201.3	1162	1203	904	862.7	1281
	Buy	0.098	0.069	0.152	0.133	0.096	0.124	0.108
		(1.81)	(2.79)	(1.95)	(2.78)	(1.41)	(1.35)	(1.37)
	Sell	-0.044	-0.050	-0.112	-0.035	-0.013	-0.045	-0.039
		(-1.59)	(-2.13)	(-1.51)	(-2.61)	(-1.26)	(-1.34)	(-1.15)
	Buy > 0	0.55	0.55	0.56	0.62	0.56	0.56	0.61
	Sell > 0	0.50	0.46	0.47	0.53	0.54	0.53	0.54
	Buy-Sell	0.142	0.119	0.263	0.168	0.110	0.169	0.147
		(2.95)	(4.27)	(2.99)	(4.69)	(2.20)	(2.22)	(2.16)

The introduction of the 1 percent filter in Table 5.6 results in a fall in buy signals in favour of sell signals across all GCC markets, which is in line with the VMA results. Tables 5.5 and 5.6 show that mean returns during buy (sell) periods have the expected sign across the seven

GCC markets in every case except for the sell return of the (200,0.01) rule for Oman. When statistical significance is taken into account, 16 out of 42 (or 38 percent) of the VTBR rules tested across the seven GCC markets generate significantly different positive (negative) buy (sell) returns to those earned by the passive buy-and-hold strategy at the 5 percent significance level (using a two-tailed test); 20 out of 42 (or 47 percent) of the VTRB rules become statistically significant at the marginal level of 10 percent. In the bottom part of Table 5.5 the average buy (sell) returns across the three rules range from 0.151 percent (-0.129 percent) for Dubai to 0.061 percent (-0.067 percent) for Bahrain. With very few exceptions, the introduction of the 1 percent filter slightly boosts the average buy (sell) returns across the same set of rules.

The fraction of positive returns that follow buy signals exceeds those that follow sell signals across all the VTRB in every case. On average, the buy-sell spreads are significantly different from zero at the 5 percent level across the seven GCC markets. Taken altogether, the VTRB rules appear to have predictive power consistent with the findings of Chang *et al.* (2004) and Tabak and Lima (2009).

Fixed Trading Range Breakout Rules (FTRB)

The results for the same set of trading-range breakout trading rules, but with a fixed holding-period of 10 days are reported in Table 5.7 (without a filter) and Table 5.8 (with 1 percent filter) in the same fashion as in the previous section.

Table 5.7: Traditional test results for the fixed trading range breakout (FTRB) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0)	N(Buy)	540	610	400	730	750	534	813
	N(Sell)	430	447	366	360	320	300	360
	Buy	0.234	0.087	0.442	0.224	0.153	0.396	0.129
		(4.22)	(2.67)	(4.61)	(5.85)	(2.72)	(5.52)	(1.67)
	Sell	-0.228	-0.129	-0.236	-0.173	-0.131	-0.160	-0.079
		(-2.87)	(-3.84)	(-1.77)	(-3.30)	(-1.64)	(-1.50)	(-0.82)
	Buy > 0	0.61	0.58	0.62	0.68	0.57	0.67	0.61
	Sell > 0	0.43	0.41	0.45	0.49	0.49	0.46	0.51
	Buy-Sell	0.462	0.216	0.678	0.397	0.284	0.556	0.207
		(4.88)	(5.11)	(4.32)	(5.75)	(2.50)	(3.55)	(1.45)
(150,0)	N(Buy)	330	410	229	510	540	344	520
	N(Sell)	200	297	226	180	110	120	190
	Buy	0.289	0.092	0.459	0.225	0.185	0.331	0.212
		(4.05)	(2.54)	(3.76)	(5.08)	(3.40)	(3.70)	(2.81)
	Sell	-0.188	-0.142	-0.265	-0.263	-0.188	-0.432	-0.203
		(-1.36)	(-3.20)	(-1.42)	(-2.98)	(-0.81)	(-1.57)	(-1.01)
	Buy > 0	0.62	0.59	0.63	0.67	0.59	0.62	0.63
	Sell > 0	0.41	0.40	0.46	0.45	0.49	0.43	0.48
	Buy-Sell	0.477	0.234	0.724	0.488	0.373	0.764	0.414
		(2.90)	(4.36)	(3.43)	(4.62)	(1.28)	(2.40)	(1.75)
(200,0)	N(Buy)	300	350	190	510	500	310	490
	N(Sell)	170	237	206	140	110	110	150
	Buy	0.329	0.114	0.550	0.225	0.181	0.362	0.244
		(4.32)	(3.26)	(3.89)	(5.01)	(3.13)	(3.84)	(3.25)
	Sell	-0.234	-0.184	-0.133	-0.267	-0.033	-0.261	-0.086
		(-1.52)	(-3.44)	(-0.68)	(-2.74)	(-0.29)	(-0.98)	(-0.42)
	Buy > 0	0.63	0.59	0.65	0.67	0.57	0.64	0.63
	Sell > 0	0.41	0.38	0.48	0.44	0.51	0.45	0.52
	Buy-Sell	0.563	0.298	0.683	0.492	0.214	0.623	0.330
		(3.11)	(4.95)	(3.05)	(4.22)	(0.75)	(1.87)	(1.15)

Table 5.7. ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Average	N(Buy)	390	456.7	273	583.3	596.7	396	607.7
	N(Sell)	266.7	327	266	227	180	176.7	233
	Buy	0.284	0.097	0.484	0.225	0.173	0.363	0.195
		(4.20)	(2.83)	(4.08)	(5.31)	(3.09)	(4.35)	(2.58)
	Sell	-0.217	-0.152	-0.211	-0.234	-0.117	-0.284	-0.122
		(-1.92)	(-3.49)	(-1.29)	(-3.01)	(-0.91)	(-1.35)	(-0.75)
	Buy > 0	0.62	0.58	0.63	0.67	0.58	0.64	0.62
	Sell > 0	0.41	0.40	0.46	0.46	0.50	0.45	0.51
	Buy-Sell	0.501	0.249	0.695	0.459	0.290	0.647	0.317
		(3.63)	(4.81)	(3.60)	(4.86)	(1.51)	(2.61)	(1.45)

Table 5.8: Traditional test results for the fixed trading range breakout (FTRB) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0.01)	N(Buy)	360	200	350	260	360	440	390
	N(Sell)	480	397	416	370	360	320	400
	Buy	0.303	0.098	0.436	0.317	0.207	0.380	0.223
		(4.19)	(1.53)	(3.77)	(4.91)	(2.59)	(4.19)	(2.16)
	Sell	-0.117	-0.145	-0.163	-0.190	-0.111	-0.204	-0.028
		(-1.93)	(-4.04)	(-1.33)	(-3.69)	(-1.61)	(-1.93)	(-0.49)
	Buy > 0	0.59	0.59	0.61	0.70	0.59	0.63	0.63
	Sell > 0	0.49	0.38	0.47	0.45	0.50	0.44	0.51
	Buy-Sell	0.420	0.243	0.599	0.507	0.318	0.585	0.251
		(4.55)	(3.56)	(3.71)	(6.27)	(2.80)	(3.82)	(1.67)
(150,0.01)	N(Buy)	240	140	200	170	260	300	300
	N(Sell)	220	277	256	198	150	120	200
	Buy	0.370	0.132	0.602	0.380	0.240	0.347	0.206
		(4.00)	(2.04)	(3.94)	(4.66)	(3.02)	(3.21)	(1.67)
	Sell	-0.079	-0.168	-0.209	-0.255	-0.045	-0.405	-0.130
		(-0.82)	(-3.54)	(-1.14)	(-3.15)	(-0.43)	(-1.52)	(-0.72)
	Buy > 0	0.62	0.59	0.66	0.70	0.60	0.61	0.65
	Sell > 0	0.46	0.38	0.46	0.43	0.52	0.41	0.51
	Buy-Sell	0.449	0.300	0.811	0.635	0.285	0.752	0.336
		(3.03)	(3.87)	(3.57)	(5.46)	(1.27)	(2.39)	(1.38)

Table 5.8 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(200,0.01)	N(Buy)	230	120	190	170	240	280	280
	N(Sell)	200	227	236	158	120	110	160
	Buy	0.385	0.083	0.613	0.380	0.246	0.357	0.287
		(4.03)	(1.26)	(3.84)	(4.62)	(2.88)	(3.19)	(2.58)
	Sell	-0.081	-0.170	-0.123	-0.241	-0.041	-0.204	0.008
		(-0.75)	(-2.98)	(-0.63)	(-2.75)	(-0.34)	(-0.81)	(-0.10)
	Buy > 0	0.62	0.57	0.65	0.70	0.60	0.61	0.66
	Sell > 0	0.47	0.39	0.49	0.43	0.45	0.46	0.54
	Buy-Sell	0.466	0.253	0.735	0.621	0.286	0.561	0.279
		(2.85)	(2.91)	(3.14)	(5.01)	(1.06)	(1.68)	(0.97)
Average	N(Buy)	276.7	153.3	247	200	286.7	340	323.3
	N(Sell)	300.0	300	303	242	210	183.3	253
	Buy	0.352	0.104	0.550	0.359	0.231	0.362	0.239
		(4.07)	(1.61)	(3.85)	(4.73)	(2.83)	(3.53)	(2.14)
	Sell	-0.092	-0.161	-0.165	-0.228	-0.066	-0.271	-0.050
		(-1.17)	(-3.52)	(-1.04)	(-3.20)	(-0.79)	(-1.42)	(-0.43)
	Buy > 0	0.61	0.58	0.64	0.70	0.59	0.62	0.65
	Sell > 0	0.47	0.38	0.47	0.44	0.49	0.44	0.52
	Buy-Sell	0.445	0.265	0.715	0.587	0.296	0.633	0.289
		(3.47)	(3.45)	(3.47)	(5.58)	(1.71)	(2.63)	(1.34)

Tables 5.7 and 5.8 indicate that the FTRB rules generate fewer buy (sell) trading signals. The buy (sell) signals are, on average, 28.2 percent (27.4 percent) of their VTRB counterparts, which are substantially more than the proportion of FMA signals with respect to VMA. The bottom part of Table 5.7 reveals that the average number of buy signals considerably exceeds the number of sell signals across the seven GCC markets. However, upon the introduction of the 1 percent filter, in Table 5.8 the number of buy signals declines in favour of sell signals in all seven GCC markets; sell signals become more than buy signals in four out of the seven GCC markets (Abu Dhabi, Bahrain, Dubai, and Kuwait).

The performance of the FTRB rules is noteworthy. Tables 5.7 and 5.8 show that mean returns during buy (sell) periods have the expected sign across the seven markets in every case, except for the sell return of the (200,0.01) rule for the Saudi market. The success of the FTRB rules is limited in producing statistically significant mean buy (sell) returns than those that are available with the passive buy-and-hold strategy. Only 11 out of 42 (or 26 percent) trading rules generate statistical significance at the 5 percent level, while the number of successful rules slightly increases to 14 (or 33 percent) if the 10 percent level is used to judge statistical significance. However, the bottom parts of Tables 5.7 and 5.8 reveal that the majority of buy-sell spreads are, on average, statistically significant in 10 out of 14 cases at the 5 percent level.

While the majority of FTRB rules fail to generate significantly different buy (sell) returns from the buy-and-hold strategy, these rules seems to predict the direction of market movements remarkably well. The fraction of positive returns following buy signals is considerably greater than those that follow sell signals. The bottom part of Table 5.7 indicates that the proportion of positive returns that follow buy (sell) signals ranges from 67 percent (46 percent) for Kuwait, to 58 percent (50 percent) for Oman. Table 5.8 paints a similar picture.

The Profitability of Technical Trading Rules

Table 5.9 reports the break-even costs, which are the percentage round-trip transaction costs that totally offset the incremental returns earned by using technical trading rules, over and above those offered by the passive buy-and-hold strategy. Table 5.9 displays the break-even costs for 10 VMA rules in panel A, 10 FMA rules in panel B, six VTBR rules in panel C, and six FTRB in panel D.

As mentioned previously, reliable transaction-cost estimates are not available for the GCC markets. The only publicly available statistic is commission fees. Therefore, we briefly discuss the calculated break-even costs. Panel A of Table 5.9 indicates that the average break-even cost for the VMA rules ranges from 4.50 percent for Oman to 2.45 percent for Bahrain. On the other hand, the FMA average break-even cost in Panel B of Table 5.9 is considerably lower, ranging from 0.76 percent for Oman to -0.002 percent for Dubai. A close look at Panel B reveals that several FMA rules have negative break-even costs in the markets of Dubai, Qatar, and Saudi Arabia, which confirms the failure of these rules in generating profitability. These findings are consistent with the results of Bessembinder and Chan (1995).

Panel C of Table 5.9 shows that the break-even costs for the VTRB rules are relatively high compared to other trading rules. The average break-even cost for the VTRB rules ranges from 15.42 percent for Kuwait to 8.09 percent for Bahrain. The break-even costs of the FTRB in Panel D of Table 5.9 are, on average, lower than their variable holding-period counterparts (VMA and VTRB), but they remain above the FMA rules. Overall, while the results are inconclusive due to the lack of an estimate of transaction costs as a benchmark, they shed light on the potential profitability of these rules.

Table 5.9: Break-even cost for the "double or out" strategy

Rules	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel A:VMA rules							
(1,50,0)	1.11	1.24	1.66	2.03	3.67	1.71	1.10
(1,50,0.01)	1.39	0.76	2.31	2.62	1.92	1.50	1.41
(1,150,0)	2.32	2.73	4.70	3.31	3.45	2.45	2.38
(1,150,0.01)	3.08	2.88	3.43	3.28	3.38	2.97	2.72
(5,150,0)	4.69	4.52	5.65	5.13	5.59	6.19	4.75
(5,150,0.01)	4.34	4.34	4.94	4.53	5.39	6.22	4.12
(1,200,0)	3.51	1.58	4.40	4.27	5.43	2.68	3.23
(1,200,0.01)	3.20	1.72	4.45	3.88	4.33	4.36	3.63
(2,200,0)	4.24	2.59	6.50	4.97	7.08	3.76	3.57
(2,200,0.01)	3.56	2.13	6.56	4.27	4.75	5.01	4.59
Average break-even cost	3.14	2.45	4.46	3.83	4.50	3.68	3.15

Table 5.9 ***(Continued)***

Rules	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Panel B:FMA rules							
(1,50,0)	0.01	0.28	0.16	0.48	0.81	0.67	0.57
(1,50,0.01)	0.02	0.32	0.34	0.45	0.21	0.49	0.86
(1,150,0)	0.64	0.72	0.68	1.02	0.62	-0.19	-0.48
(1,150,0.01)	0.48	0.84	0.70	0.61	0.28	-0.04	-0.21
(5,150,0)	0.02	0.59	-0.17	1.35	0.60	0.62	-0.38
(5,150,0.01)	0.43	0.86	-0.25	0.72	0.55	1.01	-0.06
(1,200,0)	0.33	0.22	-0.91	0.92	1.42	0.00	0.06
(1,200,0.01)	0.24	0.34	-0.36	0.11	1.02	0.51	-0.20
(2,200,0)	0.19	0.24	0.02	0.93	1.33	0.18	-0.04
(2,200,0.01)	0.11	0.43	-0.22	0.03	0.72	0.45	0.01
Average break-even cost	0.25	0.48	-0.002	0.66	0.76	0.37	0.01
Panel C:VTRB rules							
(50,0)	4.95	3.83	12.11	7.07	6.88	7.60	4.70
(50,0.01)	3.49	4.82	9.23	5.13	4.50	6.01	4.55
(150,0)	8.90	6.21	20.64	23.52	12.16	19.00	11.71
(150,0.01)	12.23	12.07	20.77	20.58	10.43	18.77	15.52
(200,0)	11.50	11.89	13.38	19.46	8.39	14.23	13.28
(200,0.01)	10.40	9.71	12.91	16.79	6.50	13.90	11.84
Average break-even cost	8.58	8.09	14.84	15.42	8.14	13.25	10.27
Panel D:FTRB rules							
(50,0)	1.25	0.56	1.85	1.13	0.81	1.62	0.60
(50,0.01)	1.03	0.66	1.51	1.29	0.84	1.66	0.65
(150,0)	1.36	0.61	1.96	1.33	1.02	1.79	1.13
(150,0.01)	1.21	0.79	1.89	1.60	0.89	2.00	0.91
(200,0)	1.57	0.76	1.78	1.34	0.84	1.71	1.12
(200,0.01)	1.28	0.69	1.69	1.60	0.91	1.74	0.93
Average break-even cost	1.28	0.68	1.78	1.38	0.89	1.75	0.89

5.5 Robustness Checks

The Risk-return Trade-off: Jensen's Alpha

High returns could potentially be a consequence of high risk, which makes it necessary to estimate risk-adjusted returns by utilising the CAPM. The use of CAPM to evaluate the performance of technical trading rules is motivated by results in a noteworthy paper where Brown *et al.* (1998) conjecture that because investors who employ technical trading rules are frequently out of the market, adjustment for systematic risk when evaluating the performance of these rules is warranted. The empirical evidence supports their conjecture.

In the spirit of Brown *et al.* (1998) and Fang *et al.* (2014), we regress the buy and sell returns as well as the buy-sell spreads in excess of the risk-free rate on an intercept, and the market risk premium in the usual manner as:

$$r_t^b - r_t^f = \alpha^b + \beta^b\left(r_t - r_t^f\right) + \varepsilon_t^b \tag{5.28}$$

$$r_t^s - r_t^f = \alpha^s + \beta^s\left(r_t - r_t^f\right) + \varepsilon_t^s \tag{5.29}$$

$$\left(r_t^b - r_t^s\right) - r_t^f = \alpha^{b-s} + \beta^{b-s}\left(r_t - r_t^f\right) + \varepsilon_t^{b-s} \tag{5.30}$$

where α is Jensen's alpha and it represents the differential between the return on the trading rule in excess of the risk-free rate and the return explained by the CAPM; β captures the systematic risk of the trading rule; and ε_t is an error term assumed to be independently and identically distributed (iid). In order to mitigate the potential size-distortion of the *t*-test that arises due to the autocorrelation of the residuals, the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987) via the Andrews (1991) automatic-selection procedure can be used to compute the *t*-statistics.

