Profitability of Trading Rules in MENA Stock Markets

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Abstract

Technical trading rules have been used in financial markets in order to examine their ability to yield a superior return. In the early empirical literature, a body of studies showed that trading rules do not outperform a simple buy and hold strategy. However, more recent research finds evidence that supports technical trading rules.

This study examines the profitability of trading rules in 14 Middle East and North African (MENA) markets. The trading rules that used are: moving average trading rules (MA), trading range breakout (TRB) trading rules, filter trading rules, channel trading rules, Bollinger band (BB) trading rules and moving average coverage divergence (MACD) trading rules. The markets used in this work include the Bahrain stock market, the Jordan stock market, the Kuwait stock market, the Lebanon stock market, the Maltese stock market, the Morocco stock market, the Oman stock market, the Qatar stock market, the Saudi Arabian stock market, the Tunisia stock market, the Turkey stock market, the United Arab Emirates stock markets, the Cyprus stock market and the Egypt stock market.

Our results indicate that according to mean return criterion, the best simple moving average (SMA), exponential moving average (EMA), triangular moving average (TMA), trading range breakout (TRB), filter and moving average coverage divergence (MACD) trading rules are for Turkey market. Malta, Bahrain and Oman have the highest percentage of rules that generate positive mean return. In terms of the Sharpe ratio, the best trading rules according to TMA, SMA, filter and channel trading rules are for Turkey market. Furthermore, Turkey has the highest percentage of rules that have a positive Sharpe ratio followed by Cyprus and Egypt.

Controlling for data snooping, the results show that the number of trading rules that generate positive return comparing with buy and hold strategy has been reduced but there are still a large number of profitable rules through some markets.

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Chapter 1 Introduction

According to the efficient market hypothesis (EMH), stock markets prices fully reflect all available information so any new information will be quickly reflected in the price of the security. This means that any attempt to generate profits by using the available information in the market is futile. In the weakest form of market efficiency, where the information is limited to the information contained in the past price history of the market, market efficiency implies that technical trading rules should not be profitable.

Therefore, examining whether technical rules can outperform simple buy-and-hold strategy is, implicitly, a test of market efficiency. In actual fact, technical trading rules have been used in financial markets for long time and their ability to generate a superior return has been extensively examined in the academic literature.

In the early empirical literature there exists a body of studies that show that trading rules do not outperform a simple buy and hold strategy (see, for example: Alexander, 1961-1964; Fama and Blum, 1966; Sweeny, 1988). However, there also exists a more recent body of work that finds that technical trading rules can be used to predict the future prices, namely that an examination of past prices will in some way help to predict the future prices (see for example Brock, Lakonishok, and LeBaron, 1992; Bessembinder and Chan, 1995; and Bessembinder and Chan, 1998; Gunasekaragea and Power, 2001; Wong et al., 2003; Lento, 2009; and Milionis and Papanagiotou, 2011).

Whilst this more recent body of literature, inspired by the seminal work of Brock et al. (1992), suggests there are market inefficiencies as the applied trading rules can predict the future price and can be used in order to yield positive mean return, these studies have in turn attracted criticism. Studies that support a trading rule strategy (e.g. Brock et al., 1992) have been challenged by subsequent studies due to inappropriate testing procedures. One of the most controversial issues is data snooping. Data snooping occurs when researchers rely on the same data set to test the significance of different models individually. Sullivan et al. (1999) apply the White Reality Check (2000), RC, bootstrap method in order to test trading rules while accounting for data snooping bias in the DJIA. Sullivan et al. (1999) apply five different trading rules (filter trading rules, moving average trading rules, support and resistance trading rules, channel break-outs and on-balance volume average trading rules) in their study. They show that the best trading rules are capable of generating superior performance even after accounting for data snooping under mean return and Sharpe ratio criteria comparing to benchmark.

Hansen (2005) argues that Reality Check test is conservative since its null distribution is generated under the least favorable configuration. Furthermore, the RC test does not identify all models which significantly deviate from the null hypothesis. Hansen (2005) introduces the Superior Predictive Ability (SPA) test in order to improve the power of RC test and avoid the least favourable configuration by re-centring the bootstrap distribution. However, Hansen (2005)'s SPA has this limitation as RC test in which it does not identify all models which significantly deviate from the null hypothesis. Hus et al. (2010) introduce the Step-SPA (SSPA) test that controls data snooping and also identifies all rules that are still significant after controlling for the data snooping bias. Hus et al. (2010) combine the Romano and Wolf stepwise procedure with the more powerful SPA test.

This study examines the profitability of a wide range of trading rules across14 Middle East and North African (MENA) markets. These markets are of particular interest as (i) the economies in the MENA region are not as well integrated vis-à-vis those developed economies typically used in the trading rule literature. (ii) There is little existing work on the MENA region[1]. Specially, this study contributes to the existing literature by applying the largest and most comprehensive battery of trading rules (63468) to these MENA markets, and further contributes by adopting a robust treatment of data snooping via the application of the SPA and SSPA tests.

The trading rules applied are as follows: moving average trading rules (MA), trading range breakout (TRB) trading rules, filter trading rules, channel trading rules, Bollinger Bands (BB) trading rules and moving average convergence divergence (MACD)trading rules. The markets used in this work include Bahrain stock market, Jordan stock market, Kuwait stock market, Lebanon stock market, Maltese stock market, Morocco stock market, Oman stock market, Qatar stock market, Saudi Arabian stock market, Tunisia stock market, Istanbul stock market, United Arab Emirates stock, Cyprus stock market and Egypt stock market. Trading rules are evaluated by computing the mean return and the Sharpe ratio for each strategy.

Our finding suggests that according to the mean return criterion, the best simple moving average (SMA), exponential moving average (EMA), triangular moving average (TMA), trading range breakout (TRB), filter and moving average convergence divergence (MACD) trading rules are found in Turkey market. Malta, Bahrain and Oman have the highest percentage of rules that generate positive mean return. In terms of the Sharpe ratio, the best TMA, simple moving average (SMA), filter and channel trading rules are for Turkey market similar to mean return criteria. Furthermore, Turkey has the highest percentage of rules that yield positive Sharpe ratio followed by Cyprus

[1] The notable exception is Lagoarde-Segot and Lucey (2005, 2008) study MENA stock markets using data from stock market price indices from Morocco, Tunisia, Egypt, Lebanon, Jordan, Turkey and Israel. In their study they apply moving average and TRB trading rules. Lagoarde-Segot and Lucey (2005, 2008) investigate both the weak-form efficiency hypothesis and the presence of abnormal return. They found that different trading rules generate different results depending on the market under the study.

and Egypt. The percentage of rules that generate positive Sharpe ratio has been reduced when we apply Sharpe ratio criteria comparing to mean return criteria.

Controlling for data snooping, the results show that a number of significant trading rules reduce in many of the trading rule groups that are applied. However, we still find a large number of significant rules for almost all the markets are used in our study. The results show that there are a large number of significant rules for Jordan through 5 trading rules classes (EMA, TMA, filter, channel and BB), for Bahrain through 3 trading rule groups (filter, channel and BB), for Cyprus through 4 trading rule classes (TRB, filter, channel and BB), for Dubai through 1 trading rule class (BB), for Egypt through 4 trading rule classes (TRB, filter, channel and BB), for Lebanon through 5 trading rule classes (EMA, TMA, filter, BB and TRB), for Malta through 6 trading rule classes (SMA, EMA, TMA, filter, channel and TRB), for Morocco through 5 trading rule classes (SMA, EMA, TMA, filter and channel), for through 4 trading rule groups (EMA, TRB, filter and BB), for Qatar through 3 classes (EMA, TRB and filter), for Saudi Arabia through 3 trading rule groups (EMA, TMA and channel), for Tunisia through 4 trading classes (SMA, EMA, TMA and BB), for turkey through 4 trading rule groups (TMA, TRB and filter).

The obtained results can be explained by efficient market hypothesis. The results indicate that these markets are not efficient and this result is in line with previous literature that examine the EMH in MENA countries such as Walid (2010), Mazin et al. (2010), Kinga and Graham (2013), Fouad and Eduardo (2015) and Lanouar and Karim (2016) who examine the EMH in MENA markets and GCC countries. These works argue that MENA markets are not efficient due to many reasons such as the US war in Iraq that started in 2003, the Gulf market's crash and the Israeli-Lebanon war in 2006, the global financial crisis of 2007/2008 and the Dubai debt crisis in late 2009.