The results obtained by fitting the CAPM to each of the technical trading rules under investigation, without and with a 1 percent filter, are reported in the appendix to this chapter:

Tables 5A.1 and 5A.2 for the VMA rules, Tables 5A.3 and 5A.4 for the FMA rules, Tables 5A.5 and 5A.6 for the VTRB rule, and Tables 5A.7 and 5A.8 for the FTRB rules. Jensen's alpha (α) captures the differential superior or inferior performance of the trading rule that is predicted by the CAPM, given a risk level (β). If Jensen's alpha is positive and statistically significant, it is concluded that the trading rule delivers a superior performance that can be attributed to market-timing ability. Tables 5A.1 and 5A.2 indicate that all of the VMA have positive and highly statistically significant alphas at the 1 percent level. The exception is the (2,200,0) rule for Qatar, which is significant at the 5 percent level. In contrast, Tables 5A.3 and 5A.4 reveal that the majority of FMA rules fail to produce a superior performance on a risk-adjusted basis to that available from the naïve buy-and-hold strategy, with only a handful (14 out of 70 rules) of FMA generating positive and statistically significant alphas.

With respect to the TRB rules, Tables 5A.5 and 5A.6 show that the VTRB rules perform quite well, with 36 out of 42 generating positive and significant alphas at the 5 percent level. The FTRB performance is noteworthy. Despite having a holding period of 10 days, Tables 5A.7 and 5A.8 reveal that it fares slightly better than its variable holding-period counterpart with 37 out 42 rules producing positive and highly significant alphas at the 5 percent level.

The beta coefficient is useful to characterise the systematic risk after buy and sell signals. In looking over Tables 5A.1 to Table 5A.8, we find that the beta of sell returns is predominantly higher than the beta of buy returns. Across four out of the seven GCC markets, the beta of sell returns exceeds the beta of buy returns for all trading rules. For the remaining three markets (Abu Dhabi, Bahrain, and Kuwait) the same holds when the 1 percent filter is imposed, except for the VTRB (200, 0.01) rule.

The Risk-return Trade-off: Sharpe Ratio

As a robustness check, the Sharpe ratio is used to quantify the risk-return trade-off, which is defined as a reward-to-volatility ratio. The Sharpe ratio is based on total rather than systematic risk, which (unlike the CAPM) does not require a specification of a reference portfolio (a market index); therefore, it is not subject to the Roll critique (Roll, 1977). For each trading strategy, the Sharpe ratio is formulated as:

$$S^{b\&h} = \frac{(\bar{r}_t - \bar{r}_t^f)}{\sigma(r_t)} \tag{5.31}$$

$$S^{b} = \frac{(\bar{r}_t^b - \bar{r}_t^f)}{\sigma(r_t^b)} \tag{5.32}$$

$$S^{s} = \frac{(\bar{r}_t^s - \bar{r}_t^f)}{\sigma(r_t^s)} \tag{5.33}$$

$$S^{b\&s} = \frac{\left(\left(\bar{r}_t^b - \bar{r}_t^s\right) - \bar{r}_t^f\right)}{\sigma(r_t^b - r_t^s)} \tag{5.34}$$

The Sharpe ratio is useful to characterise the total reward from taking risk after buy and sell signals. In other words, the Sharpe ratio captures compensation in the form of excess returns for each unit of risk. In the appendix to this chapter, Tables 5A.9 to 5A.12 present the results of the comparison between the Sharpe ratio of the buy-and-hold trading strategy and the VMA, FMA, VTRB, and FTRB, respectively. Table 5A.9 indicates that the Sharpe ratios for sell returns are uniformly negative and lower in terms of magnitude than the ratios of buy returns. This implies that the VMA trading rules possess value in terms of predicting the direction of market movements. In addition, Table 5A.9 shows that the Sharpe ratios of buy returns for the VMA rules are persistently higher than for the same period's buy-and-hold Sharpe ratios across all the seven GCC markets. The Sharpe ratios of buy returns range from 23.47 percent for Kuwait to 11.96 percent for Saudi when the (1,50,0.01) rule is considered. Therefore, it is evident that the VMA rules compensate the investor more for the exposure to an extra unit of risk compared to the buy-and-hold trading strategy.

The performance of the FMA rules is, nevertheless, less impressive compared to its variable holding-period counterpart. Table 5A.10 reveals that the performance of the FMA rules is highly erratic. The Sharpe ratios of buy and sell returns indicate that the FMA rule fails to provide reliable trading signals. For example the Sharpe ratios for buy returns in the Kuwaiti market range from as high as 40.22 percent (for the (5,150,0) rule) to as low as -24.59 percent (for the (2,200,0.01) rule). These findings cast serious doubt as to the usefulness of the FMA trading rules.

Table 5A.11 indicates that as with their VMA counterparts, the VTRB rules are generally able to discern upward and downward movements in indices for the seven GCC markets. The Sharpe ratios of the buy returns offered by VTRB are consistently higher than that of the buy-and-hold strategy; they range from 17.49 percent for Kuwait to 6.62 percent for Saudi in the case of the (50,0) rule. Looking at Table 5A.12, it appears that the FTRB performance is noteworthy. Despite the fixed holding-period, the signals generated by the FTRB are valuable. The FTRB rule is largely successful in predicting market direction, as with its variable holding-period counterparts. All of the FTRB rules outperform the buy-and-hold strategy by generating higher buy returns' Sharpe ratios across the seven GCC markets. The Sharpe ratios of the buy returns of the FTRB rules range from 40.88 percent for Kuwait to 10.11 percent for Bahrain when the (200,0.01) is considered. Comparing the results generated by the four trading rules, it can be concluded that the VMA, VTRB, and FTRB are able to offer better reward-to-volatility than the buy-and-hold strategy. While some FMA rules generate exceptionally high Sharpe ratios, the performance of this trading rule is generally unstable.

Market Timing

Technical trading rules, in general, transform historical prices and volumes into trading signals. When a trading rule issues a buy signal, it implies that the return in the subsequent period is predicted to be positive. On the other hand, the opposite prediction is implied by a sell signal. In order to determine whether the signals generated by the trading rules under investigation have market-timing value, we apply market-timing measures to the time series of the returns generated by these trading rules. Following Brown *et al.* (1998) and Gencay (1998), this is achieved by utilising the market-timing test introduced by Merton (1981) and Henriksson and Merton (1981), and further refined by Cumby and Modest (1987) and Breen *et al.* (1989). In the Henriksson and Merton (1981) framework, no information is required with respect to the magnitude of market movements. Instead, the forecasting-performance evaluation can be conducted by converting actual returns into discrete binary random variables in the following fashion:

$$MD_t = \begin{cases} 1 \; if \; r_t > 0 \\ 0 \; otherwise \end{cases} \tag{5.35}$$

where MD_t is the actual market sign at time t. With their large sample, Chou and Chu (2011) suggest that it is more convenient to perform the Henriksson and Merton (1981) test by regressing market direction (MD_t) on either the buy or sell signals generated by the trading rules. This is because buy and sell signals are not only mutually exclusive, but they are collectively exhaustive when the holding period is variable. Hence, including both of the trading signals simultaneously in the regression equation leads to the dummy-variable trap. The Henriksson and Merton (1981) model is specified as:

$$E(MD_t | I_{t-1}^b) = \alpha + \beta I_{t-1}^b \tag{5.36}$$

where the intercept α has a useful interpretation as the proportion of positive returns when the sign of the return is predicted to be negative ($E\left(MD_t \middle| I_{t-1}^b = 0\right) = \alpha$); the slope ($\beta$) captures the difference in the proportions of positive returns between positive and negative signs predictions; $\alpha + \beta$ represents the proportion of positive returns when the sign of the return is predicted to be positive ($E(MD_t | I_{t-1}^b = 1) = \alpha + \beta$). For empirical purposes, the equation can be expressed in a stochastic form as:

$$MD_t = \alpha + \beta I_{t-1}^b + \varepsilon_t \tag{5.37}$$

Then null hypothesis to be tested here is $H_0 : \beta = 0$, which pertains to the significance of the differential proportion of positive returns. If the null hypothesis is rejected, the trading rule is said to possess market-timing value. However, when the holding period is set to be fixed, the buy and sell signals are not collectively exhaustive, albeit mutually exclusive, as there will be days on which neither a buy nor a sell signal is generated. Therefore, the regression equation is adjusted to evaluate the market-timing value of buy and sell signals simultaneously in the following fashion:

$$MD_t = \alpha + \beta^b I_{t-1}^b + \beta^s I_{t-1}^s \tag{5.38}$$

where α the intercept, which represents the proportion of positive returns during days where neither a buy nor a sell signal is generated, or neutral days ($E\left(MD_t \middle| I_{t-1}^b = I_{t-1}^s = 0\right) = \alpha$); β^b denotes the partial slope, which captures the difference between the proportion of positive returns when the return is predicted to be positive, and that of neutral days; β^s is the partial slope which captures the difference between the proportion of positive returns when the return is predicted to be negative, and that of neutral days; ($E\left(MD_t \middle| I_{t-1}^b = 1\right) = \alpha + \beta^b$) and ($E(MD_t | I_{t-1}^s = 1) = \alpha + \beta^s$) are, respectively, the proportion of positive returns when the return is predicted to be positive (negative). For empirical purposes, the equation can be expressed in a stochastic form as:

$$MD_t = \alpha + \beta^b I_{t-1}^b + \beta^s I_{t-1}^s + \varepsilon_t \tag{5.39}$$

The null hypothesis is $H_0\colon \beta^b = \beta^s = 0$. If the null hypothesis is rejected, it is concluded that the trading rule is said to possess market-timing value. For this purpose, a Wald test is used.

There is more to be gleaned from this test. Considering Eq. (5.37), if β is statistically greater than zero, a momentum strategy is more likely to be implemented than a contrarian strategy, and vice versa. Notwithstanding the simplicity, intuitiveness, and prevalence of this version of the Henriksson and Merton (1981) market-timing test, this test can be misleading. In a key paper, Granger and Newbold (1974) cautioned against spurious relationships that may manifest from a regression of the levels of two autocorrelated continuous time series which are independent. By the same token, it is shown that the discrete version of the OLS regression *t*-statistic can be inflated in a similar fashion to continuous time series when the discrete time series are autocorrelated (Chou and Chu, 2011; Shintani *et al.*, 2012). To guard against the potential size distortion of the *t*-test that arises due to the autocorrelation of the residuals, the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987)—via the Andrews (1991) automatic-selection procedure—can be used to compute the *t*-statistics. Among others, Breen *et al.* (1989) have applied this approach.

In the appendix to this chapter, the results of estimating Eq. (5.37) (the slope coefficient estimates and the *t*-statistics) for the variable holding-period trading rules (VMA and VTRB) are shown in Tables 5A.13 and 5A.14, respectively. The results of Eq. (5.39) (all coefficient estimates along with their *t*-statistics, in addition to the Wald *F*-statistic with its *P*-value) for the fixed holding-period trading rules (FMA and FTRB) are reported in Tables 5A.15 and 5A.16 for the FMA rules without and with a 1 percent filter, respectively. Likewise, the FTRB results are presented in Tables 5A.17 and 5A.18.

By examining Table 5A.13, it can be observed that the VMA rules possess market-timing ability. The slope coefficient estimates, which represent the difference between the fraction of positive buy returns and the fraction of positive sell returns are positive across all the VMA rules for all seven GCC markets. For all markets except Qatar, the slope coefficient estimates are statistically significant at the 5 percent level. For the Qatari market only the (1,50,0) and (1,50,0.01) rules generate statistically significant slope coefficient estimates, with the reminder of the rules having positive slope coefficients; they are statistically indistinguishable from zero. The slope coefficients range from about 10 percent for Kuwait to 3 percent for Qatar in the case of the (1,150,0) rule.

Table 5A.14 reveals that the market-timing power of the VTRB rules is less remarkable than for their VMA counterparts. While the slope coefficient estimates are positive across the VTRB rules, for 12 out of 42 trading rules, these slope coefficient estimates are statistically insignificant at the 5 percent level. The slope coefficient estimates range from about 13 percent for Kuwait to 6 percent for Qatar when considering the (50,0) rule. It is evident that this VTRB possesses market-timing ability across the VTRB rules for the markets of Bahrain, Dubai, Kuwait, and Saudi Arabia. For the rest of the markets, however, the success of the VTRB in forecasting the direction of market movements is limited.

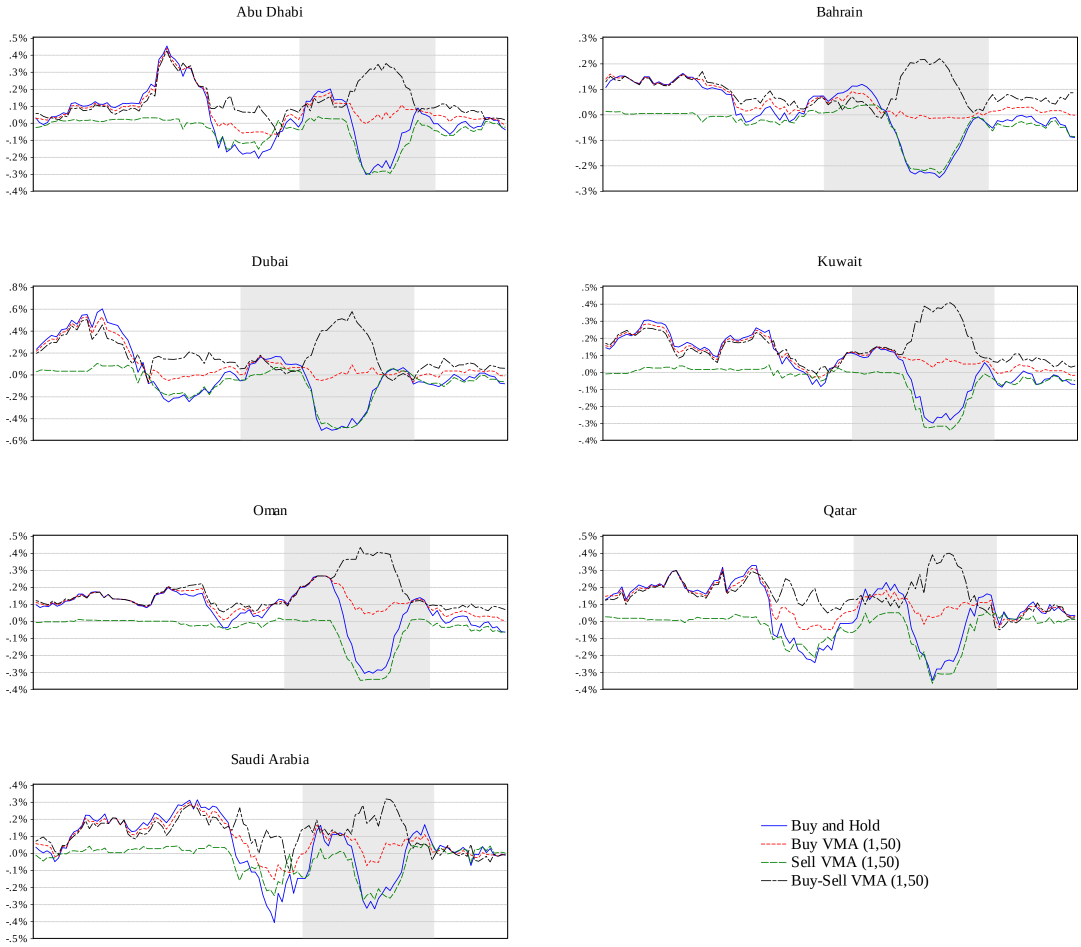
Tables 5A.15 and 5A.16 report the results of the FMA rules without and with a 1 percent filter. As discussed earlier, the market-timing ability of fixed holding-period rules is judged by the means of the post-estimation Wald test. A look at Tables 5A.15 and 5A.16 reveals that only 18 out of 70 FMA rules possess market-timing ability when the 5 percent level is used; for the reminder of FMA rules, the null hypothesis of no market-timing ability cannot be rejected. In contrast to their fixed holding-period counterparts, Tables 5A.17 and 5A.18 show that the performance of the FTRB rules is remarkable. Across the FTRB rules, the post-estimation Wald test is statistically significant at the 5 percent level for all GCC markets except Oman; there, the null hypothesis of no market-timing ability is rejected only for one out of the six rules—that is, the (200,0.01) rule.

The Stability of Trading Rules: Rolling Regression

The results obtained from classical hypothesis-testing can be potentially driven by any particular period. Therefore, to track the evolution of the mean return over the sample period, we run a rolling regression in the spirit of Fang *et al.* (2014). Although the length of the rolling window is arbitrary, we attempt to select the length such that it not only minimises noise, but also remains sufficiently sensitive to detect patterns in the data.

To this end, the unconditional and conditional returns are, respectively, regressed on an intercept using the OLS estimation technique with a step of 20 trading days and a fixed 250-trading-days window. The estimates of the intercept coefficient (which are equivalent to mean returns) obtained from the rolling regression are plotted in Figure 5.3 to enable visual inspection of the fluctuation in the mean return of the trading rules over the sample period. We use the results of the VMA (1,50,0) as an example to demonstrate our findings.

Figure 5.3: Year rolling-window returns of the variable moving average (VMA) (1,50,0) rule on the seven GCC markets



Naturally, for a trading rule to be considered stable, its buy (sell) signals should consistently generate positive (negative) returns that are greater (less) than the buy-and-hold strategy. The buy-sell spread should persistently exceed the buy-and-hold returns. Figure 5.3 provides preliminary evidence indicating that the VMA (1,50,0) rule strongly outperforms the buy-and-hold strategy across all GCC markets, particularly during financial crises, most notably the Global Financial Crisis (GFC); this is highlighted by the shaded area. In this analysis, the GFC spans the period 9 August 2007 to 9 May 2010.[45] Nonetheless, performance of the VMA (1,50,0) rule is less impressive over the rest of the sample period.