Furthermore, their efficiency paths are instable being affected by the contemporaneous crises and these markets are highly sensitive to past shocks indicating that undesirable shocks extend their influence for a long period. Lanouar and Karim (2016) argue that the recent financial shocks such as Arab spring and subprime crises have a significant impact on the time path evolution of market efficiency.

The reminder of this thesis proceeds as follows: chapter 1 presents an overview of the technical trading rule literature review; chapter 2 presents the data and methodology, chapter 3 presents an overview of the Middle East and North African countries, chapter 4 presents the empirical results and chapter 5 presents the conclusion.

Chapter 2 Literature Review

The early academic studies of technical trading rules conclude that technical analysis is not useful. However, a recent study demonstrates that a relatively simple set of technical trading rules can possess significant forecastability. This literature provides a number of results suggesting that the predictability of stock returns may differ between markets of different maturities and different degree of development. According to the different results between markets, and given this study's regional focus, this literature first presents the key findings from studies focusing on developed markets, emerging markets, and then finally MENA markets.

2.1. Developed markets

One of the earliest works for trading rules in developed markets is Alexander (1961). This study is the first to investigate the profitability of technical trading on US markets. Alexander (1961) applies fixed percentage filter rules and finds substantial risk adjusted returns comparing with the naive buy and hold strategy when testing the Dow Jones Industrial Average (DJIA) over the 1897-1929 period and the S&P Industrials Index over the 1929-1959 period. Alexander (1964) re-examines his earlier work applying transaction costs and finds that any profitability disappears when trading costs are considered. Fama and Blume (1966) apply the Alexander filter rule and they conclude that these rules cannot be used successfully in the US equity markets when accounting for trading costs. This opens the debate as to whether trading rules, when accounting for transaction costs, can offer profitability, spawning a large literature.

Studies later also support the previous findings. Van Horne and Parker (1968) use stock prices for 30 securities on the NYSE and they find that trading rules based on moving average and relative strength rules do not yield profits. Sweeney (1988) use same assets where Fama and Blume argue that filter rules generate profits using these assets. However, Sweeney (1988) shows that these profits which Fama and Blume obtain from filter trading rules are sensitive when transaction costs are applied. Overall, in the early studies, very limited evidence of technical trading rules has been found in stock markets.

However, there are some limitations related to testing procedures used by early studies. Most early studies do not examine whether the returns from these trading rules are statistically significant. Furthermore, since data snooping bias is not considered in early studies, this mislead into arguing that these rules are profitable. Data snooping happens when the researchers use the same data to test the significance of various models individually and because the individual statistic are obtained using same data set and since they are related to each other, it is difficult to construct join test especially when the number of rules that are applied in the study is large.

Later, studies apply various bootstrap methodologies to test if the profits generated by trading rules are statistically significant. One of the most significant works on technical trading rules using this method is Brock et al. (1992). According to Park and Irwin (2004), Brock et al. (1992) use a very long price history and bootstrap methods for making statistical inferences about technical trading profits. According to Brock et al. (1992), bootstrap methodology has many advantages. The bootstrap procedure makes it possible to perform a joint test of significance for different trading rules by constructing empirical distributions. Additionally, the traditional *t*-test assumes normal, stationary, and time-independent distributions for the data series. However, it is known that the return distributions of financial assets are generally leptokurtic, autocorrelated, conditionally heteroskedastic, and time varying. Since the bootstrap procedure can accommodate these characteristics of the data using distributions generated from a simulated null model, it can provide more powerful inference than the *t*-test alone. Brock et al. (1992) use a random walk with drift, an autoregressive process of order one (AR (1)), a generalized autoregressive conditional heteroskedasticity in-mean model (GARCHM) and an exponential GARCH (EGARCH) model in order to simulate the price series to combine the trading rules with bootstrap techniques to generate the distributions of statistic under the null hypothesis. Brock et al. (1992) apply two simple technical trading rules, a moving average and a trading range breakout on the Dow Jones Industrial Average (DJIA) from 1897 to 1986. Brock et al. (1992) indicate that trading rules outperform buy and hold strategy and generate positive return through the four sub-periods. Additionally, they show that these returns cannot be explained by risk as buy signals which have higher average return than sell ones that have a lower standard deviation than sell signals.

Ready (2002) compares the performance of Brock et al. (1992) moving average rules applying technical trading rules that are formed by genetic programming. Ready (2002) shows that the Brock et al. (1992) trading rules do not outperform a buy and hold strategy because of trading costs and the time it takes to make the actual trade. Furthermore, Brock et al. (1992) best trading rule (1/150 moving average without a band) for the 1963–1986 period has higher excess returns when it compared to the average of trading rules realized by genetic programming after transaction costs but not for the period of 1957-1962 so Ready (2002) argues that the successful result of the Brock et al. (1992) moving average rules is a result of data snooping.

The findings of Brock et al. (1992) have been tested on a number of developed markets. For example, Hudson et al. (1996) examine whether their findings can be replicated on UK data and whether these rules generate excess returns when transaction costs are applied. Hudson et al. (1996) use data from 1935 to 1994 which broken down in sub-sample as: 1935-51, 1951-66, 1966-81 and 1981-94. They find that trading rules used by Brock et al. (1992) have some ability to forecast the FT30 series of returns, but no significant gains are found after adjusting for trading costs. However, Hudson (1996) argues that there are several shortcomings in Brock et al. (1992). Firstly, only returns of each trading rule were calculated without accounting for transaction costs. Secondly, trading rule optimization and out-of-sample tests were not conducted where these procedures may help to determining the genuine profitability of technical trading rules. Thirdly, results may have been affected by data snooping problems. If a large number of trading rules are tested over time, some rules may work by pure chance even though they do not possess real predictive power for returns.

In another UK study that follows Brock et al. (1992) method, Mills (1997) used data from London Stock Exchange FT30 for the period 1935-1994 where the subsamples are: 1935-1954, 1955-1974 and 1975-1994. They find that the mean daily returns from trading rules are not significantly different from a buy-and-hold return over 1975–1994. Returns are much higher than buy-and-hold returns for the 1935–1954 and 1955–1974 periods. Furthermore, Mills (1997) argues that the results for first forty years are the same as Brock et al. (1992) for DJIA. However, Mills (1997) argues that from the early 1980s the simple buy and hold strategy outperforms trading rules which is not same as Brock et al. (1992) results. Mills argues that this might be due to the structural shift that take place around 1982 where Brock et al. (1992) sample ended in 1986 and their final sub-period start in 1962.

The trading rules that are applied in Brock et al. (1992) are also used by Bessembinder and Chan (1998) study. Bessembinder and Chan (1998) use data that is on dividend-adjusted DJIA over the period 1926-1991 which are divided into four sub-periods from1926 to 1943, 1944 to 1959, 1960 to 1975, and 1976 to 1991.

Bessembinder and Chan (1998) use one-way trading costs which are 0.39% for the full sample and 0.22% since 1975. They concluded that, although the technical trading rules used by Brock et al. (1992) revealed some forecasting ability, it was unlikely that traders could have used the trading rules to improve net returns after transaction costs.

Other studies attempt to solve data snooping bias using White's (2000) bootstrap reality check methodology. Sullivan et al. (1999) apply the bootstrap reality check methodology to the DJIA over 1897–1996. They use the same sample period (1897–1986) as Brock et al. (1992) for in-sample tests and examine an additional 10 years from 1987 to 1996 for out-of-sample tests. Two performance measures, the mean return and the Sharpe ratio are used. Among the 26 trading rules examined by Brock et al. (1992), the best rule which is a 50-day variable moving average rule with 1% band for the same sample period gets an annual mean return of 9.4% and a bootstrap reality check *p*-value of zero, which mean that their findings are robust to data snooping biases. Over the 10-year out-of-sample period (1987–1996), the best rule (a 5-day moving average rule) yields a mean return of only 2.8% per year with a nominal *p*-value of 0.32, indicating that the best rule does not continue to create an economically and statistically significant return in the subsequent period.

The approach of Sullivan et al. (1999) has been applied to a number of different markets. For example, this approach has been used by Metghalchi et al. (2008). They apply the same reality check test as Sullivan et al. (1999) where they use data from Swedish stock and they find that trading rules have predictive power for period from 1/2/1986 to 9/13/2004. They apply the standard moving average rule (SMA), the increasing moving average rule (IMA), and the Arnold and Rahfeldt (1986) moving average rule, (ARMA). Overall, the results indicate that moving average rules have predictive power since most buy–sell differences are positive and the *t*-statistics for these differences are highly significant, rejecting the null hypothesis of equality of buy days returns to sell days returns.