45 http://www.theguardian.com/business/2011/aug/07/global-financial-crisis-key-stages

The Stability of Trading Rules: The Profitability over Time

In a similar vein to the preceding section, we illustrate varying profitability through time. To that end, we calculate the cumulative wealth index at time t (CWI_t) with reference to initial wealth ($WI_{t=L}$) for the unconditional buy-and-hold and conditional buy-returns series. These are, respectively, computed using an expanding sample that begins at time $t = L + 1$. As mentioned earlier, L represents the length of the long window of the respective trading rule, with a step of one day ahead until the conclusion of the sample period is reached. Hence,

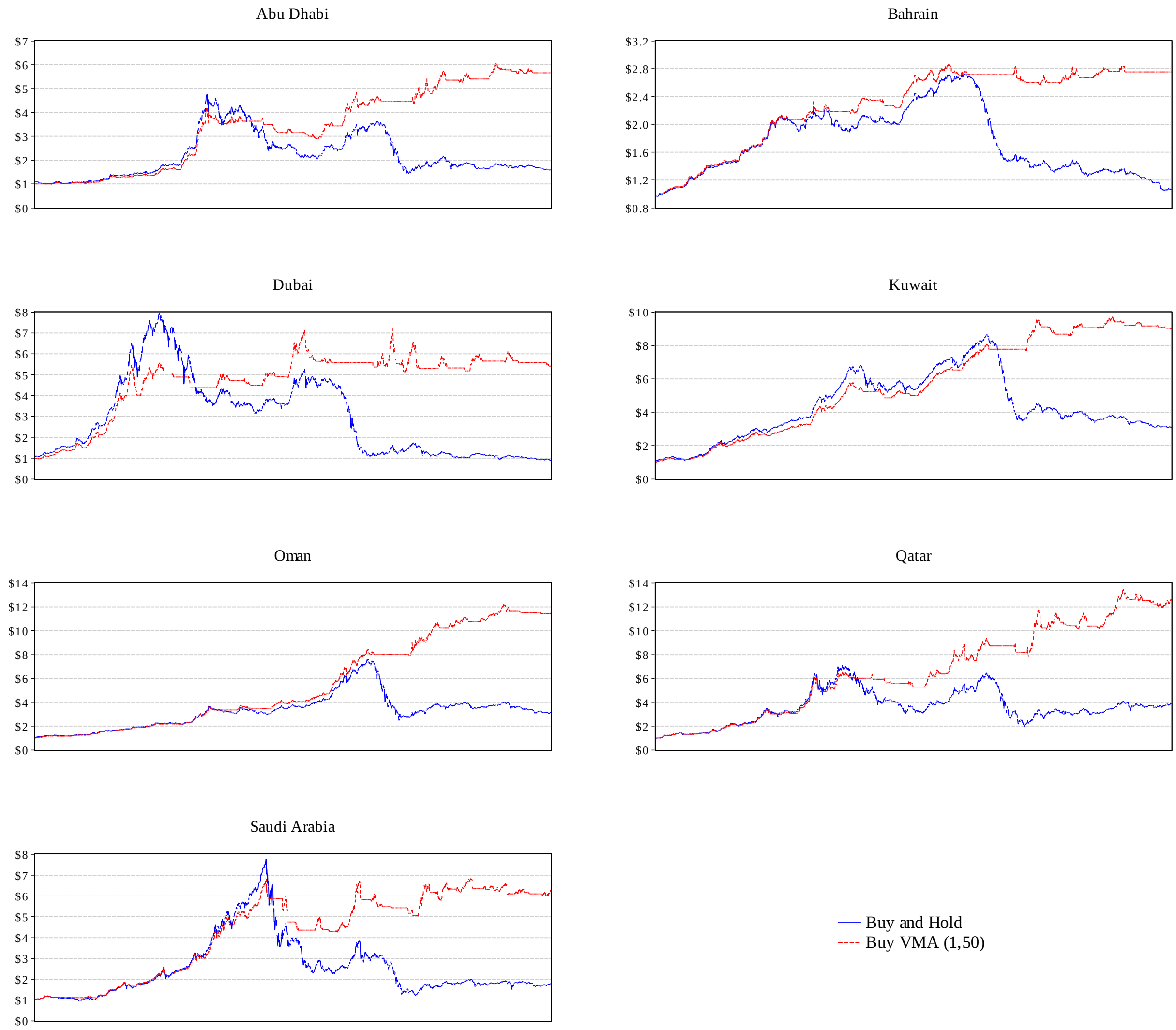
$$CWI_t = WI_{t=L+1} \prod_{t=L+1}^{N} (1 + r_t) \tag{5.40}$$

$$CWI_t^b = WI_{t=L+1} \prod_{t=L+1}^{N} (1 + r_t^b) \tag{5.41}$$

The change in cumulative wealth throughout the sample period is exhibited in Figure 5.4. In the present study, we set initial wealth to \$1. To conserve space, the VMA (1,50,0) trading rule is used as an example.

Figure 5.4 indicates that the of buy-and-hold strategy and VMA (1,50,0) trading rule perform quite similarly during the early periods of the sample across the seven GCC markets. Upon the onset of the GFC in late 2008, however, the VMA (1,50,0) rule clearly outperforms its passive buy-and-hold counterpart across the seven GCC markets. The outperformance of the VMA (1,50,0) rule is sustained until the end of the sample period, with the end-of-period cumulative wealth ranging from \$13.55 for Qatar to \$2.89 for Bahrain; their corresponding buy-and-hold end-of-period cumulative wealth is merely \$3.85 for Qatar and \$1.05 for Bahrain.

Figure 5.4: Cumulative wealth of the of the variable moving average (VMA) (1,50,0) rule on the seven GCC markets



Taken together, Figures 5.3 and 5.4 reveal that it is, potentially, possible that the profitability of technical trading rules is time-varying. Furthermore, it is evident that the GFC had a profound impact on the performance of the trading rules. Indeed, one can statistically evaluate the stability of the trading rules' performance over time by running the following time series regression over the entire sample period:

$$r_t^b - r_t = \alpha + \beta \, TIME_t + \varepsilon_t \tag{5.42}$$

where $r_t^b - r_t$ is the excess return that can be earned above the buy-and-hold return by employing a long-only technical trading rule; α is the intercept parameter; β is the slope parameter that captures the change in excess return above the buy-and-hold return over time; $TIME_t$ is a time-trend variable equal to the elapsed number of trading days from the start of the sample period; ε_t is an error term assumed to be independently and identically distributed (iid).

As discussed earlier, the heteroscedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987) via the Andrews (1991) automatic-selection procedure are used to compute the *t*-statistics. The null hypothesis to be tested here is $H_0: \beta = 0$. If the sign of the slope coefficient (β) is positive and statistically significant, it can be concluded the profitability of technical trading rules is increasing over time. If the sign of β is negative and statistically significant, the profitability of technical trading rules is diminishing over time. The regression is estimated using only the buy returns of the VMA (1,50,0) rule for all seven GCC countries (to conserve space). The results of Eq. (5.42) are presented in Table 5.10.

Table 5.10: The results of the time series regression: $\mathbf{r_t^b - r_t = \alpha + \beta\ TIME_t + \varepsilon_t}$

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
α	-0.00001	-0.019	0.013	-0.025	-0.007	0.016	0.012
	(-0.00)	(-1.39)	(0.27)	(-1.11)	(-0.49)	(0.56)	(0.38)
β	0.000036	0.000053	0.000060	0.000056	0.000046	0.000018	0.000018
	(1.96)	(3.60)	(1.40)	(2.87)	(2.36)	(0.70)	(0.74)
R^2	0.00084	0.00583	0.00054	0.00355	0.00137	0.00011	0.00010

The positive β coefficients across the seven GCC markets show that the profitability of the technical trading rules under investigation has tended to increase over time. Indeed, this increase is statistically significant, at least at the 5 percent level, in the markets of Abu Dhabi, Bahrain, Kuwait, and Oman. However, the null hypothesis cannot be rejected for the rest of the markets.

The prior approach is suggested to be more objective, as it does not require the imposition of an arbitrary cut-off point to investigate profitability variations between periods. However, Figure 5.3 portrays a strong pattern during the GFC. In order to account for the effect of the GFC on the stability of the performance of the trading rules over the sample period, an alternative specification can be formulated as:

$$r_t^b - r_t = \alpha + \beta\ GFC_t + \varepsilon_t \tag{5.43}$$

where the slope parameter β captures the difference between the mean excess-buy return during the GFC and the mean of typical trading days excess-buy return, and GFC_t is a dummy variable that takes the value of 1 during the GFC and 0 otherwise. As mentioned earlier the GFC is taken to span the period 9 August 2007 to 9 May 2010 for this analysis.

As with the prior specification, the *t*-statistics are computed using HAC standard errors. The null hypothesis is $H_0\colon \beta = 0$. If the sign of the slope coefficient is positive and significant, we can conclude that excess buy returns during the GFC are higher than the excess buy returns over the rest of the sample period. The exact opposite holds if the slope coefficient is negative and statistically significant. In a similar fashion, the results of Eq. (5.43) are presented in Table 5.11.

Table 5.11: The results of the time series regression: $\mathbf{r_t^b - r_t = \alpha + \beta\ GFC_t + \varepsilon_t}$

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
α	0.029	0.024	0.042	0.009	0.022	0.021	0.021
	(1.62)	(2.23)	(1.29)	(0.66)	(1.98)	(0.94)	(0.73)
β	0.074	0.054	0.111	0.129	0.102	0.066	0.062
	(1.30)	(1.77)	(1.25)	(2.67)	(1.83)	(0.85)	(0.85)
R^2	0.00124	0.00332	0.00113	0.00785	0.00280	0.00060	0.00037

An examination of Table 5.11 reveals that the slope coefficient β is positive across the seven GCC markets. This implies that mean excess buy returns generated by the trading rules under investigation were higher during the GFC. Nonetheless, when statistical significance is taken into account, only one out of the seven GCC markets (Kuwait) has a slope coefficient that is distinguishable from zero at conventional levels of significance. The slope coefficients for the markets of Bahrain and Oman are significant at the marginal level of 10 percent; the null hypothesis is not rejected for the rest of the markets.

5.6 Conclusion

Motivated by the proliferation of studies that utilise the technical trading rules initially tested by Brock *et al.* (1992) as an alternative test of the EMH in its weak form, this chapter carries out an empirical analysis to investigate whether or not these technical trading rules are profitable when applied to GCC data.

The conclusions drawn from this analysis largely resemble those reached in prior studies. The results that emerge from traditional analysis indicate that the majority of the technical trading rules outperform the passive buy-and-hold trading strategy across the seven GCC markets. Several studies argue that such findings should be viewed with caution, as they could have emerged simply as a result of using a long time series of stock returns.

Thus, we have subjected these findings to a number of robustness checks. The main results hold up across the different performance measures—for the majority of rules, the CAPM generated positive and statistically significant Jensen's Alphas; the Sharpe ratio for trading rules is higher than that of the passive buy-and-hold strategy; and the market-timing test indicates that trading rules possess market-timing ability.

In addition, the profitability of trading rules is evaluated by computing the round-trip break-even cost. It seems that the majority of the trading rules under examination are potentially profitable, even after transaction costs are accounted for—and are noticeably more profitable compared to their regression-based counterparts that were examined in Chapter 4. An important caveat to these findings, however, is that when the performance of trading rules is tracked over time, we find that the performance of these rules is highly temporal and that their profitability is largely confined to the period in which the GFC took place. These findings—that is, the time-varying nature of the profitability of trading rules—lend support to the adaptive-market hypothesis.

APPENDIX TO CHAPTER 5
ROBUSTNESS CHECKS

This appendix contains tabulated results for three robustness checks (CAPM, Sharpe ratio, and a market-timing test) that measure the performance of the technical trading rules under investigation. Tables 5A.1 to 5A.8 display the estimation results for the CAPM model (represented by Eq. (5.28), (5.29), and (5.30). Tables 5A.9 to 5A.12 contain the results of the Sharpe ratio, which are obtained using Eq. (5.31), (5.32), and (5.33). Finally, Tables 5A.13 to 5A.18 report the estimation results of the of the Henriksson and Merton market-timing test, as given by Eq. (5.37) and Eq. (5.39).

Table 5A.1: The CAPM estimation results for the variable moving average (VMA) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0)	α^b	0.061	0.044	0.084	0.071	0.082	0.078	0.060
		(4.23)	(5.57)	(3.58)	(6.18)	(6.70)	(4.06)	(3.64)
	β^b	0.40	0.52	0.35	0.43	0.36	0.38	0.32
		(7.02)	(10.99)	(8.94)	(10.15)	(5.17)	(7.45)	(9.68)
	α^s	-0.061	-0.044	-0.084	-0.071	-0.082	-0.078	-0.060
		(-4.23)	(-5.57)	(-3.58)	(-6.18)	(-6.70)	(-4.05)	(-3.64)
	β^s	0.60	0.48	0.65	0.57	0.64	0.62	0.68
		(10.50)	(10.22)	(16.94)	(13.24)	(9.29)	(12.02)	(20.92)
	α^{b-s}	0.113	0.080	0.159	0.135	0.154	0.148	0.114
		(3.97)	(5.14)	(3.41)	(5.88)	(6.31)	(3.87)	(3.44)
	β^{b-s}	-0.20	0.04	-0.31	-0.13	-0.28	-0.23	-0.37
		(-1.74)	(0.38)	(-4.00)	(-1.54)	(-2.06)	(-2.28)	(-5.62)

Table 5A.1 *(Continued)*

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,150,0)	α^b	0.049	0.038	0.084	0.053	0.054	0.062	0.058
		(3.28)	(4.93)	(3.93)	(4.28)	(3.94)	(3.11)	(3.40)
	β^b	0.44	0.47	0.39	0.50	0.36	0.47	0.37
		(7.54)	(10.01)	(13.34)	(9.66)	(5.20)	(7.96)	(10.70)
	α^s	-0.049	-0.038	-0.084	-0.053	-0.054	-0.062	-0.058
		(-3.28)	(-4.93)	(-3.93)	(-4.28)	(-3.94)	(-3.11)	(-3.40)
	β^s	0.56	0.53	0.61	0.50	0.64	0.53	0.63
		(9.72)	(11.37)	(20.90)	(9.51)	(9.14)	(8.94)	(17.96)
	α^{b-s}	0.090	0.070	0.160	0.100	0.098	0.116	0.109
		(3.02)	(4.49)	(3.73)	(4.01)	(3.59)	(2.93)	(3.21)
	β^{b-s}	-0.13	-0.06	-0.22	0.01	-0.27	-0.06	-0.25
		(-1.09)	(-0.68)	(-3.79)	(0.07)	(-1.97)	(-0.49)	(-3.63)
(5,150,0)	α^b	0.044	0.034	0.068	0.052	0.051	0.061	0.053
		(2.87)	(4.19)	(3.06)	(4.23)	(3.65)	(3.05)	(2.93)
	β^b	0.45	0.48	0.43	0.52	0.37	0.48	0.38
		(7.50)	(10.10)	(11.67)	(10.26)	(5.09)	(8.02)	(9.37)
	α^s	-0.044	-0.034	-0.068	-0.052	-0.051	-0.061	-0.053
		(-2.87)	(-4.19)	(-3.06)	(-4.23)	(-3.65)	(-3.05)	(-2.93)
	β^s	0.55	0.52	0.57	0.48	0.63	0.52	0.62
		(9.16)	(11.00)	(15.57)	(9.65)	(8.51)	(8.78)	(15.03)
	α^{b-s}	0.081	0.061	0.127	0.097	0.092	0.114	0.099
		(2.63)	(3.76)	(2.87)	(3.95)	(3.32)	(2.87)	(2.75)
	β^{b-s}	-0.10	-0.04	-0.14	0.03	-0.25	-0.05	-0.23
		(-0.83)	(-0.45)	(-1.95)	(0.31)	(-1.71)	(-0.38)	(-2.83)
(1,200,0)	α^b	0.054	0.031	0.076	0.052	0.056	0.054	0.056
		(3.62)	(3.93)	(3.35)	(4.10)	(4.05)	(2.67)	(3.20)
	β^b	0.46	0.47	0.37	0.50	0.36	0.45	0.38
		(7.63)	(10.09)	(9.51)	(9.87)	(5.21)	(7.78)	(10.78)
	α^s	-0.054	-0.031	-0.076	-0.052	-0.056	-0.054	-0.056
		(-3.62)	(-3.93)	(-3.35)	(-4.10)	(-4.05)	(-2.67)	(-3.20)
	β^s	0.54	0.53	0.63	0.50	0.64	0.55	0.62
		(9.12)	(11.41)	(16.45)	(9.81)	(9.27)	(9.66)	(17.89)
	α^{b-s}	0.100	0.056	0.143	0.097	0.103	0.101	0.105
		(3.36)	(3.49)	(3.16)	(3.82)	(3.71)	(2.49)	(3.01)
	β^{b-s}	-0.09	-0.06	-0.27	0.00	-0.28	-0.11	-0.25
		(-0.74)	(-0.66)	(-3.47)	(0.03)	(-2.03)	(-0.94)	(-3.55)

Table 5A.1 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0)	α^b	0.051	0.032	0.079	0.052	0.053	0.051	0.050
		(3.34)	(4.02)	(3.56)	(4.02)	(3.69)	(2.50)	(2.72)
	β^b	0.46	0.47	0.37	0.50	0.37	0.46	0.38
		(7.55)	(10.15)	(10.00)	(9.86)	(5.11)	(7.84)	(9.33)
	α^s	-0.051	-0.032	-0.079	-0.052	-0.053	-0.051	-0.050
		(-3.34)	(-4.02)	(-3.56)	(-4.02)	(-3.69)	(-2.50)	(-2.72)
	β^s	0.54	0.53	0.63	0.50	0.63	0.54	0.62
		(8.74)	(11.44)	(17.35)	(9.69)	(8.76)	(9.13)	(15.05)
	α^{b-s}	0.094	0.057	0.150	0.097	0.097	0.096	0.093
		(3.10)	(3.57)	(3.36)	(3.75)	(3.37)	(2.33)	(2.54)
	β^{b-s}	-0.07	-0.06	-0.27	0.01	-0.26	-0.08	-0.23
		(-0.60)	(-0.65)	(-3.68)	(0.09)	(-1.82)	(-0.65)	(-2.86)