Similar to Sullivan et al. (1999), the findings of Gencay (1998a, 1998b), Chong and Ng (2008), Nauzer et al. (2008) also support the profitability of trading rules in developed markets.

Similar to Brock et al. (1992), Gencay (1998a, 1998b) uses data set form Dow Jones Industrial Average Index from 1897 to 1988. Gencay (1998a, 1998b) applies non-liner methodology in order to measure the profitability of trading rules. Gencay (1998a) applies a feed forward neutral network in testing the profitability of trading rules and finds that nonparametric models with technical rules generate significant excess returns when compared to a simple buy and hold strategy after adjusting for the transaction costs. Gencay (1998b) uses same data as in Gencay (1998a) to test the linear and non-linear predictability of stock market returns by incorporating past trading signals from technical trading rules. The results indicate that non-linear models based on past trading signals from trading rules provide more accurate predictions than the models that based on past returns. Furthermore, the results from subsample show that the applied moving average provide at least 10% predict improvement in the Great Depression and the trendy period from 1980-1988. Gencay and Stengos (1998) extend their previous non-liner researches applying 10-day volume indicators. The results show that these volume indicators improve the predictability of the trading rules.

Similar to Hudson et al. (1996) and Mills (1997), Chong and Ng (2008) use data from London Stock Exchange FT30 Index for a period from July 1935 to January 1994. In order to avoid data snooping, the sample has been split into three subsamples where each sample contains 5000 observations. The results indicate that all buy; sell and buy–sell returns are significant at the 5% or 10% level with exception for the sell return in the period from 1955 to 1974 subsequently Chong and Ng (2008) argue that RSI and MACD trading rules outperform simple buy and hold strategy.

The daily close prices for DJIA are also used by Nauzer et al. (2008) similar to Brock et al. (1992)'s study where they use modern models as Bollinger Band and channel rules to examine the profitability of trading rule in three US stock markets. Nauzer et al. (2008) also use daily close prices for the NASDAQ Composite Index (NASDAQ) and the Standard and Poor's 500 Index (S&P500) from December 1990 to December 2007 in addition to DJIA. Three trading rules: dual moving average crossover, channel breakout rule and the Bollinger band breakout rule are applied. Nauzer et al. (2008) find that the returns generated by MA crossover rule, the Bollinger band breakout rule and channel breakout rule are significantly positive when considering transaction cost of 0.50 per cent. However, they find significant negative returns on regular trend following version of the same rules. Nauzer et al. (2008) argue that the investor can make abnormal profits applying the contrarian use of technical trading rules.

Brock et al. (1992) bootstrapping method has been applied by Wang et al. (2014) in order to assess the trading rules performance. They use three bootstrapping methodologies: a random walk model, an autoregressive AR (1) model and a GARCH (1, 1) model. They use performance based reward strategy (PRS) where moving average and trading rang breakout are combined together. Wang et al. (2014) apply different combinations of parameters for MA and TRB and for each combined rules, they assign a starting weight and a reward/penalty method depending on the rules' recent profit in order to update their weights over time. They use an improved time variant particle swarm optimization (TVPSO) algorithm for determining the best values for PRS. The results show that PRS is able to identify the best combined strategy that generates more profit when compared with single trading rules.

Some studies in developed markets find mixed results depending of the degree of the development of the countries under the study. Fifield et al. (2005) use daily closing prices for the period from 1 January 1991 to 31 December 2000 for 11 European stock market indices. The results from moving average indicate that these rules do not have predictive power in developed stock market indices since none of the moving average rules applied outperformed the passive buy-and-hold strategy. Furthermore, 46 of the 70 rules examined in developed markets not only underperformed the buy and hold strategy, but generated large losses. For emerging markets, the profits from a number of the trading strategies were positive and exceeded the profit available from a passive buy and hold strategy even after accounting for transaction costs in four markets (Greece, Hungary, Portugal and Turkey). Overall, they find that while the emerging markets have some degree of predictability in share returns, the developed markets did not. Fifield et al. (2008) examine the profitability of moving average rules using data from 15 emerging and three developed markets (Japan, the United Kingdom and the United States) for the period from 1 January 1989 to 31 December 2003. They find that only in Japan the moving average rules have predictive ability for changes among developed stock market returns since the profit from the trading strategy exceeds the profit from the buy and hold strategy. In seven developing countries, all 36 variations of the moving average rules provided profits which compare favourably with the profits from the buy and hold strategy. These seven markets are in the Far East, which suggests that share price predictability may depend on the geographic region in which a country is located. Furthermore, For nine out of the 15 emerging markets, the (1, 50, 0) rule is the most profitable which re-emphasizes the finding as the long-run moving average, short-run moving average and bandwidth increase, the profitability of the moving average rules decreases.

Milionis and Papanagiotou (2011) also get mixed results as Fifield et al. (2005, 2008) using different length of MA and their results are mixed depending on the markets considered. Milionis and Papanagiotou (2011) apply an approach that considers the variability of the performance of the MA trading rule due to different length of the longer MA. They use three different capital markets, NYSE, the ASE and the VSE for the period from1993 to 2005. Both costly and costless transactions as well as three sub-periods were considered. Without transaction costs, the cumulative returns from the trading rules for the ASE and the VSE were significantly higher than the corresponding buy and hold return. However, the cumulative returns from the trading rule for the NYSE were found to be significantly lower than buy and hold return. When transaction costs were considered, for the ASE, it was found that on some occasions the cumulative returns from the trading rule were still significantly higher than the corresponding buy and hold return. The cumulative returns from the trading rule on the VSE did not differ significantly from the corresponding buy and hold return. By contrast, for the NYSE, if an investor used the trading rule in the presence of transaction costs he would lose a substantial part of her/his initial capital.

Similar to early studies, some studies later do not support technical trading rules. Allen and Karjalainen (1999) use data from S&P 500 index for the period over 3 January 1928 to 29 December 1995. Their results are generally consistent with market efficiency since the trading rules optimized by genetic programming do not outperform simple buy and hold strategy after adjustment for the transaction costs in most markets under the study. Wang (2000) and Neely (2003) also use this method and they find same results to Allen and Karjalainen (1999) in term that genetically optimized trading rules do not outperform the buy-and-hold strategy in used markets. However, some studies applied same procedure, genetic programming, show that genetic technical trading rules outperform buy and hold strategy return in futures and foreign markets.

2.2. Emerging markets

Many studies in emerging markets follow Brock et al. (1992)'s procedure in applying bootstrap methodology (Ratner and Leal, 1999; Coutts and Cheung, 2000; Gunasekaragea and Power, 2001) or in applying the same trading rules (Bessembinder and Chan, 1995; Ming-Ming and Siok-Haw, 2006). Similar to developed countries, studies in emerging markets are divided into two groups. On one hand, many studies in this category found that trading rules generate excess return. Ratner and Leal (1999) is one of the studies in these markets that use data from Latin America and Asian. Ratner and Leal (1999) applied bootstrap model similar to Brock et al. (1992)'s study that used data from developed markets. Ratner and Leal (1999) use data from January 1982 through April 1995 from ten emerging equity markets in Latin America and Asia in order to examine the profitability of ten variable length moving Average (VMA) technical rules. Their results indicate that the VMA returns outperform the buy and hold returns in seven markets out of ten markets. However, when trading costs are considered, VMA returns exceed the buy and hold strategy only in four markets. Wong et al. (2003) also find similar results when they apply moving average and relative strength index for daily close of the Singapore for the period from 1 January 1974 to 31 December 1994 in order to test whether the buy and sell signals yield significantly positive return. Wong et al. (2003) divide the full sample into three sub-periods of 7 years each. They find that technical indicators can play a useful role in the timing of stock market entry and exits so applying technical indicators can generate substantial profits. Additionally, they find that single moving averages produce the best results, followed by the dual moving average and the relative strength index.

Another study that follows Brock et al. (1992) bootstrap methodology is done by Coutts and Cheung (2000) who use data from the Hang Seng Index for period from January 1985 to June 1997. Coutts and Cheung (2000) find that both applied trading rules, MA- Oscillator and TRB, generate profit over short period. The buy returns of the TRB are higher than the buy return of MA- Oscillator.

Similar to Coutts and Cheung (2000), Gunasekaragea and Power (2001) also apply Brock et al. (1992)'s bootstrap methodology in order to examine the predictability of trading rules in emerging markets. They use data form South Asian markets and apply variable length moving average and fixed length moving average filters. They find that these rules have a strong degree of predictability in their security returns and this predictability can be exploited to earn excess returns so South Asian capital markets are not weak form efficient.

Lento (2009) also finds that trading rules generate excess return using eight equity markets which include Australia, India, Indonesia, Korea, Japan, Hong Kong, Singapore, Taiwan over different time periods ranging from January 1987 to November 2005. Lento (2009) applies three trading rules in order to yield nine individual buy and sell signals on each data set. Additionally, this study has applied combining individual signals by using three combined signal approach (CSA) strategies. The results provide strong support for the ability of the CSA to outperform the buy and hold trading strategy in 22 of 24 variants tested after adjusting for transaction costs.

In another study in emerging markets that applies same trading rules as Brock et al. (1992) get supportive results done by Ming-Ming and Siok-Haw (2006). They test profitability of trading rules in nine Asian market indices. They used data rang from 1st

January 1988 to 31st December 2003. The results support VMA and FMA in 8 markets. The profit generate from VMA is higher than FMA and the length of 20 and 60 days are most profitable for VMA and FMA.

On other hand, other studies found that trading rules do not generate excess return in emerging markets. For example, Bessembinder and Chan (1995) apply trading rules used by Brock et al. (1992), VMA, FMA and TRB, for data from emerging markets and get results in that the trading rules are successful in predicting the movements in stock price in Japan, Hong Kong, South Korea, Malaysia, Thailand and Taiwan. However, considering the transaction cost will eliminate all gains from the trading rules. Chang et al. (2004) also examine whether emerging stock markets in Latin America and Asia are predictable applying the random walk hypothesis using a multivariate version of the variance ratio test and applying technical trading rules such as the variable moving average (VMA) and trading range break (TRB). The results imply that these rules have forecast power for price movements in countries that have been investigated. However, even these rules have forecasting power, they are not able to produce significant excess returns when compared to a buy and hold strategy with adjusting for transaction costs. Additionally, on average TRB rules tend to perform worse than moving average trading rules.

Mitra (2011) get similar results to Chang et al. (2004) in that trading rules do not have excess return when transaction cost is considered. Mitra (2011) applies 18 moving average based trading rules in each of two stock indices used in India for the period December 2000 to November 2010. Mitra (2011) finds that trading rules are profitable when trading cost is ignored or kept at a low level. Furthermore, Mitra (2011) finds that trading cost is an important factor determining profitability of the trading rules. An increase in trading cost can make a profitable trading rule to report losses.

Similar to Fifield et al. (2005, 2008) study in developed markets, Loh (2007) and Hao et al. (2013) get mixed results depending on the markets and its development degree. Loh (2007) shows that the empirical evidence suggest that technical rules have predictive power, although the excess returns from trading tend to be largely reduced after transaction costs are accounted for. Loh (2007) uses daily closing prices data from five Asian-Pacific stock markets. Loh (2007) argues that the studies on the performance of simple technical trading rules in different emerging markets indicate that technical rules tend to be more profitable in emerging markets relative to the more developed stock markets. The result suggests that trend indicators have some predictive ability and that about 50% of the trading signals yield accurately predict future directional movements in prices. The results also indicate that applying the practitioner's approach to technical analysis; it is possible to capture the information content in past prices more effectively. Similar to Loh (2007), Hao et al. (2013) get similar results as Loh (2007) in that the performance of the trading rules is different depending on the degree of the development of the markets under the study. They use date form different markets that are different in degree of the development. He/She applies moving average and trading rang breakout rules in five Southeast Asian markets for period from 1991 to 2008 in order to examine the predictability and profitability of trading rules. The results indicate that technical trading rules have stronger predictive power in the emerging markets than in more developed stock market. However, Hao et al. (2013) find that these rules fail to generate profit when they consider transaction costs. Furthermore, Hao et al. (2013) find that long term variants are less useful in predicting the movements in stock prices than the short term variants.

2.3. Middle East and North African markets

There is a shortage in studies that apply technical trading rules in MENA countries. There are only two studies, Lagoarde-Segot and Lucey (2005, 2008), which examine the performance of trading rules in MENA markets.

Lagoarde-Segot and Lucey (2005, 2008) investigate the predictability of trading rules in MENA markets. Lagoarde-Segot and Lucey (2005) test for predictability of MENA stock markets which includes stock market price indices from Morocco, Tunisia, Egypt, Lebanon, Jordan, Turkey and Israel by investigating both the weak-form efficiency hypothesis and the presence of abnormal returns. Their study uses daily data starting from 1/1/1998 until 11/16/2004. They find that the region's largest markets, Israel and Turkey, follow a random walk. However, they highlight that variable moving average (VMA) and trade range breaking (TRB) trade rules yield significant abnormal returns. The VMA strategy generates returns in Jordan, Tunisia, Turkey and Israel. The TRB performs better, as extra profits can be expected in all countries apart from Lebanon.

Lagoarde-Segot and Lucey (2008) use same period as before for same markets, Morocco, Tunisia, Egypt, Lebanon, Jordan, Turkey and Israel. They investigate informational efficiency in a set of seven emerging MENA stock markets. They aggregate the results of random walk tests and technical trade analysis into a single efficiency index in order to rank the MENA markets in terms of their relative informational efficiency. They calculate an index as an average of a series of dummy variables for each test which they apply, trading rules and variance ratio test, for each markets. Their results show an evidence of weak form efficiency in Turkey, Israel, Jordan, Tunisia, Egypt, Lebanon and Morocco. They also apply two methods of trading rules; one is to determine the existence of predictability using past return series or price information. The other is to check whether technical trading rules can be exploited as a profit making strategy. The results from VMA technical trading rules indicate that the number of buy signals is greater than the number of sell signals in the case of Egypt, Jordan, Israel and Lebanon. They find the opposite for Turkey, Morocco and Tunisia. Moreover, TRB technical trading rule results show that the number of buy signals is greater than the number of sell signals in the case of Egypt, Morocco and Lebanon. The opposite result is obtained for Israel, Tunisia, Jordan and Turkey. This result means that different trading rules can lead to different market orders. They also test the impact of market development, corporate governance and economic liberalization applying a multinomial ordered logistic regression. They argue that extent of weak-form efficiency in the MENA markets is primarily explained by differences in stock market size. While, corporate governance factors have explanatory power, the role of economic liberalization does not appear significant.

However, the main weakness in the above two works in MENA is that they test the profitability of trading rules without accounting for data snooping bias. In our work, we will adopt a robust treatment of data snooping bias by applying the SPA and SSPA tests.

Chapter 3 Financial and economics background for Middle East and North African area

The MENA area is home of 5.5% of the world's population, 48% of its energy subsides and 3.3% of world's GDP. MENA countries can be grouped into two classes. The first is oil exporters which include GCC countries (Bahrain, Qatar, Oman, Saudi Arabia, and finally United Arab Emirates) and non-GCC countries (Algeria, Libya, Iraq and Iran). The second group in the MENA region are oil importers which include Egypt, Jordan, Lebanon, Morocco, Syria, Tunisia, Turkey, Cyprus and Malta. In this chapter, we discuss some financial and economic background in MENA area.

3.1. GDP

The performance of MENA countries is mixed. The countries in this area were expected to grow by 3% in 2014 according to World Bank report. However, there is difference between high income countries and developing ones as shown in Table (1). The high income countries are expected to grow by 4.9% and developing countries by 0.7%. The weak performance for some of the countries in this area is due to the violent conflicts including the civil war in Syria which has had a wider impact on MENA area. Furthermore, political turmoil in Egypt and Tunisia in addition to political openings in Morocco and Jordan has resulted in these not achieving their output potential. The World Bank has quantified some of these costs: the conflicts in Egypt, Tunisia, Syria, Yemen and Libya cost around $168 billion during 2011-2013 which is 19% of the combined GDP of these countries. Strikingly, the real output for Syria is 40% lower than the pre-crisis level in 2010. Furthermore, Syrian war cost Lebanon $7 billion, 23% of 2010 GDP. Some countries are expected to slow down such as Bahrain, Qatar, United Arab Emirates, Iraq, Libya, Yemen, and Morocco, whereas the of rest countries are expected to improve their growth as shown in Table (1).

3.2. Foreign direct investment to MENA

According to World Bank report in 2013, foreign direct investment flows to the countries in this region increased in the 2000s and reached its highest point in the second half of decade as is shown in Figure (1). However, this flow for FDI was not the same for all economics and industries in MENA area as shown in Figure (1). The largest inflows went to GCC countries and commercial service sectors and resources and non-tradable activities. The oil importing countries got only 30% of the region's total FDI inflows and large amount of this FDI came from MENA countries especially for GCC economics.