Table 5A.2: The CAPM estimation results for the variable moving average (VMA) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0.01)	α^b	0.062	0.038	0.097	0.076	0.073	0.075	0.069
		(4.31)	(5.03)	(4.29)	(6.86)	(5.84)	(3.83)	(4.46)
	β^b	0.37	0.43	0.32	0.38	0.33	0.35	0.27
		(6.78)	(9.30)	(8.63)	(9.38)	(4.95)	(7.13)	(9.17)
	α^s	-0.062	-0.038	-0.097	-0.076	-0.073	-0.074	-0.069
		(-4.31)	(-5.03)	(-4.29)	(-6.86)	(-5.84)	(-3.81)	(-4.46)
	β^s	0.63	0.57	0.68	0.62	0.67	0.65	0.73
		(11.74)	(12.41)	(18.68)	(15.46)	(9.95)	(13.12)	(24.85)
	α^{b-s}	0.116	0.070	0.185	0.146	0.136	0.142	0.132
		(4.05)	(4.58)	(4.10)	(6.55)	(5.46)	(3.64)	(4.25)
	β^{b-s}	-0.27	-0.14	-0.37	-0.24	-0.34	-0.30	-0.46
		(-2.48)	(-1.56)	(-5.02)	(-3.04)	(-2.50)	(-2.99)	(-7.84)

Table 5A.2 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,150,0.01)	α^b	0.052	0.038	0.082	0.054	0.053	0.061	0.055
		(3.54)	(4.81)	(3.84)	(4.37)	(3.94)	(3.05)	(3.27)
	β^b	0.42	0.44	0.38	0.48	0.35	0.46	0.36
		(7.26)	(9.56)	(13.59)	(9.48)	(5.16)	(7.84)	(10.20)
	α^s	-0.052	-0.038	-0.082	-0.054	-0.053	-0.061	-0.055
		(-3.54)	(-4.81)	(-3.84)	(-4.37)	(-3.94)	(-3.05)	(-3.27)
	β^s	0.58	0.56	0.62	0.52	0.65	0.54	0.64
		(10.12)	(12.07)	(21.85)	(10.16)	(9.50)	(9.33)	(18.19)
	α^{b-s}	0.097	0.069	0.156	0.101	0.097	0.114	0.104
		(3.29)	(4.36)	(3.64)	(4.09)	(3.59)	(2.87)	(3.08)
	β^{b-s}	-0.16	-0.12	-0.23	-0.03	-0.30	-0.09	-0.28
		(-1.42)	(-1.26)	(-4.13)	(-0.34)	(-2.17)	(-0.75)	(-4.00)
(5,150,0.01)	α^b	0.049	0.037	0.064	0.051	0.050	0.062	0.053
		(3.29)	(4.69)	(2.88)	(4.07)	(3.56)	(3.16)	(3.01)
	β^b	0.42	0.45	0.39	0.49	0.37	0.46	0.37
		(7.29)	(9.80)	(10.34)	(9.63)	(5.05)	(7.98)	(9.49)
	α^s	-0.049	-0.037	-0.064	-0.051	-0.050	-0.062	-0.053
		(-3.29)	(-4.69)	(-2.88)	(-4.07)	(-3.56)	(-3.16)	(-3.01)
	β^s	0.58	0.55	0.61	0.51	0.63	0.54	0.63
		(10.03)	(12.02)	(16.16)	(9.87)	(8.70)	(9.23)	(16.12)
	α^{b-s}	0.089	0.067	0.119	0.094	0.090	0.116	0.099
		(3.03)	(4.25)	(2.69)	(3.79)	(3.22)	(2.98)	(2.83)
	β^{b-s}	-0.16	-0.10	-0.22	-0.01	-0.27	-0.07	-0.26
		(-1.37)	(-1.12)	(-2.91)	(-0.12)	(-1.82)	(-0.62)	(-3.31)
(1,200,0.01)	α^b	0.055	0.031	0.077	0.055	0.058	0.057	0.054
		(3.69)	(3.84)	(3.42)	(4.34)	(4.21)	(2.84)	(3.08)
	β^b	0.45	0.43	0.35	0.49	0.35	0.44	0.37
		(7.45)	(9.39)	(9.31)	(9.71)	(5.18)	(7.74)	(10.27)
	α^s	-0.055	-0.031	-0.077	-0.055	-0.058	-0.057	-0.054
		(-3.69)	(-3.84)	(-3.42)	(-4.34)	(-4.21)	(-2.84)	(-3.08)
	β^s	0.55	0.57	0.65	0.51	0.65	0.56	0.63
		(9.26)	(12.43)	(17.47)	(10.25)	(9.53)	(9.85)	(17.48)
	α^{b-s}	0.102	0.054	0.145	0.103	0.106	0.107	0.101
		(3.43)	(3.39)	(3.23)	(4.07)	(3.87)	(2.66)	(2.89)
	β^{b-s}	-0.11	-0.14	-0.30	-0.03	-0.30	-0.12	-0.26
		(-0.90)	(-1.52)	(-4.08)	(-0.27)	(-2.18)	(-1.05)	(-3.61)

Table 5A.2 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0.01)	α^b	0.052	0.030	0.080	0.053	0.055	0.052	0.053
		(3.42)	(3.74)	(3.58)	(4.14)	(3.97)	(2.56)	(2.95)
	β^b	0.45	0.43	0.36	0.49	0.35	0.44	0.38
		(7.37)	(9.39)	(9.70)	(9.63)	(5.13)	(7.66)	(9.63)
	α^s	-0.052	-0.030	-0.080	-0.053	-0.055	-0.052	-0.053
		(-3.42)	(-3.74)	(-3.58)	(-4.14)	(-3.97)	(-2.56)	(-2.95)
	β^s	0.55	0.57	0.64	0.51	0.65	0.56	0.62
		(8.97)	(12.31)	(17.14)	(10.14)	(9.53)	(9.68)	(15.98)
	α^{b-s}	0.096	0.053	0.152	0.099	0.100	0.097	0.099
		(3.17)	(3.30)	(3.39)	(3.87)	(3.62)	(2.38)	(2.77)
	β^{b-s}	-0.10	-0.13	-0.28	-0.03	-0.30	-0.12	-0.25
		(-0.80)	(-1.46)	(-3.72)	(-0.25)	(-2.20)	(-1.01)	(-3.18)

Table 5A. 3:The CAPM estimation results for the fixed moving average (FMA) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0)	α^b	0.001	0.006	0.005	0.011	0.011	-0.002	0.003
		(0.20)	(1.66)	(0.48)	(2.13)	(1.88)	(-0.22)	(0.40)
	β^b	0.06	0.07	0.07	0.05	0.05	0.10	0.06
		(3.78)	(3.83)	(4.67)	(3.59)	(1.99)	(4.21)	(3.61)
	α^s	0.001	-0.004	-0.001	-0.009	-0.011	-0.031	-0.024
		(0.13)	(-0.77)	(-0.09)	(-1.36)	(-1.70)	(-2.32)	(-1.95)
	β^s	0.08	0.07	0.11	0.13	0.06	0.11	0.16
		(4.56)	(3.66)	(3.52)	(5.13)	(2.76)	(3.95)	(6.71)
	α^{b-s}	-0.007	0.003	-0.002	0.013	0.012	0.021	0.021
		(-0.68)	(0.49)	(-0.13)	(1.51)	(1.33)	(1.26)	(1.39)
	β^{b-s}	-0.02	0.00	-0.04	-0.08	-0.01	-0.01	-0.10
		(-0.76)	(0.05)	(-1.02)	(-2.48)	(-0.31)	(-0.18)	(-2.90)

Table 5A.3 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,150,0)	α^b	0.008	0.004	0.014	0.008	0.007	0.011	-0.004
		(1.93)	(1.57)	(1.90)	(2.42)	(1.93)	(2.04)	(-0.56)
	β^b	0.02	0.02	0.03	0.03	0.01	0.02	0.04
		(2.17)	(2.42)	(3.50)	(3.22)	(1.86)	(2.27)	(2.07)
	α^s	-0.004	-0.007	0.001	-0.012	-0.004	0.012	0.005
		(-0.68)	(-2.03)	(0.09)	(-1.91)	(-0.75)	(1.50)	(0.63)
	β^s	0.09	0.06	0.10	0.09	0.06	0.06	0.06
		(2.51)	(3.45)	(4.09)	(2.56)	(2.92)	(3.16)	(3.05)
	α^{b-s}	0.005	0.005	0.004	0.013	0.002	-0.009	-0.016
		(0.65)	(1.01)	(0.24)	(1.85)	(0.25)	(-0.89)	(-1.41)
	β^{b-s}	-0.07	-0.04	-0.08	-0.06	-0.05	-0.03	-0.03
		(-1.87)	(-1.80)	(-3.30)	(-1.76)	(-2.08)	(-1.59)	(-1.04)
(5,150,0)	α^b	0.002	0.004	0.009	0.009	0.005	0.011	-0.007
		(0.35)	(1.25)	(1.34)	(2.78)	(1.44)	(2.05)	(-0.81)
	β^b	0.02	0.02	0.03	0.02	0.01	0.02	0.05
		(2.54)	(2.42)	(3.11)	(3.18)	(1.97)	(2.21)	(1.95)
	α^s	0.000	-0.004	0.013	-0.014	-0.005	0.000	-0.001
		(0.06)	(-1.68)	(1.09)	(-2.43)	(-0.79)	(0.08)	(-0.15)
	β^s	0.07	0.05	0.07	0.09	0.06	0.03	0.05
		(2.37)	(2.84)	(3.43)	(2.78)	(2.22)	(3.05)	(2.50)
	α^{b-s}	-0.006	0.002	-0.012	0.017	0.000	0.003	-0.013
		(-0.85)	(0.42)	(-0.86)	(2.40)	(0.00)	(0.37)	(-0.96)
	β^{b-s}	-0.06	-0.02	-0.05	-0.07	-0.04	-0.01	0.00
		(-1.72)	(-1.65)	(-2.29)	(-1.98)	(-1.56)	(-0.78)	(-0.12)
(1,200,0)	α^b	0.002	0.001	-0.009	0.000	0.008	0.003	-0.005
		(0.29)	(0.38)	(-1.13)	(0.14)	(2.06)	(0.39)	(-0.63)
	β^b	0.02	0.05	0.03	0.02	0.01	0.04	0.03
		(2.13)	(3.39)	(3.74)	(2.31)	(1.74)	(2.40)	(1.90)
	α^s	-0.004	-0.003	0.008	-0.015	-0.009	0.002	-0.006
		(-0.76)	(-0.63)	(0.72)	(-2.22)	(-1.40)	(0.24)	(-0.80)
	β^s	0.06	0.05	0.07	0.08	0.07	0.05	0.05
		(2.19)	(2.72)	(2.44)	(2.61)	(2.86)	(3.00)	(3.19)
	α^{b-s}	-0.002	-0.003	-0.025	0.009	0.008	-0.006	-0.005
		(-0.27)	(-0.55)	(-1.73)	(1.20)	(1.13)	(-0.63)	(-0.45)
	β^{b-s}	-0.04	-0.01	-0.04	-0.05	-0.06	-0.02	-0.02
		(-1.38)	(-0.35)	(-1.37)	(-1.79)	(-2.50)	(-0.75)	(-0.77)

Table 5A.3 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0)	α^b	0.004	0.002	0.002	0.000	0.008	0.008	-0.005
		(0.65)	(0.77)	(0.39)	(0.03)	(1.97)	(1.37)	(-0.79)
	β^b	0.02	0.04	0.02	0.02	0.01	0.03	0.03
		(2.16)	(3.14)	(1.93)	(2.36)	(1.71)	(2.30)	(1.82)
	α^s	0.000	-0.002	0.002	-0.016	-0.007	0.004	-0.005
		(0.06)	(-0.40)	(0.21)	(-2.27)	(-1.09)	(0.67)	(-0.62)
	β^s	0.05	0.05	0.07	0.08	0.06	0.04	0.05
		(1.88)	(2.81)	(2.27)	(2.61)	(2.71)	(2.61)	(2.39)
	α^{b-s}	-0.004	-0.003	-0.009	0.009	0.006	-0.004	-0.007
		(-0.49)	(-0.60)	(-0.69)	(1.20)	(0.74)	(-0.46)	(-0.66)
	β^{b-s}	-0.03	-0.02	-0.05	-0.05	-0.05	-0.01	-0.02
		(-1.14)	(-0.74)	(-2.05)	(-1.78)	(-1.90)	(-0.56)	(-0.67)

Table 5A.4: The CAPM estimation results for the fixed moving average (FMA) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0.01)	α^b	0.009	0.013	0.017	0.013	0.015	0.011	0.016
		(1.32)	(2.91)	(1.63)	(2.29)	(2.88)	(1.20)	(2.08)
	β^b	0.06	0.09	0.07	0.05	0.05	0.07	0.04
		(4.13)	(4.91)	(4.77)	(3.45)	(1.98)	(3.94)	(4.81)
	α^s	0.008	-0.001	0.004	-0.006	0.007	-0.011	-0.021
		(1.13)	(-0.16)	(0.36)	(-0.88)	(1.00)	(-1.24)	(-2.07)
	β^s	0.08	0.10	0.09	0.13	0.07	0.08	0.15
		(3.73)	(4.39)	(3.47)	(5.15)	(2.97)	(4.31)	(4.70)
	α^{b-s}	-0.007	0.007	0.005	0.011	-0.001	0.015	0.029
		(-0.63)	(1.07)	(0.30)	(1.28)	(-0.11)	(1.14)	(2.19)
	β^{b-s}	-0.02	-0.01	-0.03	-0.08	-0.01	-0.01	-0.10
		(-0.80)	(-0.35)	(-0.87)	(-2.66)	(-0.37)	(-0.20)	(-3.39)

Table 5A.4 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,150,0.01)	α^b	0.005	0.005	0.012	0.007	0.008	0.010	0.001
		(1.09)	(1.60)	(1.74)	(1.86)	(2.29)	(1.85)	(0.13)
	β^b	0.02	0.04	0.02	0.03	0.02	0.03	0.04
		(2.92)	(2.93)	(3.81)	(3.03)	(2.50)	(2.55)	(2.01)
	α^s	-0.005	-0.008	-0.001	-0.007	0.001	0.009	0.004
		(-0.76)	(-2.31)	(-0.05)	(-1.32)	(0.14)	(1.01)	(0.48)
	β^s	0.09	0.05	0.10	0.09	0.08	0.07	0.07
		(2.56)	(2.56)	(3.82)	(2.71)	(3.07)	(3.24)	(2.99)
	α^{b-s}	0.002	0.006	0.004	0.007	-0.002	-0.006	-0.010
		(0.20)	(1.28)	(0.27)	(1.05)	(-0.29)	(-0.53)	(-0.90)
	β^{b-s}	-0.07	-0.01	-0.08	-0.06	-0.06	-0.04	-0.03
		(-1.87)	(-0.43)	(-2.90)	(-1.84)	(-2.18)	(-1.80)	(-1.04)
(5,150,0.01)	α^b	0.003	0.004	0.004	0.004	0.005	0.011	-0.006
		(0.69)	(1.47)	(0.72)	(1.20)	(1.77)	(2.96)	(-0.69)
	β^b	0.02	0.04	0.02	0.03	0.02	0.02	0.06
		(2.76)	(3.19)	(2.62)	(3.12)	(2.64)	(1.90)	(2.26)
	α^s	-0.005	-0.008	0.009	-0.011	-0.003	-0.005	-0.005
		(-0.80)	(-2.78)	(0.69)	(-1.95)	(-0.61)	(-0.83)	(-0.67)
	β^s	0.09	0.05	0.09	0.08	0.05	0.04	0.06
		(2.52)	(2.96)	(3.55)	(2.48)	(2.01)	(2.89)	(2.88)
	α^{b-s}	0.000	0.006	-0.014	0.008	-0.001	0.009	-0.008
		(0.04)	(1.35)	(-0.92)	(1.19)	(-0.09)	(1.13)	(-0.58)
	β^{b-s}	-0.07	-0.01	-0.07	-0.06	-0.03	-0.02	0.00
		(-1.84)	(-0.48)	(-3.22)	(-1.65)	(-1.33)	(-1.49)	(-0.02)
(1,200,0.01)	α^b	0.001	0.003	-0.001	-0.009	0.007	0.010	-0.008
		(0.21)	(0.91)	(-0.26)	(-2.26)	(1.25)	(2.11)	(-1.29)
	β^b	0.02	0.04	0.02	0.03	0.02	0.02	0.03
		(2.23)	(2.99)	(2.04)	(2.87)	(2.27)	(2.02)	(1.78)
	α^s	-0.003	-0.003	0.006	-0.011	-0.010	0.001	-0.006
		(-0.63)	(-0.68)	(0.42)	(-1.86)	(-1.55)	(0.17)	(-0.75)
	β^s	0.06	0.06	0.09	0.05	0.08	0.05	0.05
		(2.07)	(3.04)	(3.91)	(2.07)	(2.75)	(2.96)	(2.95)
	α^{b-s}	-0.003	-0.001	-0.016	-0.005	0.007	0.002	-0.009
		(-0.36)	(-0.28)	(-1.07)	(-0.63)	(0.92)	(0.20)	(-0.88)
	β^{b-s}	-0.04	-0.02	-0.07	-0.02	-0.05	-0.03	-0.02
		(-1.09)	(-0.82)	(-3.22)	(-0.86)	(-2.01)	(-1.73)	(-0.80)

Table 5A.4 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0.01)	α^{b}	0.001	0.003	-0.001	-0.009	0.004	0.009	-0.005
		(0.14)	(0.85)	(-0.35)	(-2.38)	(0.69)	(1.91)	(-0.81)
	β^{b}	0.02	0.04	0.02	0.03	0.02	0.02	0.03
		(2.23)	(2.84)	(1.82)	(3.09)	(2.22)	(1.78)	(1.66)
	α^{s}	-0.001	-0.004	0.003	-0.010	-0.009	0.001	-0.006
		(-0.30)	(-0.93)	(0.26)	(-1.75)	(-1.36)	(0.13)	(-0.73)
	β^{s}	0.05	0.06	0.06	0.05	0.08	0.05	0.05
		(1.84)	(2.83)	(2.06)	(2.02)	(2.84)	(3.00)	(2.87)
	α^{b-s}	-0.005	0.000	-0.013	-0.006	0.003	0.001	-0.006
		(-0.66)	(-0.08)	(-0.98)	(-0.81)	(0.38)	(0.07)	(-0.57)
	β^{b-s}	-0.03	-0.02	-0.05	-0.02	-0.05	-0.04	-0.02
		(-0.86)	(-0.88)	(-1.77)	(-0.83)	(-1.95)	(-1.89)	(-0.88)

Table 5A.5: The CAPM estimation results for the variable trading range breakout (VTRB) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0)	α^{b}	0.053	0.037	0.099	0.060	0.062	0.067	0.045
		(3.74)	(4.71)	(4.69)	(5.06)	(4.78)	(3.35)	(2.62)
	β^{b}	0.41	0.52	0.40	0.47	0.38	0.38	0.42
		(6.91)	(10.63)	(11.21)	(9.64)	(5.22)	(7.15)	(10.24)
	α^{s}	-0.053	-0.037	-0.099	-0.060	-0.062	-0.066	-0.045
		(-3.74)	(-4.71)	(-4.69)	(-5.06)	(-4.78)	(-3.34)	(-2.62)
	β^{s}	0.59	0.48	0.60	0.53	0.62	0.62	0.58
		(9.92)	(9.94)	(17.01)	(10.85)	(8.65)	(11.55)	(14.26)
	α^{b-s}	0.098	0.067	0.191	0.113	0.114	0.126	0.083
		(3.48)	(4.28)	(4.50)	(4.77)	(4.41)	(3.16)	(2.42)
	β^{b-s}	-0.18	0.03	-0.21	-0.06	-0.25	-0.24	-0.16
		(-1.50)	(0.35)	(-2.90)	(-0.61)	(-1.72)	(-2.20)	(-2.01)

Table 5A.5 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(150,0)	α^b	0.033	0.027	0.061	0.051	0.039	0.049	0.044
		(2.07)	(3.16)	(2.71)	(4.13)	(2.74)	(2.51)	(2.46)
	β^b	0.47	0.47	0.39	0.49	0.44	0.48	0.40
		(7.51)	(9.77)	(9.57)	(9.39)	(5.26)	(8.04)	(9.95)
	α^s	-0.033	-0.027	-0.061	-0.051	-0.039	-0.049	-0.044
		(-2.07)	(-3.16)	(-2.71)	(-4.13)	(-2.74)	(-2.51)	(-2.46)
	β^s	0.53	0.53	0.61	0.51	0.56	0.52	0.60
		(8.50)	(10.94)	(15.09)	(9.72)	(6.78)	(8.76)	(14.69)
	α^{b-s}	0.058	0.047	0.114	0.096	0.068	0.091	0.081
		(1.83)	(2.75)	(2.52)	(3.85)	(2.41)	(2.33)	(2.28)
	β^{b-s}	-0.06	-0.06	-0.22	-0.02	-0.13	-0.04	-0.19
		(-0.49)	(-0.59)	(-2.76)	(-0.16)	(-0.76)	(-0.36)	(-2.37)
(200,0)	α^b	0.032	0.028	0.048	0.040	0.028	0.038	0.039
		(2.13)	(3.47)	(2.05)	(3.09)	(1.84)	(1.87)	(2.15)
	β^b	0.54	0.42	0.47	0.58	0.45	0.48	0.43
		(8.22)	(9.00)	(11.28)	(11.38)	(5.26)	(8.21)	(10.41)
	α^s	-0.032	-0.028	-0.048	-0.040	-0.028	-0.038	-0.039
		(-2.13)	(-3.47)	(-2.05)	(-3.09)	(-1.84)	(-1.87)	(-2.15)
	β^s	0.46	0.58	0.53	0.42	0.55	0.52	0.57
		(6.97)	(12.38)	(12.85)	(8.18)	(6.38)	(8.97)	(13.98)
	α^{b-s}	0.057	0.050	0.088	0.073	0.046	0.069	0.072
		(1.88)	(3.04)	(1.86)	(2.82)	(1.53)	(1.70)	(1.97)
	β^{b-s}	0.08	-0.16	-0.06	0.16	-0.10	-0.04	-0.15
		(0.63)	(-1.69)	(-0.78)	(1.60)	(-0.56)	(-0.38)	(-1.79)

Table 5A.6: The CAPM estimation results for the variable trading range breakout (VTRB) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0.01)	α^b	0.043	0.033	0.085	0.045	0.049	0.059	0.040
		(3.09)	(4.47)	(3.98)	(3.83)	(3.89)	(2.98)	(2.39)
	β^b	0.38	0.37	0.37	0.39	0.32	0.35	0.31
		(6.44)	(8.42)	(10.36)	(8.14)	(4.93)	(6.82)	(8.54)
	α^s	-0.043	-0.033	-0.085	-0.045	-0.049	-0.058	-0.040
		(-3.09)	(-4.47)	(-3.98)	(-3.83)	(-3.89)	(-2.97)	(-2.39)
	β^s	0.62	0.63	0.63	0.61	0.68	0.65	0.69
		(10.73)	(14.43)	(17.65)	(12.57)	(10.51)	(12.60)	(19.04)
	α^{b-s}	0.079	0.060	0.161	0.083	0.088	0.110	0.073
		(2.83)	(4.02)	(3.78)	(3.53)	(3.51)	(2.79)	(2.20)
	β^{b-s}	-0.25	-0.26	-0.26	-0.21	-0.36	-0.30	-0.38
		(-2.15)	(-3.01)	(-3.64)	(-2.21)	(-2.79)	(-2.89)	(-5.25)
(150,0.01)	α^b	0.035	0.028	0.061	0.045	0.036	0.049	0.045
		(2.27)	(3.49)	(2.75)	(3.63)	(2.55)	(2.46)	(2.53)
	β^b	0.45	0.38	0.37	0.48	0.38	0.47	0.39
		(7.34)	(8.37)	(9.21)	(9.20)	(5.07)	(7.95)	(9.08)
	α^s	-0.035	-0.028	-0.061	-0.045	-0.036	-0.049	-0.045
		(-2.27)	(-3.49)	(-2.75)	(-3.63)	(-2.55)	(-2.46)	(-2.53)
	β^s	0.55	0.62	0.63	0.52	0.62	0.53	0.61
		(8.87)	(13.42)	(15.71)	(9.87)	(8.20)	(8.93)	(14.45)
	α^{b-s}	0.063	0.050	0.114	0.084	0.062	0.091	0.084
		(2.03)	(3.05)	(2.56)	(3.35)	(2.22)	(2.28)	(2.34)
	β^{b-s}	-0.09	-0.23	-0.26	-0.04	-0.24	-0.06	-0.23
		(-0.76)	(-2.52)	(-3.25)	(-0.33)	(-1.56)	(-0.49)	(-2.68)
(200,0.01)	α^b	0.030	0.023	0.046	0.035	0.023	0.037	0.035
		(1.94)	(2.77)	(1.97)	(2.65)	(1.50)	(1.84)	(1.93)
	β^b	0.50	0.40	0.46	0.57	0.44	0.48	0.42
		(7.73)	(8.55)	(11.21)	(11.13)	(5.21)	(8.20)	(10.30)
	α^s	-0.030	-0.023	-0.046	-0.034	-0.023	-0.037	-0.035
		(-1.94)	(-2.77)	(-1.97)	(-2.65)	(-1.50)	(-1.84)	(-1.93)
	β^s	0.50	0.60	0.54	0.43	0.56	0.52	0.58
		(7.60)	(13.08)	(12.96)	(8.35)	(6.73)	(9.01)	(13.97)
	α^{b-s}	0.052	0.038	0.084	0.062	0.036	0.067	0.064
		(1.70)	(2.34)	(1.79)	(2.38)	(1.18)	(1.66)	(1.75)
	β^{b-s}	0.01	-0.21	-0.07	0.14	-0.13	-0.05	-0.15
		(0.06)	(-2.26)	(-0.88)	(1.39)	(-0.76)	(-0.41)	(-1.84)

Table 5A.7: The CAPM estimation results for the fixed trading range breakout (FTRB) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0)	α^{b}	0.045	0.023	0.083	0.058	0.037	0.077	0.032
		(4.21)	(3.16)	(4.76)	(7.02)	(3.65)	(5.33)	(2.26)
	β^{b}	0.16	0.32	0.16	0.19	0.18	0.14	0.17
		(5.29)	(7.12)	(6.15)	(7.48)	(4.29)	(4.99)	(6.56)
	α^{s}	-0.044	-0.028	-0.044	-0.039	-0.037	-0.039	-0.021
		(-3.74)	(-4.35)	(-2.21)	(-3.49)	(-3.36)	(-2.49)	(-1.42)
	β^{s}	0.35	0.25	0.31	0.30	0.43	0.34	0.31
		(6.47)	(7.60)	(8.14)	(7.16)	(6.09)	(6.68)	(6.70)
	α^{b-s}	0.082	0.044	0.119	0.090	0.064	0.109	0.047
		(4.29)	(3.82)	(3.96)	(5.42)	(3.75)	(4.41)	(1.93)
	β^{b-s}	-0.19	0.06	-0.15	-0.11	-0.25	-0.20	-0.14
		(-2.51)	(0.92)	(-2.66)	(-1.92)	(-2.42)	(-2.94)	(-2.20)
(150,0)	α^{b}	0.036	0.018	0.054	0.043	0.036	0.042	0.039
		(3.19)	(2.65)	(3.47)	(5.13)	(3.77)	(3.29)	(3.62)
	β^{b}	0.12	0.22	0.10	0.15	0.12	0.10	0.10
		(4.04)	(5.56)	(4.61)	(6.05)	(4.16)	(4.08)	(6.48)
	α^{s}	-0.020	-0.020	-0.029	-0.028	-0.023	-0.035	-0.022
		(-1.85)	(-3.29)	(-1.55)	(-2.55)	(-2.18)	(-2.56)	(-1.67)
	β^{s}	0.25	0.19	0.21	0.20	0.35	0.24	0.25
		(4.53)	(5.99)	(5.17)	(4.59)	(4.70)	(4.56)	(5.38)
	α^{b-s}	0.048	0.031	0.074	0.064	0.050	0.070	0.054
		(2.72)	(2.96)	(2.82)	(4.05)	(3.23)	(3.46)	(2.80)
	β^{b-s}	-0.14	0.03	-0.11	-0.04	-0.24	-0.15	-0.14
		(-1.87)	(0.50)	(-2.15)	(-0.77)	(-2.33)	(-2.13)	(-2.72)
(200,0)	α^{b}	0.038	0.021	0.055	0.043	0.033	0.043	0.044
		(3.33)	(3.40)	(3.55)	(5.11)	(3.41)	(3.24)	(4.18)
	β^{b}	0.11	0.17	0.10	0.16	0.11	0.09	0.10
		(3.94)	(4.77)	(4.54)	(6.05)	(4.05)	(3.92)	(6.62)
	α^{s}	-0.021	-0.020	-0.012	-0.023	-0.016	-0.024	-0.012
		(-2.18)	(-3.32)	(-0.71)	(-2.03)	(-1.56)	(-1.79)	(-0.94)
	β^{s}	0.22	0.17	0.18	0.15	0.34	0.22	0.23
		(4.08)	(5.06)	(4.79)	(3.66)	(4.46)	(4.56)	(5.21)
	α^{b-s}	0.051	0.033	0.059	0.059	0.040	0.060	0.049
		(3.03)	(3.47)	(2.38)	(3.74)	(2.61)	(3.00)	(2.61)
	β^{b-s}	-0.11	0.00	-0.08	0.01	-0.23	-0.13	-0.14
		(-1.54)	(-0.05)	(-1.67)	(0.09)	(-2.30)	(-1.96)	(-2.71)

Table 5A.8: The CAPM estimation results for the fixed trading range breakout (FTRB) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0.01)	α^{b}	0.039	0.009	0.072	0.029	0.023	0.055	0.028
		(3.40)	(1.58)	(4.38)	(3.78)	(2.80)	(3.72)	(2.10)
	β^{b}	0.14	0.16	0.18	0.11	0.14	0.16	0.13
		(4.55)	(4.16)	(7.43)	(4.30)	(3.90)	(4.89)	(4.45)
	α^{s}	-0.027	-0.028	-0.035	-0.042	-0.037	-0.047	-0.015
		(-2.29)	(-4.62)	(-1.72)	(-4.09)	(-3.23)	(-3.13)	(-0.92)
	β^{s}	0.28	0.23	0.34	0.30	0.45	0.33	0.33
		(5.99)	(5.62)	(7.99)	(7.27)	(6.09)	(6.51)	(6.71)
	α^{b-s}	0.059	0.029	0.099	0.064	0.051	0.095	0.036
		(3.03)	(3.20)	(3.19)	(4.42)	(3.18)	(3.94)	(1.51)
	β^{b-s}	-0.14	-0.07	-0.16	-0.18	-0.31	-0.18	-0.20
		(-2.07)	(-1.02)	(-2.41)	(-3.22)	(-3.04)	(-2.40)	(-3.02)
(150,0.01)	α^{b}	0.033	0.009	0.062	0.024	0.022	0.037	0.020
		(2.78)	(1.88)	(4.21)	(2.85)	(3.02)	(2.66)	(1.52)
	β^{b}	0.11	0.09	0.12	0.09	0.09	0.11	0.11
		(3.66)	(3.54)	(5.61)	(3.52)	(3.80)	(4.08)	(3.96)
	α^{s}	-0.011	-0.022	-0.025	-0.030	-0.018	-0.033	-0.018
		(-1.11)	(-3.53)	(-1.26)	(-2.99)	(-1.68)	(-2.49)	(-1.17)
	β^{s}	0.20	0.19	0.26	0.20	0.37	0.23	0.26
		(4.45)	(4.51)	(5.75)	(4.86)	(4.65)	(4.43)	(5.38)
	α^{b-s}	0.036	0.024	0.078	0.047	0.031	0.063	0.031
		(2.08)	(2.75)	(2.83)	(3.26)	(2.15)	(3.06)	(1.42)
	β^{b-s}	-0.08	-0.10	-0.13	-0.11	-0.28	-0.11	-0.15
		(-1.30)	(-1.78)	(-2.23)	(-1.90)	(-2.92)	(-1.61)	(-2.23)
(200,0.01)	α^{b}	0.034	0.006	0.062	0.025	0.021	0.037	0.029
		(2.78)	(1.33)	(4.11)	(2.84)	(2.86)	(2.58)	(2.84)
	β^{b}	0.11	0.08	0.12	0.10	0.09	0.11	0.09
		(3.61)	(3.34)	(5.68)	(3.53)	(3.74)	(3.90)	(4.80)
	α^{s}	-0.011	-0.017	-0.013	-0.024	-0.017	-0.021	-0.007
		(-1.18)	(-2.97)	(-0.65)	(-2.26)	(-1.67)	(-1.59)	(-0.47)
	β^{s}	0.21	0.18	0.22	0.16	0.35	0.22	0.25
		(4.01)	(4.09)	(5.39)	(3.85)	(4.30)	(4.67)	(5.32)
	α^{b-s}	0.037	0.016	0.066	0.041	0.029	0.051	0.029
		(2.14)	(2.01)	(2.41)	(2.76)	(2.09)	(2.53)	(1.50)
	β^{b-s}	-0.10	-0.10	-0.10	-0.06	-0.26	-0.11	-0.16
		(-1.36)	(-1.75)	(-1.83)	(-1.13)	(-2.67)	(-1.56)	(-2.88)

Table 5A.9: The Sharpe ratio results for the variable moving average (VMA) rules

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
B & H	$S^{b\&h}$	1.38	-0.38	0.32	4.96	4.05	3.81	1.73
(1,50,0)	S^{b}	11.54	12.73	10.62	19.84	18.78	13.76	9.41
	S^{s}	-8.44	-15.51	-7.44	-12.02	-10.53	-5.61	-4.46
	$S^{b\&s}$	22.53	28.78	20.20	36.66	36.83	22.09	16.90
(1,50,0.01)	S^{b}	13.61	13.78	13.53	23.47	18.62	14.39	11.96
	S^{s}	-7.54	-11.06	-8.07	-11.29	-7.60	-4.53	-4.79
	$S^{b\&s}$	22.10	24.39	23.70	38.97	29.99	20.62	19.94
(1,150,0)	S^{b}	8.97	11.09	9.21	14.72	12.04	9.51	8.15
	S^{s}	-6.52	-13.63	-8.53	-9.54	-6.17	-5.43	-4.82
	$S^{b\&s}$	16.90	26.11	19.36	26.23	23.70	17.56	15.49
(1,150,0.01)	S^{b}	10.05	11.82	9.28	15.47	12.30	9.69	8.14
	S^{s}	-6.75	-12.56	-8.08	-8.83	-5.70	-4.85	-4.31
	$S^{b\&s}$	18.07	25.05	18.50	25.67	22.57	16.51	14.49
(5,150,0)	S^{b}	8.15	9.51	6.86	14.28	11.44	9.34	7.44
	S^{s}	-5.88	-12.31	-7.21	-9.34	-5.73	-5.34	-4.30
	$S^{b\&s}$	15.06	22.80	14.74	25.31	21.92	17.17	13.83
(5,150,0.01)	S^{b}	9.35	11.32	7.03	14.57	11.47	9.77	7.74
	S^{s}	-6.17	-12.30	-6.45	-8.18	-5.16	-5.09	-4.11
	$S^{b\&s}$	16.60	24.11	14.14	23.82	20.37	16.85	13.64
(1,200,0)	S^{b}	9.60	8.11	8.77	15.19	12.45	8.72	7.83
	S^{s}	-7.55	-12.27	-7.36	-8.51	-6.35	-3.84	-4.45
	$S^{b\&s}$	18.84	21.09	17.01	24.66	25.05	14.66	14.75
(1,200,0.01)	S^{b}	10.10	8.67	9.32	16.34	13.03	9.21	7.82
	S^{s}	-7.34	-11.33	-7.24	-8.68	-6.24	-4.13	-4.07
	$S^{b\&s}$	18.66	20.70	17.47	25.74	24.78	15.46	13.84
(2,200,0)	S^{b}	9.07	8.27	9.24	15.13	11.83	8.37	7.07
	S^{s}	-7.14	-12.41	-7.61	-8.50	-5.80	-3.64	-3.80
	$S^{b\&s}$	17.66	21.34	17.72	24.52	23.03	13.80	12.86
(2,200,0.01)	S^{b}	9.60	8.40	9.52	15.88	12.51	8.64	7.62
	S^{s}	-6.92	-11.18	-7.58	-8.16	-5.57	-3.39	-3.94
	$S^{b\&s}$	17.55	20.26	17.85	24.65	22.88	13.63	13.36