MENA markets have become important in offering investment opportunities. The importance of these markets is that most of the equity markets in the region are recently open to foreign investors. However, Assaf (2006) argues that the underdevelopment of the MENA markets comes down to different factors. One of these factors is that tourism and foreign direct investment (FDI) in MENA countries are still weak. Table (2) shows that Turkey has the highest amount of FDI, $ 13 billion, but is still a small figure when compared to US' FDI which is about $ 236 billion. Apergis and Payne (2014) argue that FDI has positive impact on economic growth for MENA countries. Tang and Abosedra (2014) examine the effects of tourism, energy consumption and political instability on economic growth in MENA countries from 2001 to 2009. They find that energy consumption and tourism have significant effect on economic growth of these countries and the results support tourism growth and energy led growth hypotheses in MENA area. However, the political instability has negative impact on economic growth and development on MENA countries. Moosa (2009) finds that economies in this area that pay attention to education and research, that have low country risk, and that have high return on capital due to the lack of domestic investment in fixed capital are able to attract FDI.

3.3. Inflation

According to World Bank report in 2013, Iran was one of the countries that had the highest inflation rates in the world as shown in Figure (2). Inflation in Egypt is also high as shown in Figure (2) and has been affected by the price of food and energy where these prices were increased. Furthermore, the political instability also has impact on inflation in Egypt. In Morocco, the rate of inflation rose in the first half of 2013 but was moderate before as appears in Figure (2) and this due to increase the price in education services, food and transport services. In Tunisia, the inflation was affected by currency depreciation and increase in food and fuel prices but the monetary policy in end of 2012 help to slow this trend. In Jordan and Lebanon, the inflation is slowdown which mean that the economic activity is weak. However, the inflation rate in Algeria and Iraq stayed low due to the increase in the wage which come to half in Algeria. For Iraq, the central bank help to keep the inflation rate low through exchange rate policy. Bahrain and Cyprus have low inflation rate according to Figure (2) comparing to US' inflation whereas the inflation in the rest of economies are high when compared to US as shown in Figure (2).

3.4. Oil

Oil production in oil exporter countries in MENA region has fallen over the past year by slightly more than 5% due to many factors. MENA oil exporters play an important role in the world energy markets and these countries earnings from oil and gas is about 73% of total exports and 78% of budget revenues in 2012 according to World Bank report. Oil production in oil exporter countries in MENA area has fallen because of many factors, including security setbacks, infrastructure problems and strikes, according to World Bank report 2013. The GCC oil exporters also had a lost in oil production since these countries support the region's transition economies financially.

Given the impact of oil on the region, it is logical to assume that there is a relationship between oil and economic growth. Indeed, Apergis and Payne (2014) examine this relationship in MENA countries, also controlling for educational attainment, trade openness, domestic investment, and foreign direct investment (FDI). These variables have a positive impact on economic growth for MENA countries. However, Apergis and Payne (2014) find that the coefficient of oil reserves has a negative impact on growth through 2003 but changing to a positive impact on growth after 2003 until the end of their sample period. They argue that the change in the coefficient on oil reserves might be due to the improvement in the quality of institutions and economic reforms that have occurred over time in the MENA countries.

3.5. MENA Stock Markets

MENA markets form an important segment of emerging markets. MENA is an economically diverse region where the oil-rich economies in the Gulf and countries that are resource-scarce in relation to population are located. Lucey and Lagoarde-segot (2008) argue that MENA markets suffer from many of institutional underdevelopments. Firstly, due to the involvement of the governments in economic activities, market makers are missing. Secondly, short selling is still illegal. Additionally, derivatives are not available and the access for foreign participants to the markets was liberalized last decade. Table (3) shows market development indicators that include market capitalization, value traded, listed firms and turnover ratio. As shown in Table (3), Turkey, Jordan and Saudi Arabia are the region's most developed markets. Turkey has the highest number of firms listed (405) followed by Jordan (243). The Saudi Arabia market has the highest value traded (70.1) followed by Turkey (44.2). Jordan's capitalization is the largest in the region (87.0). Saudi Arabian is the most liquid market (144.4). Looking at each market, it can be seen that Saudi Arabia is the region's best performing market since it displays a positive variation through three indicators. The rest markets have mixed results where the decrease in one or two indicators opposites the others.

Chapter 4 Data and Methodology

4.1. Data

We use daily data as is done in the literature from stock market price indices from MENA countries. The start dates for the data for each stock are subject to availability but all of them end in 2012. The stock markets used in this study are as follows: Bahrain stock market from 2003, Jordan stock market from 1996, Kuwait stock market from 2000, Lebanon stock market from 1996, Maltese stock market from 1998, Morocco stock market from 2002, Oman stock market 2002, Qatar stock market from 1998, Saudi Arabian stock market from 1998, Tunisia stock market from 1997, Turkey stock market from 1991, United Arab Emirates stock market from 2001, Cyprus stock market from 2000 and Egypt stock market from 1998.

As we mentioned earlier, this study will apply two performance measurements. These measurements are mean return and Sharpe ratio. In term of Sharpe ratio, we employ 3-months Treasury Bills for 9 countries (Turkey, Lebanon, Kuwait, Egypt, Malta, Jordan, Bahrain, Morocco, Tunisia) and 30 days Treasury bills for Cyprus as proxy of risk free rate. For Oman, Qatar, Saudi Arabia, United Arab Emirates we apply interbank rates as proxy for risk free rate where T-bills data are not available.

4.2. Sample statistics

Table (4) contains summary statistics for all series. Returns are calculated as log differences of the level. The most volatile series are Cyprus, Dubai, Kuwait, Qatar and Turkey. 10 series out of 14 exhibit negative skewness ranging from -0.225 in Jordan to the -0.697 in Lebanon. All the return series are leptokurtic. The daily return for Jordan demonstrates that there is no autocorrelation in five considered lags at 5% level and only at first lag for Dubai. This implies that daily returns in MENA markets are stationary so these markets are not efficient with exception to Jordan and Dubai where the results indicate that the daily returns in both markets are not stationary so the stock markets in Jordan and Dubai are efficient. This in line with Fama's (1970 and 1991) definition of EMH where he argues that in weak from of EMH, the stock returns are uncorrelated.

4.3. Trading Rules

4.3.1. Technical trading rule

This study applies the following trading rules as they are most common used ones in testing the profitability of technical trading rules: moving average (simple moving average, exponential moving average and triangular moving average), trading range break, filter rule, moving average coverage divergence, Bollinger bands, and channel breakout. The following sub-section presents each in turn.

4.3.1.1. Filter Rule

According to Fama and Blume (1966) an x per cent filter is defined as follows: If the daily closing price of a security moves up at least by x per cent, buy and hold the security until the price of the same security moves down at least by x per cent from a subsequent high, at which time simultaneously sell and go short. The short position is maintained until the daily closing price rises at least x per cent above a subsequent low at which time one covers and buys. Moves less than x per cent in either direction are ignored.

4.3.1.2. Moving Average (MA)

The moving average rule triggers buy and sell signals conditional on behaviour of two moving averages of the level of the index, the long moving average and the short moving average. A buy (sell) signal is generated when the short moving average rises above (fall below) the long moving average. This rule is aimed to replicate returns from trading rule where the trader buys when short moving average penetrates the long from below and stays in the market till the short moving average penetrates the long from above. After this signal the trader moves out of the market or sells short. The first moving average in this study is the simple moving average (SMA) which given by:

$$M_{t,n} = \frac{1}{n}\sum_{i=t-n+1}^{t} P_i = (P_t + P_{t-1} + \cdots .. + P_{t-n+1})/n \qquad (1)$$

Where $M_{t,n}$ is the simple n-day moving average at period t and P_i is the closing price for period *i*. MA based strategies depend on averaging a moving period of prices prior to the present.

The second moving average used is the exponential moving average. The exponential moving average assigns a greater weight to the most recent data but it uses all the available data instead of using a fixed number of points. Each price entry becomes less significant although it is still involved in the calculation. The exponential moving average for a price series is calculated as follows:

$Y_1 = P_1$

$$Y_t = \alpha . P_{t-1} + (1-\alpha) . Y_{t-1} \qquad (2)$$

Where α is the degree of weighting decrease between 0 and 1 and Y_t is the value of EMA at any time t. For example a 10 day EMA average, applies an 18.18% weighting to most recent price. (18.18=2/ (10+1)) applying (2/ (time period+1)) formula.