Table 5A.10: The Sharpe ratio results for the fixed moving average (FMA) rules

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
B & H	$S^{b\&h}$	1.38	-0.38	0.32	4.96	4.05	3.81	1.73
(1,50,0)	S^{b}	2.34	12.71	3.19	22.65	19.65	2.16	3.91
	S^{s}	1.85	-6.91	-0.45	-4.02	-12.07	-14.95	-7.80
	$S^{b\&s}$	-0.54	19.93	2.57	17.49	27.45	16.58	10.32
(1,50,0.01)	S^{b}	9.91	21.96	10.84	28.53	26.58	10.79	15.46
	S^{s}	7.68	-1.08	2.19	-0.66	10.23	-4.05	-7.45
	$S^{b\&s}$	0.21	21.62	6.02	18.66	17.46	14.33	16.31
(1,150,0)	S^{b}	28.41	23.80	22.94	35.13	34.16	24.06	-4.07
	S^{s}	-3.42	-23.88	-0.08	-15.46	-3.25	17.44	6.76
	$S^{b\&s}$	18.21	38.33	14.11	35.17	20.15	-0.42	-10.41
(1,150,0.01)	S^{b}	14.46	19.12	20.47	27.02	33.50	19.72	2.50
	S^{s}	-4.16	-32.04	-1.30	-7.08	5.63	13.08	5.54
	$S^{b\&s}$	11.92	48.68	13.87	22.00	12.65	-1.24	-3.76
(5,150,0)	S^{b}	5.76	21.00	14.80	40.22	23.10	24.25	-8.31
	S^{s}	2.23	-18.40	9.92	-21.55	-5.04	4.06	0.11
	$S^{b\&s}$	0.34	30.98	0.46	41.02	17.45	12.60	-9.03
(5,150,0.01)	S^{b}	9.98	16.13	7.12	16.85	23.11	34.27	-5.91
	S^{s}	-4.62	-36.21	5.58	-14.71	-3.28	-4.38	-5.01
	$S^{b\&s}$	9.64	49.46	-1.64	23.46	15.70	30.23	-0.85
(1,200,0)	S^{b}	6.45	2.47	-13.07	5.12	51.19	6.47	-5.68
	S^{s}	-4.59	-10.84	6.12	-29.02	-10.51	5.88	-6.52
	$S^{b\&s}$	7.82	11.91	-15.50	31.11	35.45	-1.44	2.47
(1,200,0.01)	S^{b}	4.83	9.99	-3.58	-23.84	26.68	28.89	-11.52
	S^{s}	-3.19	-10.13	2.87	-34.99	-11.05	5.85	-6.10
	$S^{b\&s}$	6.34	17.90	-5.36	23.64	26.57	10.24	-1.34
(2,200,0)	S^{b}	13.58	6.74	2.97	3.92	49.39	16.95	-6.54
	S^{s}	1.86	-7.68	1.04	-29.99	-8.45	10.28	-4.90
	$S^{b\&s}$	6.38	11.84	0.43	31.47	32.35	3.59	0.21
(2,200,0.01)	S^{b}	3.53	9.66	-3.78	-24.59	15.61	28.62	-7.44
	S^{s}	-0.88	-14.70	1.46	-31.59	-9.39	5.43	-5.62
	$S^{b\&s}$	3.03	21.56	-4.22	19.92	18.22	10.36	-0.17

Table 5A.11: The Sharpe ratio results for the variable trading range breakout (VTRB) rules

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
B & H	$S^{b\&h}$	1.38	-0.38	0.32	4.96	4.05	3.81	1.73
(50,0)	S^{b}	10.21	10.68	11.84	17.49	14.30	12.28	6.62
	S^{s}	-7.13	-13.37	-9.24	-9.57	-7.22	-4.05	-3.40
	$S^{b\&s}$	14.34	21.75	18.64	22.56	14.23	11.44	7.53
(50,0.01)	S^{b}	9.77	13.98	10.78	17.10	14.51	12.75	7.85
	S^{s}	-4.90	-8.70	-7.46	-3.95	-2.99	-2.32	-1.85
	$S^{b\&s}$	12.65	20.89	15.99	18.79	12.30	11.53	7.45
(150,0)	S^{b}	6.59	7.84	7.09	16.06	8.57	7.70	6.81
	S^{s}	-3.88	-9.32	-5.98	-7.66	-4.48	-3.98	-3.05
	$S^{b\&s}$	9.30	15.72	12.20	22.23	7.89	7.86	8.01
(150,0.01)	S^{b}	7.61	10.14	7.82	15.06	9.22	7.75	7.33
	S^{s}	-3.97	-8.69	-5.64	-5.95	-2.31	-3.76	-3.07
	$S^{b\&s}$	10.96	16.81	13.09	20.03	7.08	7.72	8.50
(200,0)	S^{b}	5.47	8.35	4.50	12.84	6.91	6.77	5.86
	S^{s}	-4.95	-10.34	-5.21	-6.57	-1.32	-1.67	-2.64
	$S^{b\&s}$	8.55	16.82	9.60	19.22	4.02	5.48	6.60
(200,0.01)	S^{b}	6.02	6.80	4.40	11.99	6.43	6.76	5.45
	S^{s}	-3.49	-8.33	-4.98	-4.74	0.18	-1.50	-2.15
	$S^{b\&s}$	8.65	13.44	9.33	16.87	2.73	5.44	5.86

Table 5A.12: The Sharpe ratio results for the fixed trading range breakout (FTRB) rules

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
B & H	$S^{b\&h}$	1.38	-0.38	0.32	4.96	4.05	3.81	1.73
(50,0)	S^{b}	21.85	12.01	25.91	32.97	17.62	33.27	9.67
	S^{s}	-13.58	-19.79	-9.63	-14.70	-7.14	-6.51	-3.30
	$S^{b\&s}$	26.23	30.45	26.41	31.84	14.00	21.36	7.77
(50,0.01)	S^{b}	24.75	11.02	21.79	37.05	18.80	26.23	13.71
	S^{s}	-8.42	-21.85	-6.84	-16.52	-6.41	-8.62	-1.34
	$S^{b\&s}$	27.84	34.09	23.62	41.98	16.37	23.57	9.62
(150,0)	S^{b}	25.42	12.69	25.79	31.34	22.76	26.20	16.73
	S^{s}	-9.06	-20.46	-10.28	-19.90	-6.52	-12.92	-6.59
	$S^{b\&s}$	21.78	31.28	26.95	35.47	12.00	22.25	12.86

Table 5A.12 *(Continued)*

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(150,0.01)	S^b	28.12	16.85	28.40	40.88	24.03	23.30	11.75
	S^s	-4.77	-23.08	-7.86	-20.03	-2.06	-12.42	-4.31
	$S^{b\&s}$	24.25	38.73	29.06	48.05	10.37	22.45	10.41
(200,0)	S^b	28.17	16.94	28.83	31.34	22.16	28.02	19.78
	S^s	-11.01	-24.91	-5.52	-20.54	-1.42	-7.85	-2.67
	$S^{b\&s}$	25.31	38.03	26.43	36.41	6.85	18.06	9.35
(200,0.01)	S^b	28.97	10.11	28.23	40.88	23.99	23.88	18.33
	S^s	-4.48	-22.04	-4.87	-19.26	-1.73	-6.24	0.04
	$S^{b\&s}$	23.25	30.72	27.07	47.73	9.58	16.41	7.91

Table 5A.13: The Henriksson and Merton test results for the variable moving average (VMA) rules

Rules	coefficient	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0)	β	0.10	0.13	0.10	0.15	0.13	0.10	0.09
		(4.10)	(5.70)	(4.25)	(6.20)	(5.50)	(4.05)	(4.21)
(1,50,0.01)	β	0.09	0.12	0.11	0.16	0.11	0.09	0.10
		(4.02)	(5.21)	(4.60)	(7.35)	(4.37)	(3.78)	(5.29)
(1,150,0)	β	0.10	0.09	0.10	0.10	0.06	0.03	0.08
		(3.89)	(3.78)	(4.37)	(3.82)	(2.27)	(0.99)	(3.78)
(1,150,0.01)	β	0.10	0.10	0.10	0.10	0.06	0.03	0.08
		(3.92)	(3.97)	(4.36)	(3.97)	(2.17)	(1.14)	(3.88)
(5,150,0)	β	0.10	0.09	0.09	0.09	0.06	0.03	0.07
		(3.98)	(3.53)	(3.96)	(3.46)	(2.03)	(1.09)	(3.59)
(5,150,0.01)	β	0.09	0.09	0.08	0.09	0.06	0.03	0.08
		(3.59)	(3.81)	(3.59)	(3.46)	(2.16)	(1.19)	(3.95)
(1,200,0)	β	0.10	0.07	0.09	0.09	0.07	0.03	0.07
		(4.03)	(2.70)	(3.66)	(3.70)	(2.52)	(1.07)	(3.55)
(1,200,0.01)	β	0.09	0.07	0.09	0.10	0.07	0.04	0.08
		(3.88)	(2.85)	(3.96)	(3.92)	(2.69)	(1.27)	(3.78)
(2,200,0)	β	0.10	0.07	0.09	0.09	0.07	0.03	0.07
		(4.01)	(2.91)	(3.91)	(3.60)	(2.43)	(0.99)	(3.42)
(2,200,0.01)	β	0.09	0.07	0.10	0.09	0.07	0.03	0.08
		(3.84)	(2.90)	(4.18)	(3.68)	(2.35)	(1.13)	(3.71)

Table 5A.14: The Henriksson and Merton test results for the variable trading range breakout (VTRB) rules

Rules	coefficient	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0)	β	0.09	0.11	0.11	0.13	0.08	0.06	0.09
		(3.59)	(4.44)	(4.83)	(5.33)	(2.73)	(2.30)	(4.22)
(50,0.01)	β	0.05	0.12	0.10	0.08	0.02	0.04	0.07
		(1.99)	(4.69)	(4.18)	(3.44)	(0.88)	(1.74)	(3.42)
(150,0)	β	0.06	0.09	0.09	0.10	0.04	0.02	0.08
		(2.26)	(3.72)	(3.53)	(4.21)	(1.21)	(0.78)	(3.72)
(150,0.01)	β	0.06	0.08	0.09	0.09	0.03	0.03	0.08
		(2.25)	(3.15)	(3.63)	(3.58)	(0.96)	(0.90)	(3.83)
(200,0)	β	0.05	0.08	0.06	0.09	0.01	0.01	0.06
		(1.86)	(3.31)	(2.61)	(3.65)	(0.22)	(0.32)	(2.84)
(200,0.01)	β	0.03	0.06	0.06	0.08	0.01	0.01	0.06
		(1.24)	(2.43)	(2.35)	(3.02)	(0.27)	(0.32)	(2.68)

Table 5A.15: The Henriksson and Merton test results for the fixed moving average (FMA) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0)	α	0.52	0.51	0.51	0.58	0.55	0.56	0.58
		(36.62)	(37.07)	(38.95)	(42.72)	(40.45)	(39.04)	(51.40)
	β^b	0.02	0.05	0.00	0.02	0.09	0.01	-0.01
		(0.49)	(1.27)	(-0.10)	(0.59)	(1.47)	(0.41)	(-0.32)
	β^s	0.01	-0.06	-0.01	-0.09	-0.07	-0.12	-0.08
		(0.26)	(-1.33)	(-0.34)	(-2.45)	(-1.38)	(-2.99)	(-2.73)
	Wald F-stat	0.14	1.92	0.06	3.37	2.10	4.85	3.73
	p-value	0.87	0.15	0.94	0.03	0.12	0.01	0.02
(1,150,0)	α	0.52	0.50	0.50	0.58	0.54	0.54	0.57
		(38.99)	(37.59)	(40.86)	(43.66)	(38.63)	(38.80)	(53.06)
	β^b	0.09	0.13	0.11	0.11	0.14	0.09	-0.05
		(1.64)	(2.50)	(1.76)	(2.55)	(2.06)	(1.51)	(-0.93)
	β^s	0.01	-0.05	0.00	-0.16	-0.03	0.00	0.03
		(0.25)	(-0.87)	(-0.08)	(-3.38)	(-0.67)	(-0.03)	(0.61)
	Wald F-stat	1.36	3.62	1.56	9.75	2.49	1.15	0.66
	p-value	0.26	0.03	0.21	0.00	0.08	0.32	0.52

Table 5A.15 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(5,150,0)	α	0.52	0.49	0.51	0.57	0.55	0.54	0.57
		(39.50)	(37.32)	(41.24)	(43.85)	(38.62)	(39.71)	(53.56)
	β^b	0.06	0.13	0.09	0.13	-0.01	0.10	-0.01
		(1.04)	(2.30)	(1.56)	(2.61)	(-0.07)	(1.61)	(-0.17)
	β^s	0.00	-0.02	-0.05	-0.19	-0.04	-0.07	-0.03
		(-0.01)	(-0.41)	(-0.95)	(-3.54)	(-0.56)	(-1.39)	(-0.59)
	Wald F-stat	0.55	2.80	1.75	10.38	0.16	2.44	0.18
	p-value	0.58	0.06	0.17	0.00	0.85	0.09	0.83
(1,200,0)	α	0.52	0.50	0.51	0.58	0.55	0.55	0.58
		(39.21)	(37.28)	(40.86)	(43.90)	(38.93)	(38.82)	(53.93)
	β^b	0.09	-0.04	-0.03	-0.03	0.13	-0.04	-0.05
		(1.34)	(-0.78)	(-0.50)	(-0.47)	(1.71)	(-0.70)	(-1.06)
	β^s	0.00	-0.07	-0.02	-0.19	-0.01	-0.02	-0.02
		(0.00)	(-1.14)	(-0.32)	(-4.00)	(-0.13)	(-0.37)	(-0.40)
	Wald F-stat	0.90	0.86	0.17	8.03	1.48	0.29	0.62
	p-value	0.41	0.42	0.84	0.00	0.23	0.75	0.54
(2,200,0)	α	0.52	0.50	0.51	0.58	0.55	0.54	0.58
		(38.94)	(37.37)	(41.25)	(43.89)	(38.90)	(38.85)	(53.85)
	β^b	0.13	-0.06	0.03	-0.04	0.13	0.08	-0.04
		(1.90)	(-1.06)	(0.40)	(-0.67)	(1.65)	(1.66)	(-0.90)
	β^s	0.03	-0.09	-0.06	-0.19	0.00	0.03	-0.03
		(0.53)	(-1.29)	(-0.96)	(-3.84)	(-0.06)	(0.57)	(-0.59)
	Wald F-stat	1.87	1.23	0.57	7.46	1.37	1.47	0.56
	p-value	0.15	0.29	0.55	0.00	0.26	0.23	0.57

Table 5A.16: The Henriksson and Merton test results for the fixed moving average (FMA) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(1,50,0.01)	α	0.52	0.50	0.51	0.57	0.54	0.55	0.58
		(36.66)	(35.68)	(38.79)	(42.83)	(37.62)	(38.50)	(51.57)
	β^b	0.06	0.11	0.02	0.05	0.15	0.03	0.01
		(1.69)	(3.12)	(0.70)	(1.08)	(3.22)	(0.79)	(0.25)
	β^s	-0.01	-0.02	0.00	-0.03	0.03	-0.06	-0.07
		(-0.19)	(-0.61)	(-0.10)	(-0.76)	(0.79)	(-1.60)	(-2.36)
	Wald F-stat	1.52	5.43	0.26	0.97	5.29	1.77	2.94
	p-value	0.22	0.00	0.77	0.38	0.01	0.17	0.05
(1,150,0.01)	α	0.52	0.50	0.51	0.57	0.54	0.54	0.57
		(39.25)	(38.21)	(41.07)	(43.01)	(37.95)	(38.55)	(53.24)
	β^b	0.10	0.07	0.09	0.08	0.11	0.07	-0.04
		(1.75)	(1.23)	(1.52)	(1.39)	(1.91)	(1.24)	(-0.88)
	β^s	-0.01	-0.14	-0.02	-0.10	0.02	0.00	-0.01
		(-0.23)	(-2.52)	(-0.48)	(-2.26)	(0.30)	(0.04)	(-0.19)
	Wald F-stat	1.59	4.10	1.31	3.63	1.84	0.77	0.40
	p-value	0.20	0.02	0.27	0.03	0.16	0.46	0.67
(5,150,0.01)	α	0.52	0.50	0.51	0.58	0.55	0.54	0.58
		(39.20)	(38.26)	(41.29)	(43.91)	(38.56)	(39.76)	(54.19)
	β^b	0.09	0.02	0.03	0.01	0.08	0.16	-0.01
		(1.52)	(0.41)	(0.59)	(0.19)	(1.56)	(3.41)	(-0.26)
	β^s	0.02	-0.14	-0.04	-0.16	-0.07	-0.08	-0.09
		(0.35)	(-2.50)	(-0.72)	(-3.23)	(-1.23)	(-1.78)	(-1.53)
	Wald F-stat	1.19	3.27	0.46	5.29	2.18	8.05	1.19
	p-value	0.31	0.04	0.63	0.01	0.11	0.00	0.30
(1,200,0.01)	α	0.52	0.50	0.51	0.59	0.55	0.54	0.58
		(39.05)	(37.24)	(41.10)	(44.71)	(39.03)	(39.51)	(54.28)
	β^b	0.08	-0.05	-0.01	-0.17	0.08	0.09	-0.05
		(1.11)	(-0.69)	(-0.11)	(-3.20)	(1.09)	(1.88)	(-1.09)
	β^s	0.00	-0.04	-0.06	-0.26	-0.04	-0.06	-0.03
		(0.07)	(-0.67)	(-1.28)	(-4.06)	(-0.64)	(-1.13)	(-0.44)
	Wald F-stat	0.62	0.65	0.82	12.73	0.77	2.58	0.67
	p-value	0.54	0.44	0.44	0.00	0.46	0.08	0.51

Table 5A.16 ***(Continued)***

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(2,200,0.01)	α	0.52	0.49	0.51	0.59	0.55	0.54	0.57
		(39.11)	(37.33)	(41.15)	(44.55)	(38.94)	(39.56)	(54.13)
	β^b	0.08	-0.02	0.01	-0.18	0.05	0.09	-0.01
		(1.06)	(-0.28)	(0.16)	(-3.28)	(0.72)	(1.55)	(-0.15)
	β^s	-0.01	-0.03	-0.05	-0.21	-0.03	-0.06	0.00
		(-0.31)	(-0.47)	(-0.92)	(-3.43)	(-0.42)	(-1.15)	(0.05)
	Wald F-stat	0.63	0.14	0.44	10.73	0.32	2.02	0.01
	p-value	0.53	0.87	0.64	0.00	0.73	0.13	0.99

Table 5A.17: The Henriksson and Merton test results for the fixed trading range breakout (FTRB) rules without a filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0)	α	0.52	0.51	0.50	0.54	0.55	0.53	0.57
		(34.96)	(29.28)	(35.08)	(35.13)	(31.40)	(35.01)	(42.45)
	β^b	0.09	0.07	0.12	0.13	0.01	0.14	0.04
		(3.20)	(2.56)	(4.15)	(5.65)	(0.53)	(4.99)	(1.76)
	β^s	-0.09	-0.10	-0.05	-0.05	-0.06	-0.07	-0.06
		(-3.12)	(-3.45)	(-1.64)	(-1.51)	(-1.68)	(-2.00)	(-1.85)
	Wald F-stat	13.01	14.42	12.08	20.78	1.96	17.73	4.44
	p-value	0.00	0.00	0.00	0.00	0.14	0.00	0.01
(150,0)	α	0.52	0.49	0.50	0.55	0.54	0.54	0.56
		(37.64)	(32.64)	(37.77)	(38.76)	(34.39)	(37.97)	(47.43)
	β^b	0.11	0.09	0.14	0.12	0.05	0.09	0.06
		(3.14)	(2.92)	(3.69)	(4.34)	(1.57)	(2.48)	(2.60)
	β^s	-0.11	-0.09	-0.04	-0.10	-0.05	-0.11	-0.08
		(-2.98)	(-2.83)	(-1.13)	(-2.22)	(-0.89)	(-2.42)	(-2.04)
	Wald F-stat	10.77	10.39	8.16	13.56	1.87	6.77	6.35
	p-value	0.00	0.00	0.00	0.00	0.15	0.00	0.00
(200,0)	α	0.52	0.49	0.49	0.55	0.54	0.53	0.56
		(38.01)	(33.61)	(37.41)	(38.28)	(34.71)	(37.84)	(47.69)
	β^b	0.12	0.10	0.16	0.12	0.03	0.10	0.07
		(3.22)	(3.11)	(3.98)	(4.31)	(0.95)	(2.82)	(2.86)
	β^s	-0.11	-0.11	-0.01	-0.11	-0.04	-0.08	-0.04
		(-2.95)	(-3.17)	(-0.23)	(-2.03)	(-0.67)	(-1.66)	(-1.00)
	Wald F-stat	10.67	11.93	8.18	12.69	0.78	5.95	5.03
	p-value	0.00	0.00	0.00	0.00	0.46	0.00	0.01

Table 5A.18: The Henriksson and Merton test results for the fixed trading range breakout (FTRB) rules with a 1 percent filter

Rules		Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
(50,0.01)	α	0.52	0.53	0.50	0.58	0.55	0.55	0.57
		(35.61)	(36.93)	(34.82)	(44.03)	(34.66)	(36.79)	(47.93)
	β^b	0.08	0.06	0.12	0.12	0.04	0.08	0.06
		(2.26)	(1.57)	(3.81)	(3.09)	(1.09)	(2.77)	(2.22)
	β^s	-0.03	-0.14	-0.03	-0.14	-0.05	-0.11	-0.06
		(-0.89)	(-5.19)	(-1.01)	(-4.48)	(-1.42)	(-3.48)	(-2.12)
	Wald F-stat	3.46	16.70	9.08	17.01	1.99	12.53	5.82
	p-value	0.03	0.00	0.00	0.00	0.14	0.00	0.00
(150,0.01)	α	0.52	0.51	0.50	0.58	0.54	0.54	0.57
		(37.92)	(36.47)	(37.73)	(43.97)	(36.11)	(38.57)	(49.91)
	β^b	0.10	0.08	0.16	0.12	0.06	0.06	0.08
		(2.43)	(1.75)	(4.34)	(2.25)	(1.58)	(1.81)	(2.95)
	β^s	-0.06	-0.13	-0.04	-0.15	-0.02	-0.13	-0.06
		(-1.61)	(-3.98)	(-1.18)	(-3.60)	(-0.48)	(-3.01)	(-1.62)
	Wald F-stat	4.73	10.50	11.03	9.71	1.48	6.77	6.29
	p-value	0.01	0.00	0.00	0.00	0.23	0.00	0.00
(200,0.01)	α	0.52	0.50	0.49	0.57	0.55	0.54	0.57
		(37.59)	(36.19)	(36.81)	(43.27)	(37.24)	(38.03)	(50.15)
	β^b	0.10	0.07	0.16	0.13	0.05	0.08	0.10
		(2.39)	(1.30)	(4.23)	(2.25)	(1.19)	(2.07)	(3.29)
	β^s	-0.05	-0.11	0.00	-0.14	-0.10	-0.08	-0.02
		(-1.18)	(-3.40)	(-0.02)	(-3.11)	(-2.41)	(-1.58)	(-0.51)
	Wald F-stat	3.87	7.17	9.13	7.92	3.97	3.78	5.75
	p-value	0.02	0.00	0.00	0.00	0.02	0.02	0.00

CHAPTER 6

THE ROLE OF FUNDAMENTAL AND TECHNICAL ANALYSIS IN PRICE FORMATION

6.1 Introduction

The collective role of fundamental and technical analysis in financial asset-price formation has increasingly caught the attention of economists. Studies dealing with this issue may be divided into three categories: (1) studies based on econometric models; (2) survey studies; (3) studies analysing the comparative profitability of fundamental and technical trading rules. The seminal paper that belongs to the first category was conducted by Frankel and Froot (1990). They developed a model to account for the strong increase in the demand for dollars during the first half of the 1980s. The Frankel-Froot model is used by Vigfusson (1997), whereas Kirman (1991) presents an extension of the model. Levin (1997) proposes a model encompassing the interaction between the expectations of chartists and fundamentalists.

Other studies that, in part, follow the model proposed by Frankel and Froot (1990) are Moosa and Korczak (2000), Moosa and Al-Loughani (2003), Al-Muraikhi and Moosa (2008), and Moosa and Li (2011). The main conclusion that emerges from these studies is that both technicians and fundamentalists have a role to play in price formation. Nevertheless, the empirical findings of these studies indicate that the "balance of power" may tip in favour of one group of traders under certain circumstances—for instance the role of technicians is more important in situations involving short investment horizons.

Moosa and Korczak (2000) examine the exchange rates of three major currencies against the US dollar. Their empirical results show that the exchange rate is determined by both technicians and fundamentalists, and that the fundamentalists played a bigger role in this respect. The second finding is justified on the grounds of using low-frequency data, which implies a long investment horizon. On the other hand, Moosa and Al-Loughani (2003) investigate the exchange rate of the Kuwaiti Dinar, which is pegged to a basket of major currencies. They find that the role of technicians is slightly more substantial than that of the fundamentalists in price formation. Al-Muraikhi and Moosa (2008) study the emerging stock and foreign exchange markets of Kuwait, whereas Moosa and Li (2011) examine the Chinese stock market; they arrive at a similar conclusion.

While these studies focus on foreign exchange markets and the stock markets of Kuwait and China, we contribute to this literature by extending the analysis to the stock markets of the GCC region. For this purpose, we employ the model proposed by Moosa and Korczak (2000) and Moosa and Al-Loughani (2003) that in part follows the model proposed by Frankel and Froot (1990). The model is estimated and tested using time series data.

6.2 Model Specification and Estimation

In their model of period-to-period changes in the exchange rate between two floating currencies, Moosa and Korczak (2000) postulate that changes in exchange rates are determined as a weighted average of the effects exerted by fundamentalists and technicians. Indeed, the behaviour of the traders who act solely on the basis of technical analysis may differ considerably from the behaviour of those who trade exclusively on the basis of fundamental analysis.

Fundamentalists perceive that there exists an equilibrium price. If a fundamental model or trend suggests that the actual price deviates from the equilibrium level, trading takes place until the asset price converges on the perceived equilibrium level. This is not necessarily the case, however. Technicians employ trend-chasing strategies, which means that if a technical trading rule indicates an initiation of a trend in the price of the asset, trading takes place until the rule suggests that the trend is reversed. The impact on prices depends on the net effect of the forces of supply and demand arising from the actions of fundamentalists and technicians.

Fundamentalists make their buy and sell decisions on the basis of the difference between the equilibrium price and actual price. Therefore, the current period's change in price attributed to the operation of fundamentalists is given by:

$$(\Delta p_t)^F = \alpha\left(\overline{p}_{t-1} - p_{t-1}\right) \tag{6.1}$$

where p_t is the logarithm of the price, a bar denotes the equilibrium price, F denotes fundamentalists, and α is a positive parameter that captures the speed of adjustment of the actual price to the deviation from equilibrium price.

On the other hand, technicians base their decisions on technical trading strategies that use historical prices and trading volumes to forecast future price movements. Indeed, there is a wide variety of technical trading strategies that range from simple moving averages to genetic trading systems. Thus, the behaviour of technicians can be modelled using any of these specifications. Following Moosa and Korczak (2000), the behaviour of technicians is modelled as a geometrically declining distributed-lag representation, which is motivated by the widespread use of the exponential moving average rule. Under this trading rule, buy and (sell) signals are generated when the exponential moving average penetrates the stock price series from below (above). The change in the price due to the activities of technicians can, therefore, be formulated as:

$$(\Delta p_t)^T = \sum_{i=1}^{\infty} \beta^i \Delta p_{t-i} \tag{6.2}$$

where $0 < \beta < 1$is ?? and the subscript T denotes technicians. If the activities of fundamentalists and technicians, collectively, contribute to price changes, the model can be expressed in a testable stochastic form as:

$$\Delta p_t = \gamma_0 + \gamma_1(\overline{p}_{t-1} - p_{t-1}) + \gamma_2 \sum_{i=1}^{\infty} \beta^i \Delta p_{t-i} + \varepsilon_t \tag{6.3}$$

such that $\gamma_1 > 0$ and $\gamma_2 > 0$. If $\gamma_1 > \gamma_2$, we can safely conclude that fundamentalists play a more significant role in price determination, and vice versa. The model represented by Eq. (6.3) will be referred to as Model I, which is estimated by OLS. This is a valid procedure, since the underlying variables are stationary. The unobserved equilibrium price $\overline{p}$ is estimated by applying the Hodrick and Prescott (1997) (*HP*) filter to p. This is a de-trending technique that is utilised to decompose an observed time series into a trend and cycle. Formally, the *HP* filter is used to estimate the trend path $\{p_t^*, t = 1,2, \dots, n\}$ of the time series $\{p_t, t = 1,2, \dots, n\}$, subject to a constraint that the sum of the squared second differences of the time series is not too large. The trend is calculated from the observed time series by solving the optimisation problem:

$$\min_{p_1^*, p_2^*, \dots, p_n^*} \left\{ \sum_{t=1}^{n} (p_t - p_t^*)^2 + \lambda \sum_{t=2}^{n=1} (\Delta^2 p_{t+1}^*)^2 \right\} \tag{6.4}$$

where the smoothing parameter, λ, is typically determined by the frequency of observations. Ultimately, the equilibrium price is taken to be the fitted *HP* trend. Despite the fact that the *HP* filter is not the only approach whereby a proxy for the equilibrium price can be obtained, it is assumed here that the long-run trend of the price reflects the behaviour of fundamental variables determining the equilibrium price. By using a specific fundamental model to estimate the equilibrium value, we run the risk of not capturing all of the fundamental variables, and hence we risk misrepresenting the equilibrium price.

To estimate the geometrically declining distributed lag, the choice of the parameter β is arbitrary. In the present study we set β to be 0.8, which is a reasonable choice because it implies that technicians assign more weight to more recent observations on Δp_{t-i}. After the estimation of Model I, we conduct standard residuals diagnostics tests for serial correlation (SC), functional form (FF), and heteroscedasticity (HS).

Numerous tests for serial correlation have been proposed, most of which deal with first order serial correlation. Since the presence of monthly seasonal effects is empirically well-established, we use the Lagrange Multiplier (LM) test of order 12 proposed by Breusch (1978) and Godfrey (1978) to account for such effects. In other words, the hypothesis is H_0: no serial correlation, versus $H_1: \hat{\varepsilon}_t = AR(12)$. This test is performed by obtaining the OLS residuals of Eq. (6.3), $\hat{\varepsilon}_t$, for all $t = 1,2, \dots, n$.. The following auxiliary regression is run:

$$\hat{\varepsilon}_t = \gamma_0 + \gamma_1(\overline{p}_{t-1} - p_{t-1}) + \gamma_2 \sum\nolimits_{i=1}^{\infty} \beta^i \Delta p_{t-i} + \sum\nolimits_{q=1}^{12} \rho_q \hat{\varepsilon}_{t-q} + e_t \tag{6.5}$$

The LM test statistic is obtained by multiplying the usual R^2 from the auxiliary regression by the sample size, less the order of serial correlation $(n-q)$. This can be expressed mathematically as $LM = (n-q)R^2$, under the null of $LM \sim \chi^2(q)$, in this case, $LM \sim \chi^2(12)$. If the LM test statistic exceeds the tabulated χ^2 critical value, there is serial correlation of up to order 12.

Several specification tests for linear regression models have been developed in the econometrics literature. One of the oldest and most commonly used tests is the regression specification error test (RESET) test proposed by Ramsey (1969). In his important paper, Ramsey (1969) posits that several specification errors—namely omitted variables, wrong functional form, and correlation between the explanatory variables and the residuals—may result in a non-zero residuals vector; thus, the null and alternative hypotheses are

$$H_0 : \varepsilon_t \sim N(0, \sigma^2 I) \tag{6.6}$$

$$H_1 : \varepsilon_t \sim N(\mu, \sigma^2 I) \qquad \mu \neq 0 \tag{6.7}$$

In order to test the null hypothesis that Eq. (6.3) is correctly specified, that is H_0, we augment Eq. (6.3) with its own fitted values raised to the power of 2, 3, and 4 as shown in Johnston and DiNardo (1997).Thus, the augmented regression model is given by:

$$\Delta p_t = \gamma_0 + \gamma_1 (\overline{p}_{t-1} - p_{t-1}) + \gamma_2 \sum_{i=1}^{\infty} \beta^i \Delta p_{t-i} + \delta_2 \widehat{\Delta p_t}^2 + \delta_3 \widehat{\Delta p_t}^3 + \delta_4 \widehat{\Delta p_t}^4 + e_t \tag{6.8}$$

The RESET test is simply the F statistic for $q = 3$ restrictions $H_0 : \delta_2 = \delta_3 = \delta_4 = 0$ in the augmented model. The distribution of the F statistic is $F(q, n - k - q)$. In our case $F(3, n - 3 - 3)$. Indeed, an LM version is also available and distributes as $LM \sim \chi^2(3)$. If the null hypothesis is rejected, it is suggested that there is a problem of some sort with the functional form.

A number of heteroscedasticity tests have been suggested through the years—one of the tests is that of Breusch and Pagan (1980). The null hypothesis to be tested here is the that the regression errors are homoscedastic is expressed as:

$$H_0 : Var\left(\varepsilon^2 \middle| \overline{p}_{t-1} - p_{t-1}, \sum_{i=1}^{\infty} \beta^i \Delta p_{t-i}\right) = \sigma^2 \tag{6.9}$$

To conduct this test, we estimate Eq. (6.3) using the OLS technique and we obtain the squared OLS residuals $\hat{\varepsilon}_t^2$. Then, we estimate the following auxiliary regression:

$$\hat{\varepsilon}_t^2 = \delta_0 + \delta_1 (\overline{p}_{t-1} - p_{t-1}) + \delta_2 \sum_{i=1}^{\infty} \beta^i \Delta p_{t-i} + e_t \tag{6.10}$$

Next, we obtain the R^2 from the auxiliary regression given by Eq. (6.10). The test statistic can be either an F statistic or an LM statistic. If the test statistic is greater than the tabulated critical value, we reject the null hypothesis of homoscedasticity. After the estimation of Model I, the importance of fundamentalists and technicians is determined by testing the null hypothesis that:

$$H_0: \gamma_1 = \gamma_2 \tag{6.11}$$

which amounts to a post-estimation Wald test, where the test statistic has a $\chi^2(1)$ distribution, since there is only one restriction on the values of the estimated coefficients. If H_0 is rejected, such that $\gamma_1 > \gamma_2$, then it can be concluded that the role of fundamentalists is more important than the role of technicians, and vice versa.