The EMA can also be expressed as follows:

EMA_{today}= $EMA_{yesterday}$ + α.($price_{today}$ - $EMA_{yesterday}$)

Expanding out $EMA_{yesterday}$ each time, yields a power series and shows how the weighting factor decrease exponentially

EMA_{today}= α .(p_1 + (1-α)p_2 + $(1-\alpha)^2 p_3$ +$(1-\alpha)^3 p_4$+…)

Where p_1 today price and p_2 yesterday price. ..

$EMA\ _{today} = \frac{p_1 + (1-\alpha)p_2 + (1-\alpha)^2 p_3 + (1-\alpha)^3 p_4 + ..}{1+(1-\alpha) + (1-\alpha)^2 + \cdots}$

As $1/\alpha = 1 + (1-\alpha) + (1-\alpha)^2 + \cdots$

The third moving average is the triangular moving average. Triangular moving average (TMA) uses also the mean price over a specific number of previous prices as other moving averages do. However, the triangular moving average double smoothes as it is averaged twice. It is a weighted average of previous n prices which is equal to a double smoothed simple moving average. It is given as follows:

$$TMA = (SMA_1 + SMA_2 + SMA_3 + \cdots ..SMA_n)/n \tag{3}$$

To ease the exposition, the following steps show how to compute a 6 period triangular moving average:

1- Add 1 to the number of periods applied in the moving average (e.g. 6+1).
2- Secondly, divide the sum from the first step onward by 2 (e.g. 7 divide by 2 is 3.5).
3- In third step, if the results from dividing by 2 contain a fractional, round it up to the nearest integer (e.g. 3.5 rounds to 4).

4- Calculate the moving average using the value from step 3 (e.g. 4 period simple moving averages).

5- Again, using the same value from step 3, calculate a simple moving average of moving average computed in step 4 as it is shown in equation (3).

Following Sullivan (1999) we will impose filters on the moving average rules. The filters assist in filtering out false trading signals (i.e., those signals that would result in losses). The fixed percentage band filter requires that the buy or sell signal exceed the moving average by a fixed multiplicative amount, *b*. Brock et al. (1992) highlight that introducing the band modifies moving average decision arguing that it reduces the number of signals since it eliminates whiplash signals when the short and long period moving averages are close. So when band is considered in the MA rule, buy (sell) signals take place when short moving average is above (below) the long moving average by an amount larger than the band. For example, the trading rule MA(1,20,1) refers that is short moving average is 1 day, the long moving average is 20 days, and the band of the MA is 1%. So when the 1 day MA is above (below) the 1% price band around the 20 day MA, the buy signal is generated. The time delay filter requires that the buy or sell signal remain valid for a pre-specified number of days, *d*, before action is taken and only one filter will be considered at a given time. For MA, holding a given long or short position for a pre-specified number of days, *c* will also be considered.

4.3.1.3. Trading Range Breakout (TRB)

According to Chang et al. (2004), investors receive a buy signal when prices penetrate the resistance level, i.e., go above a local maximum and a sell signal is given if prices fall below a local minimum (support level). If prices remain in the intermediate range, then one maintains the original position.

$\{ I_t = 1$ if $P_{t-1} = \text{Max}\ [P_{t-1}, P_{t-2}, \ldots, P_{t-H}]$

$I_t = 0$ if $P_{t-1} = \text{Min}\ [P_{t-1}, P_{t-2}, \ldots, P_{t-H}]$

$I_t = I_{t-1}$ if $P_{t-1} \in (\text{Min}\ [P_{t-1}, P_{t-2}, \ldots, P_{t-H}], \max[P_{t-1}, P_{t-2}, \ldots, P_{t-H}])\ \}$ (4)

where H is number of days in TRB.

Gradojevic (2007) argues that the TRB rule (resistance and support levels) generates a buy signal when the price breaks-out above the resistance level and a sell signal when the price breaks-out below the support level. The resistance level is defined as the local maximum, and the support level is defined as the local minimum. At the resistance (support) level, intuition would suggest that many investors are willing to sell (buy). The selling (buying) pressure will create resistance (support) against the price rising (falling) above the peak (trough) level.

Tinghino (2008) argues that the common phenomenon with support and resistance levels is that old resistance tends to become new support and similarly old support becomes new resistance later on.

As with the moving average rules, a fixed percentage band filter, *b*, and a time delay filter, *d*, will be considered. Again, positions can be held for a pre-specified number of days, *c*.

4.3.1.4. Moving Average Coverage Divergence (MADC)

MACD is rule introduced by Gerald Appel (1999). MACD simply shows the relation between two moving averages of prices. It is the difference between a 26-day and 12-day exponential moving average. It is calculated by subtracting the longer exponential moving average from the shorter EMA. A 9-day line exponential moving average that is the signal line is plotted on MACD to present buy and sell singles. According to

MACD, the trading signals generates on the crossover between the MACD line and the signal line or crossover with zero. Both the bullish crossover (upwards move) and bearish crossover (downwards move) indicate that the trend in the series is about to accelerate in the direction of the crossover. As with the moving average rules, a time delay filter, *d*, will be considered. Again, positions can be held for a pre-specified number of days, *c*.

4.3.1.5. Bollinger Bands

Bollinger bands are introduced by John Bollinger in the 1980s. Lento et al. (2007) shows that the most common applied Bollinger bands are calculated basing on a 20-day moving average and +/- 2 standard deviation which is denoted by the BB (20, 2). This indicator consists of three parts. Firstly, an *N* period moving average, an upper band at *K* times an *N*-period standard deviation, above the moving average and a lower band at *K* times an *N*-period standard deviation below the moving average. Bollinger band is used in different ways between the traders. Traders buy when price breaks above the upper Bollinger Band and sell when price falls below the lower Bollinger Bands. As with the moving average rules, a fixed percentage band filter, *b*, and a time delay filter, *d*, will be considered. Again, positions can be held for a pre-specified number of days, *c*.

Calculation

The middle band is a normal moving average and calculated as in the following formula where 'n' is the number of the days in the moving average:

$$\text{Middle band} = \frac{\sum_{j=1}^{n} P_j}{n} \tag{5}$$

The upper band is the same as the middle one but it is shifted up by the number of standard deviation as it is calculated as follow where 'D' is the number of standard deviation:

$$\text{Upper band} = \text{Middle band} + [\ D+\sqrt{\frac{\sum_{j=1}^{n}(P_j - Middle\ Band)^2}{n}}\ ] \quad (6)$$

The lower band is same as the middle band but it is shifted down by the same number of standard deviation as following:

$$\text{Lower band} = \text{Middle band} - [\ D+\sqrt{\frac{\sum_{j=1}^{n}(P_j - Middle\ Band)^2}{n}}\ ] \quad (7)$$

Bollinger recommends 20-day moving average and 2 standard deviations and he argues that moving average that is less than 10 days do not work very well.

4.3.1.6. Channel Breakout

Ryan et al. (1999) cited that a channel occurs when the high over the previous n days is within X percent of the low over the previous n days. While the buy signal is generated when the closing price exceeds the channel, the sell single is generated when the prices moves below the channel. Ben et al. (2008) and Nauzer et al. (2008) highlight that long and short positions are held for a fixed number of days, c, and a fixed percentage band, b, can be applied to the channel as a filter.

4.4. Trading rule evaluation: Step Superior Predictive Ability Test

Data snooping arises when researchers use same data set in order to test the significance of different models individually. Since individual statistics are obtained using the same data set, thus are related to each other, it is difficult to construct a join test especially when the numbers of rules under the study is large. The Reality Check (RC) test was introduced by White (2000) which considers the dependence of individual statistics. However, there are two drawbacks for RC test. Hansen (2005) highlights that RC test is conservative since its null distribution is generated under the least favorable configuration. The RC test might lose power when many poor models are included in the same test. Hansen (2005) introduces the SPA test in order to improve the power of RC test and avoid the least favorable configuration by re-centring the bootstrap distribution. RC test also examines whether there is any significant model without identifying all these models. Hansen's SPA has this limitation as RC test. The other drawback for the RC test is that this test does not identify all models which significantly deviate from the null hypothesis. Romano and Wolf (2005) introduce an RC-based stepwise test to identify as many significant models as possible. However, the shortcoming of this methodology is its conservativeness. Hse et al. (2010) extend SPA test to the stepwise SPA test (SSPA) test that combines the Romano and Wolf stepwise procedure with the more powerful SPA test. This procedure uses Politis and Romno (1994) stationary bootstrap procedure applying random blocks whose length is determined by the realization of a geometric distribution with parameter Q ϵ [0, 1]. The SSPA can identify predictive models in large-scale multiple testing problems without data snooping bias. It demonstrates that SSPA test is consistent in that it can identify the violated null hypotheses with probability approaching one.

Given m models, let $d_{k,t}$ (k=1, 2, .., m and t= 1,2,3,..n) refer to their performance measures over time. Let r_t be the return from an asset that we test if there is any trading rule that can yield positive return for this asset at time t. l $\delta_{k,t-1}$ be the trading signal generated by the k-th trading rule at time t-1. The signal take values of

1, 0, and -1 corresponding to long position, no position and a short position. So the realized return from the *k-th* trading rule will be $d_{k,t=\delta_{k,t-1}}$- r_t .

We are interested in testing of the null hypothesis that the benchmark is not inferior to any of the alternative. Let $d_{k,t} \equiv L(\xi_t, \delta_{0,t-h}) - L(\xi_t, \delta_{k,t-h})$ is the performance of model *k* relative to benchmark at time *t* where $L_{k,t} \equiv L(\xi_t, \delta_{1,t-h})$ is the observed loss of the *k*th rule and *k*=0 is the benchmark. . So $d_{k,t}$ refers to the performance of model *k* relative to benchmark at time *t* where $d_t = (d_{1,t}, \dots \dots d_{m,t})'$. As $\mu_k \equiv E(d_{k,t})$ is expected excess performance of a model *k*, the null hypothesis will be:

$$H_0^k: \mu_k \leq 0, \quad k=1, 2,\dots, m. \tag{8}$$

The model *k* is better than the benchmark if only $E(d_{k,t)}$ > 0.

Data snooping arises when the inference for Eq. (8) is obtained from the test of individual hypothesis. One way to avoid the problem is conduct a joint test of Eq. (8) with controlled significance level. A good example is the RC test with statistic as follows:

$$RC_n = \max_{k=1,\dots,m} \sqrt{n}\,\overline{d_k}, \tag{9}$$

Although the least favorable configuration (μ=0, $\mu \equiv (\mu_1, \dots, \mu_m)'$ vector of expected excess performance) of the RC test is convenient, it renders the test relatively conservative.

The Hansen (2005) SPA test statistic is as follows:

$$SPA_n = \max_{k=1,..,m} \left(\max_{k=1,\dots,m} \sqrt{n}\,\overline{d_k}, 0 \right) \tag{10}$$

Hansen (2005) argues that $RC_n \xrightarrow{D} \max\{N(0,\Omega_0)\}$ where some $\mu_i < 0$ and at least one μ_i=0. This is limiting distribution relies on the models with zero mean but not on the models that are poor. The SPA test avoids least favorable configuration by re-centering the null distribution.

The Step-SPA test applies the stationary bootstrap of Politis and Romano (1994). In step- SPA test d_t^* (b) = $d_{n_{b,t}}^*$ where t=1,…,n is the b-th resample of d_t and $n_{b,1},\ldots,n_{b,n}$ consist of blocks of (1,..,n) where first $n_{b,1}$ is randomly chosen from (1,…n) with an equal probability assigned to each number. Then for any $t > 1$, $n_{b,t}$=$n_{b,t-1} + 1$ with probability Q;[2]or $n_{b,t}$ is chosen randomly from (1,…,n). For re-sample to be done, n observations are drawn. If we denote $\bar{d}^*(b)$ =$\frac{\sum_{t=1}^{n} d_t^*(b)}{n}$ the sample average, repeating the procedure L times gives a distribution of $\bar{d}^*$with L realizations. The critical value is given by the following considering pre-specified level α_0:

$$\hat{q}_{\alpha_0}^* = \max(\hat{q}_{\alpha_0},0) \tag{11}$$

Where $\hat{q}_{\alpha_0}$= inf {q|$P^*\left[\sqrt{n}\, max_{k=1,\ldots,m}\left(\bar{d}_k^* - \bar{d}_k + \widehat{M}_K\right) \le q\right] \ge 1 - \alpha_0$}. $(1 - \alpha_0)$ is the re-centered empirical distribution and P^* is the bootstrapped probability measure.

The Step-SPA test proceeds following the next four steps:

Firstly, re-arrange $\bar{d}_k$ in a descending order. Secondly, reject the top model K when $\sqrt{n}\bar{d}_k$ is greater than$\hat{q}_{\alpha_0}^*$. Then remove $\bar{d}_k$ of the rejected model from the data. If no one can be rejected, the procedure stops. Finally, repeat the third step till no model can be rejected.

Following Sullivan et al. (1999) and Park and Irwin (2010) we use q=0.1 and B=500. Park and Irwin (2010) argue that the number of bootstrap sample should be large since it may affect the accuracy of p-values. They also show that Brock et al.

(1992) and Kho (1996) demonstrated that their bootstrap p-values were insensitive to the replication size of *B* when it extends beyond 500.

Chapter 5 Empirical results

5.1. Performance of best trading rules under mean return criterion

Table (5) presents trading rule parameters and Table (6) presents the annual return and Sharpe ratio for buy and hold strategy. Results from trading strategies under mean return are presented in Tables (7, 8, 9, 10). This study uses a total of 19,656 rules for each MA trading rules, a total of 2520 TRB trading rules, a total 900 filter trading rules, a total of 1080 channel breakout trading rules, a total of 42 MACD trading rules and a total of 72 BB trading rules for each country as it presents in Table (5). Table (7) presents mean annual return for the best MA performing trading rule. Among the best MA trading rule, those based on the SMA has the highest mean return for most countries (11 countries) followed by TMA (3 countries). In this family of rules, the best performing trading rule is the SMA for Turkey with annualized return of 9.81% followed by TMA and EMA for Turkey again with annualized return of 9.27% and 9.19% respectively. The returns from MA outperform simple buy-hold strategy as seen in Figure (4). From Table (10) which presents the number of the rules that generate positive return for each rule and each country, EMA has highest percentage of rules that generate positive return for 7 series out of 14 followed by SMA for 4 series out of 14. Form the results of MA in Table (10), it appears that Malta has high percentage of significant rules in average (91%) through all MA that applied followed by Bahrain (71%) and Jordan (53%).

The results are not unexpected as there are many studies which show that these rules have predictive ability in emerging markets as in and Ranter and Leal (1999), Bessembinder and Chan (1995, 1998) and lento (2007) in other emerging markets. For MENA markets, these results consistent with Lagoarde-Segot and Lucey (2008) in 3 cases (Turkey, Jordan and Tunisia). The high result for Malta can be explained by

Fifield et al. (2004), Loh (2007), Bessembinder and Chan (1995) and Chang et al. (2004) s' studies. They indicate that the degree of the market development play role in trading rule performance. Fifield et al. (2004) test the predictive ability of technical trading rules using data for a selection of European stock markets. They indicate that while the emerging stock markets displayed some evidence of share return predictability, the developed markets under the study did not. The results from moving average indicate that 46 of the 70 rules examined in developed markets not only underperformed the buy and hold strategy, but also generated large losses. For emerging markets, the profits were positive and exceeded the profit available from a passive buy and hold strategy even after accounting for transaction costs. Loh (2007) shows that MA rules are weak in detecting the future directional movements in stock prices when applied to developed markets. Bessembinder and Chan (1995) and Chang et al. (2004) also indicate that technical rules tend to be more profitable in emerging markets relative to the more developed stock markets. Malta stock market has the lowest turnover ratio as shown in Table (3) so it is a less developed market when compared with other stock markets in MENA area.

Similar to MA trading rules, the best TRB trading rules are also for Turkey market with annual return, 9.78% as shown in Table (8). From Table (10), Bahrain has the highest percentage of rules (62%) that generate positive return followed by Malta (61%) and Oman (57%). For the rest of the countries, it ranges from 1% to 32%. The returns from TRB outperform simple buy-hold strategy as seen in Table (8) and Figure (5). Compared with MA as shown in Figure (6), the annual best returns generated by TRB are higher than EMA in all cases, 3 out 14 cases for SMA and 13 out 14 cases for TMA which imply that TB trading rules have greater predictive ability than the moving average based rules. The returns from TRB outperform simple buy-hold strategy as seen in Table (8) and Figure (5). This result is in line with Bessembinder and Chan (1995), Bessembinder and Chan (1998) and Lento (2007) in other emerging markets. The average return is 4.42% which is higher than the average that Lagoarde-Segot and Lucey (2008) obtained from TRB 0.91% in MENA markets and low when it is compared with 13.08% in other emerging markets in study done by Change et al. (2004).