In order to test the hypothesis that either fundamentalists or technicians solely determine changes in stock prices, six non-nested model-selection tests are employed to choose between the two models:

$$\Delta p_t = \gamma_0 + \gamma_1(\overline{p}_{t-1} - p_{t-1}) + \gamma_2 + \varepsilon_{1t} \tag{6.12}$$

and

$$\Delta p_t = \gamma_0 + \gamma_2 \sum_{i=1}^{\infty} \beta^i \Delta p_{t-i} + \varepsilon_{2t} \tag{6.13}$$

To facilitate the description of the model-selection tests, Eq. (6.12) and Eq. (6.13) are represented by the general matrix notation as:

$$M_1: Y = XA_1 + u_1 \tag{6.14}$$

$$M_2: Y = ZA_2 + u_2 \tag{6.15}$$

where Y is the $n \times 1$ vector of observations on Δp_t; X and Z are $n \times 2$ observations for the explanatory variables of the two models (including the intercept term); A_1 and A_2 are vectors of unknown regression coefficients; and u_1 and u_2 are the disturbance vectors, such that $u_1 \sim N(0, \sigma^2 I_n)$ and $u_2 \sim N(0, w^2 I_n)$. The models M_1 and M_2 are considered to be non-nested if the explanatory variables of either of them cannot be expressed as a linear combination of the explanatory variables of the other. Clearly, M_1 and M_2 are represented by Eq. (6.14) and Eq. (6.15) are non-nested, because their explanatory variables are different.

The first of the non-nested model-selection tests is N test, which is the Cox (1956,1962) test originally derived in Pesaran (1974). The test statistic for M_1 against M_2 is computed as

$$N = \frac{\left\{\frac{n}{2}\ log(\widehat{\omega}^2/\widehat{\omega}_*^2)\right\}}{\hat{V}_1} \tag{6.16}$$

where n is the number of observations, and

$$\widehat{\omega}^2 = \frac{e_2' e_2}{n} \tag{6.17}$$

$$\widehat{\omega}_*^2 = \frac{e_1' e_1 + \hat{A}_1' X' R_2 X \hat{A}_1}{n} \tag{6.18}$$

$$\hat{V}_1^2 = \left(\left(\frac{\hat{\sigma}^2}{\widehat{\omega}_*^4}\right) A_1' X' R_2 R_1 R_2 X \hat{A}_1'\right) \tag{6.19}$$

$$\hat{\sigma}^2 = \frac{e_1' e_1}{n} \tag{6.20}$$

$$\hat{A}_1' = (X'X)^{-1} X' y \tag{6.21}$$

$$R_1 = I_n - X(X'X)^{-1} X' \tag{6.22}$$

$$R_2 = I_n - Z(Z'Z)^{-1} Z' \tag{6.23}$$

The test statistic has a *t*-distribution. A significant test statistic indicates that M_2 is favoured over M_1. By the same token, the N_2 statistic for testing M_2 against M_1 can be computed in a similar fashion.

The second non-nested model-selection test is the J test proposed by Davidson and MacKinnon (1981). The test of M_1 against M_2 is based on the *t*-statistic of φ in the regression model:

$$Y = XA_1 + \varphi(Z\hat{A}_2) + u \qquad (6.24)$$

where $\hat{A}_1 = (X'X)^{-1}X'Y$. Likewise, the test statistic for M_2 against M_1 is the *t*-statistic of ϕ in the regression model:

$$Y = ZA_2 + \varphi(X\hat{A}_1) + v \qquad (6.25)$$

where $\hat{A}_2 = (Z'Z)^{-1}Z'Y$.

The third test is the encompassing test put forward by Deaton (1982), Dastoor (1983), and Mizon and Richard (1986). When testing the null hypothesis that M_1 is preferred over M_2, the encompassing test statistic is the *F*-statistic for testing the null that $B = 0$ in the regression model:

$$Y = XA + Z^{*}B + u \qquad (6.26)$$

where Z^{*} denotes the variables in M_2 that cannot be expressed as an exact linear combination of the explanatory variables of M_1. By the same token, a test statistic can be calculated for the null that M_2 is preferred over M_1. The results are interpreted in the same way as in the two preceding tests.

In addition to the three non-nested model-selection tests discussed above, we employ the *NT* test, which is the adjusted Cox test derived in Godfrey and Pesaran (1983); the *W* test is the Wald-type test proposed by Godfrey and Pesaran (1983); and the *JA* test, is the Fisher and McAleer (1981) test. As with the N and J tests, these test statistics have *t* distribution and their results are interpreted in the same manner.

Also used is a variable-deletion test. In order to ascertain whether fundamentalists play a role in stock-price determination, the coefficient restriction $\gamma_1 = 0$ is imposed. A significance test statistic in this case implies that the restriction is invalid, suggesting that fundamentalists play a role in price-determination and (vice versa). On the basis of the residuals sum of squares of the unrestricted model (Model I), and the restricted model (resulting from the imposition of the restriction $\gamma_1 = 0$), three test statistics are computed. These are the:

- F-statistic which has an exact finite sample F distribution, at which the numerator degrees of freedom are given by the number of coefficient restrictions in the null hypothesis, and the denominator degrees of freedom are given by the total regression degrees of freedom. In the present analysis, while the numerator degrees of freedom are equal to one for all markets (because only one coefficient restriction is imposed), the denominator degrees of freedom vary across markets on the basis of the sample size. Therefore, the F-statistic has (1,113) degrees of freedom for the markets of Abu Dhabi, Kuwait, Oman, Qatar, and Saudi Arabia while, respectively, having (1,100) and (1,89) degrees of freedom for Bahrain and Dubai.
- Lagrange Multiplier (*LM*) test statistics follow a χ^2 distribution. The degrees of freedom here are given solely by the number of coefficient restrictions in the null hypothesis. Therefore, in every case the χ^2 statistic is distributed as $\chi^2(1)$.
- Likelihood Ratio (LR) test statistics follow a χ^2 distribution. The degrees of freedom here are given solely by the number of coefficient restrictions in the null hypothesis. Therefore, in every case the χ^2 statistic is distributed as $\chi^2(1)$.

By the same token, the restriction $\gamma_2 = 0$ is imposed to find out whether technicians play a role in price determination.

6.3 Empirical Results

Table 6.1 contains the estimation results for Model I, obtained by an OLS regression on Eq. (6.3) for seven GCC markets. In Table 6.1, we report the estimated coefficients and their corresponding *t*-statistics (in parentheses), the sample size, and the coefficient of determination (R^2). As well, we report the diagnostic tests for serial correlation *(SC)*, functional form *(FF)*, and heteroscedasticity *(HS)*, all of which have a χ^2 distribution with one degree of freedom, with the exception of the *SC* test that has 12 degrees of freedom.

Table 6.1: Model I estimation results for seven GCC markets

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
γ_0	-0.001	-0.0002	-0.003	-0.007	-0.102	-0.015	-0.051
	(-1.29)	(-0.68)	(-0.52)	(-1.95)	(-3.08)	(-2.72)	(-1.28)
γ_1	0.208	0.193	0.215	0.237	0.243	0.290	12.596
	(8.71)	(7.84)	(8.27)	(8.69)	(10.38)	(9.39)	(8.20)
γ_2	0.363	0.306	0.336	0.322	0.381	0.426	4.290
	(13.97)	(14.24)	(13.54)	(14.63)	(15.76)	(13.70)	(2.29)
N	120	107	96	120	120	120	120
R^2	0.639	0.671	0.675	0.661	0.691	0.639	0.365
SC	19.56	19.12	17.28	31.19	29.80	33.93	22.42
FF	0.44	0.02	2.89	2.59	1.12	0.51	111.36
HS	10.68	0.31	4.30	5.30	16.25	0.04	117.21
$H_0: \gamma_1 = \gamma_2$	32.14	18.36	18.96	9.17	30.56	15.65	16.66

A close look at Table 6.1 reveals that the estimated equations produce significantly positive slope coefficients in all cases. The null hypothesis $H_0: \gamma_1 = \gamma_2$ is rejected across the board, which means that although both fundamentalists and technicians have roles to play, the latter play a more important role in terms of exerting influence on the market price. The exception to this is the market of Saudi Arabia where the fundamentalists play the dominant role in price formation.

Table 6.2: Variable-deletion test results

Restrictions	$\boldsymbol{\gamma_1 = 0}$	$\boldsymbol{\gamma_1 = 0}$	$\boldsymbol{\gamma_2 = 0}$	$\boldsymbol{\gamma_2 = 0}$
	$LM: \chi^2(1)$	$LR: \chi^2(1)$	$LM: \chi^2(1)$	$LR: \chi^2(1)$
Abu Dhabi	47.19	59.95	75.01	117.72
Bahrain	39.73	49.66	70.74	115.79
Dubai	40.66	52.87	63.69	104.53
Kuwait	47.08	59.77	77.58	124.78
Oman	57.51	78.29	81.57	136.64
Qatar	51.54	67.35	73.91	114.83
Saudi Arabia	43.81	54.50	5.14	5.24

Table 6.2 contains the results of the variable-deletion test for the seven GCC markets. In every case, the LM and LR statistics are statistically significant, at least at the 5 percent level. Therefore, the null hypothesis that $\gamma_1 = 0$ is strongly rejected at the 1 percent significance level across all GCC markets; the null hypothesis that $\gamma_2 = 0$ is rejected at the 1 percent level for all markets except for Saudi Arabia. There, it is rejected at the significance level of 5 percent. Taken together, the results that emerge from the variable-deletion test indicate that fundamentalists and technicians collectively have a role to play in price formation in the GCC markets.

Table 6.3: Non-nested model-selection test results

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
M_1 versus M_2							
N	-40.90	-60.38	-41.53	-48.20	-37.38	-28.64	1.20
NT	-29.452	-37.369	-27.806	-34.028	-28.164	-22.662	1.326
W	-23.121	-27.661	-21.300	-25.938	-22.066	-18.317	1.350
J	13.966	14.245	13.539	14.628	15.759	13.697	-2.289
JA	-13.966	-14.245	-13.539	-14.628	-15.759	-13.697	-2.289
EN	195.042	202.906	183.291	213.975	248.349	187.616	5.240

Table 6.3 ***(Continued)***

	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
M_2 versus M_1							
N	0.858	0.961	0.911	0.556	1.219	-0.169	-585.499
NT	0.954	1.058	1.007	0.669	1.290	-0.023	-33.552
W	0.971	1.078	1.028	0.676	1.325	-0.023	-27.618
J	8.708	7.837	8.265	8.691	10.376	9.385	8.202
JA	-8.708	-7.837	-8.265	-8.691	-10.376	-9.385	8.202
EN	75.828	61.416	68.315	75.530	107.663	88.078	67.265

Table 6.3 contains the results of the non-nested model-selection tests, which tell a similar story to that of Table 6.2. For six out of the seven GCC markets (Abu Dhabi, Bahrain, Dubai, Kuwait, Oman, and Qatar) all of the non-nested model-selection tests reject M_1 (with fundamentalists only) in favour of M_2 (with technicians only), suggesting that a model without technicians is inferior and mis-specified. On the other hand, only three out of the six non-nested model-selection tests reject M_2 in favour of M_1. This again implies that there is strong evidence for the role played by technicians, but mixed evidence on the role played by fundamentalists. Indeed, the results for the Saudi market are different in that the balance of evidence is in favour of fundamentalists.

6.4 Conclusion

In this chapter, we sought to investigate the role played technicians and fundamentalists in price formation in the GCC markets. Our motivation stems from the findings of Chapter 4 and Chapter 5, which show that the technical trading rules, in general, outperform the passive buy-and-hold strategy.

To achieve that result, we utilised the model proposed by Frankel and Froot (1990) and adopted in part by Moosa and Korczak (2000), Moosa and Al-Loughani (2003), Al-Muraikhi and Moosa (2008), and Moosa and Li (2011). The conclusion to be drawn from the results presented in this chapter is that while both technicians and fundamentalists have a role to play in price formation, technicians play the dominant role in all of the GCC markets, except for the market of Saudi Arabia where the balance of evidence is in support of fundamentalists.

CHAPTER 7

CONCLUSION

7.1 Recapitulation

The introduction to this thesis emphasised the importance of investigating market efficiency, particularly in the rapidly evolving stock markets of the GCC region. While a growing number of studies examine the market efficiency hypothesis for the GCC markets, they achieve that through using statistical measures, such as autocorrelation and variance ratio, in addition to a subset of seasonal anomalies. The main conclusion that emerges from these studies is that the GCC markets are inefficient in a weak form. In order to find out whether the deviation from market efficiency can be exploited profitably, we employ an alternative test of market efficiency, which is based on evaluating the performance of trading rules. In the subsequent chapters of this thesis an attempt was made to make a contribution to our understanding of market efficiency by examining the performance of trading rules in the GCC markets.

Chapter 2 comprises a detailed literature review aimed at identifying gaps in the literature on seasonal effects in stock returns. The main conclusion to be drawn from this literature review is that seasonal patterns in stock returns are diverse and vary considerably, not only across markets but also over time periods. Therefore, a universal explanation for these anomalies is yet to be found. In addition, we found that GCC studies focus on few seasonal effects, use unsophisticated econometric techniques that rest on strong statistical assumptions, and that largely ignore the evolution in seasonal patterns over time. This could, potentially, lead to erroneous conclusions. Hence, in Chapter 3, we address these gaps and limitations by conducting a comprehensive empirical analysis for several well-established seasonal patterns.

In Chapter 3, we carry out an empirical analysis to study gaps in the seasonality literature, which were identified in Chapter 2. We employ several econometric techniques and model specifications, and we investigate the behaviour of seasonal effects over time. The main conclusion that can be derived from the results is that seasonal effects are present in all GCC markets. However, they often differ across markets in terms of their nature and strength. In addition, seasonal patterns are found to be time-varying—that is, they are more pronounced in certain time periods. The time-varying nature of seasonality in GCC stock returns is consistent with the adaptive market hypothesis. Furthermore, the empirical findings offer additional insights into the influence of institutional settings, financial developments, and crises on the nature of seasonality in stock returns in GCC markets.

Chapter 4 investigates the performance of trading rules formulated on the basis of time series regressions. The motivation of this chapter stems from the findings of prior studies that show that GCC markets are weak-form inefficient (in other words, stock returns are predictable). This conclusion is typically reached by using statistical measures such as autocorrelation or autoregression, and unit root tests. Here, we extend this work by investigating whether the documented predictability can be exploited profitably using trading rules designed on the basis of time series regressions. We expand on Chapter 3 by incorporating the documented seasonal effects into trading rules to find out whether it makes any difference to the performance of these rules. The empirical results indicate that regression-based trading rules substantially outperform the passive buy-and-hold strategy in the majority of GCC markets. The inclusion of seasonal dummies seems to have a limited impact on the performance of trading rules. In fact, we have subjected these findings to a number of robustness checks. The main results hold when the CAPM model is used. In addition, trading rules appear to be potentially profitable, even when transaction costs are taken into consideration. However, this finding should be viewed with caution because a reasonably accurate estimate of transaction costs is not available.

In Chapter 5, we investigate the performance of widely known technical trading rules (moving averages and trading-range breaks) that have been popularised by Brock *et al.* (1992) as an alternative test of market efficiency. The main conclusion to be drawn from the analysis is that they outperform, substantially, the passive buy-and-hold strategy in all seven GCC markets. These results are reasonably robust across alternative performance measures. In addition, the results obtained by using break-even cost measures indicate that these trading rules are potentially profitable—generating higher break-even cost results compared to their regression-based counterparts. As noted earlier, these finding should be taken with a grain of salt in the absence of a reasonably accurate estimate of transaction costs in GCC markets. Another aspect of our analysis is concerned with investigating the performance of trading rules over small subsamples to find out whether the gains from these rules are clustered in a certain time period, follow a seasonal pattern, or evolve in a random fashion. We found that the performance of trading rules is highly temporal, and their profitability is largely confined to the period in which the GFC occurred. This finding of the time-varying nature of the profitability of trading rules is in line with the adaptive market hypothesis.

Motivated by the findings of Chapter 4 and Chapter 5, in Chapter 6 we seek to investigate the role played by technicians and fundamentalists in price formation in GCC markets. The empirical work is conducted using the econometric model proposed by Frankel and Froot

(1990) and adopted in part by Moosa and Korczak (2000), Moosa and Al-Loughani (2003), Al-Muraikhi and Moosa (2008), and Moosa and Li (2011). The results presented in Chapter 6 indicate that while both technicians and fundamentalists have a role to play in price formation, technicians play the dominant role in all GCC markets, except for the market of Saudi Arabia where the balance of evidence is in favour of fundamentalists.

7.2 Limitations and Extensions

Throughout this thesis we highlighted the importance of measuring not only statistical but also economic significance when evaluating trading rules. We have done that by using a break-even cost measure, which is described in detail in Chapter 4 and Chapter 5. This measure is interpreted as the minimum level of transaction costs that would eliminate, completely, the additional return from the trading rules. However, to determine whether or not the trading rule is profitable, a transaction-cost estimate is required. In fact, information on commissions and brokerage fees are widely available, but this is not the case with other transaction costs such as the market impact and bid-ask spreads. Therefore, we fail to find a reliable estimate of transaction costs for the GCC market. We acknowledge this as a limitation of the thesis.

An additional caveat is that we examine the temporal behaviour of seasonal effects and the performance of trading rules using relatively basic econometric methods. Sophisticated techniques may have been used, such as structural-break tests or, perhaps, structural time series models. We plan to consider these shortcomings in future work.

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