Under filter trading rules, the best annual return which is 17.6% is for Turkey market. From Table (10), Oman has the highest number of rules (52%) that generate positive return followed by Malta (40%) and Bahrain (25%). For the rest of the countries, it ranges from (2%) to (23%). The returns from filter trading rules outperform simple buy-hold strategy as seen in Table (6) and Figure (5).Compared with MA and TRB as shown in Figure (6), the best returns generated by filter rule are higher than MA and TRB in all cases apart form one case for SMA where the return is 14.35% for SMA and 10.6% for filter rule. This indicates that filter rules have greater predictive ability than the TRB and moving average based rules. This result is in line with the literature as in Sweeney (1988) and Alexander (1961) in other developed markets and Fifield et al. (2008) for emerging markets where they found that over half of filters rules are significant and doing better than in developed markets.

Under channel trading rules, the best channel trading rules generates annual return 11.83% for Cyprus. From Table (10), Bahrain return series has the highest percentage of rules (62%) that generate positive return followed by Malta 58% and Oman 54%. Compared with MA, TRB and filter rules as shown in Figure (6), the annual best returns generated by channel are higher than SMA in 4 cases, EMA in 13 cases and TMA in 12 cases. Additionally, comparing with TRB, channel trading rules perform better than TRB in 2 cases. Finally comparing with filer trading rule, none of channel trading rule performs better than filter rules as shown in Figure (6). The returns from channel rules outperform simple buy-hold strategy as seen in Table (6) and Figure (5).

The best MACD trading rules generates annual return which is 3.25% for Turkey market as under MA, filter, and TRB trading rules. From Table (10), Qatar and Malta have the highest percentage of the rules (50%) that generate positive return followed by Cyprus, Egypt, Saudi Arabia and Tunisia (30%) each. Kuwait has the lowest percentage of significant rule (6%). The returns from MACD outperform simple buy-hold strategy as seen in Table (6) and Figure (5). Compared with previous rules from MA, TRB and filter, MACD has greater return in one case than EMA.

From Table (9), the best BB trading rule is for Jordan with annual return 2.70%. From Table (10), Jordan has the best percentage of rules that generate positive return (35%) followed by Oman (33%) and Tunisia (22%). Trading rules for Cyprus, Kuwait, Lebanon, Malta, Morocco, Qatar, Saudi Arabia and Turkey do not generate any significant rule. Compared with MA, TRB, channel and filter rules as shown in Figure (6), the annual best significant returns generated by BB is the same as SMA and EMA in 1 case. However, it does not do better than other rules in for any country. The returns from Bollinger bands outperform simple buy-hold strategy as seen in Table (6) and Figure (5) in 6 cases out of 14 ones.

From the previous discussion, it is clear that the best performing trading rules under SMA, EMA, TMA, Filter, TRB and MACD is for Turkey market since it is generating the highest annual return compared with Cyprus for channel rules and Jordan for BB rules. In term of the percentage of the rules that generate positive return, Malta, Bahrain and Oman achieving the better percentage of rules that have positive return. Malta has 60% of rules that generate positive return on average compared with 52% with Oman and 49% with Bahrain.

5.3. Results for trading rules under Sharpe ratio criterion

The calculation for Sharpe ratio requires excess returns to be measured. The excess returns are the returns from the technical trading rule less the risk-free interest rate. We employ 3-months Treasury Bills for countries (Turkey, Lebanon, Kuwait, Egypt, Malta, Jordan, Bahrain, Morocco, Tunisia) and 30 days Treasury bills for Cyprus as proxy of risk free rate. For Oman, Qatar, Saudi Arabia, United Arab Emirates we apply interbank rates as proxy for risk free rate where T-bills data are not available.

Results from trading strategies under Sharpe ratio are presented in Tables (11, 12, 13, and 14). As shown in Table (11), among the best MA trading rule, those based on the SMA has the highest Sharpe ratio for most countries (9 countries) followed by EMA (3 countries). It is clear from Table (12) that the best trading rules selected from the SMA by the Sharpe ratio criterion is for Turkey market. The best performing trading rule from EMA is for Qatar. The best performing trading rule from TMA is again for Turkey. From Table (14) which presents the number of the rules that have positive Sharpe ratio for each rule for each country, EMA has highest percentage of rules that have positive Sharpe ratio followed by TMA. It appears that Bahrain has the highest percentage of rules that have positive Sharpe ratio followed by Egypt and Turkey. The Sharpe ratio from MA outperforms simple buy-hold strategy as seen in Table (6) and Figure (8).

Results from trading strategies based on TRB rules with respect to Sharpe ratio are presented in Table (12) and (14). The best TRB rule according to Table (12) is for Jordan while Turkey has the highest percentage of rules that produce positive Sharpe ratio (7%) followed by Cyprus and Egypt (3%) each as shown in Table (14). The Sharpe ratio from TRB outperforms simple buy-hold strategy as seen in Table (6) and Figure (9).

Applying filter trading rule, the best result with Sharpe ratio is 0.815 for Turkey again. Additionally, Turkey has the highest number of rules that produce positive Sharpe ratio (11%) followed by Cyprus (7%) and Qatar (4%) according to Table (14).

The results are similar to previous rules in that the best Channel trading rules are for Turkey as shown in Table (12) and (14). Turkey market also has the highest percentage of rules (10%) followed by Egypt (9%) and Cyprus (8%).

The results for MACD are presented in tables (13) and (14). The best MACD rule is for Cyprus. From Table (15) which shows the number of rules that statistically significant each country, Egypt and Turkey have highest percentage of rules that have positive Sharpe ratio (20%).

Results for Bollinger band are presented in Table (13) and (14). While the best trading rules is for Dubai as shown in Table (13), Jordan has the best percentage of rules that have positive Sharpe ratio (10%) followed by Dubai (4%).

As it can be seen, the best results for Sharpe ratio under 4 trading rule groups (TMA, SMA, filter and channel) is for Turkey compared to Qatar, Jordan, Dubai and Cyprus where they generate best annual return under EMA, TRB, BB and MACD, respectively. In terms of percentage, Turkey, Cyprus and Egypt have the highest percent of the rules that have positive Sharpe ratio as shown in Table (14).

5.4. Controlling for data snooping

We run the SPA and the SSPA tests for robustness to data snooping bias of the significant rules. The results are presented in tables (15, 16, 17). Each of these tables presents the data snooping SPA p-value for the best performing trading rule and where possible the number of significant rules that generate positive mean return comparing with buy and hold strategy identified by the SSPA test. Table (15) shows that in 18 cases out of 42 for SMA, EMA and TMA that have robust rules. There are 3 cases out of 14 for SMA rules for the Malta, Morocco and Tunisia that are robust with p-value equal to 0. According to EMA, there are 8 case out of 14 have robust rules for Jordan, Lebanon, Malta, Morocco, Oman, Qatar, Saudi Arabia and Tunisia with p-value equal to 0. Additionally, there are 7 cases where the TMA rules have robust rules for Jordan, Lebanon, Malta, Morocco, Saudi Arabia, Tunisia and Turkey with p-value equal to 0. This result is in line with Metghalchi et al. (2012) which find that the trading rules have predictive ability even after accounting for data snooping bias in most of the applied stocks.

Table (16) presents the results for TRB, filter and channel trading rules. According to TRB, there are 7 cases that have robust rules with p-value equal to 0 for Cyprus, Egypt, Lebanon, Malta, Oman, Qatar and Turkey. Filter rules are performing better as there are 10 cases that have robust rules with p-value equal to 0 for Jordan, Bahrain, Cyprus, Egypt, Lebanon, Malta, Morocco, Oman, Qatar and Turkey. According to channel rules, there are 7 cases that have robust rules for Jordan, Bahrain, Cyprus, Egypt, Malta, Morocco and Saudi Arabia with p-value equal to 0. For BB trading rules, there are 6 cases (Bahrain, Cyprus, Dubai, Egypt, Lebanon, Oman) where there is no robust rule under MACD as shown in Table (17). From the tables (15), (16), (17), it is clear that accounting for data snooping reduces the number of robust trading rules. For most stocks, the p-value range from 0.08 to 1.00. Additionally, it is clear that Malta series has robust rules through SMA, MACD, TMA, channel and filter trading rules. Lebanon also has robust rules through BB, EMA, TMA, filter and TRB rules. Morocco has robust rules like Lebanon but not for TRB and for channel rules. Oman, Qatar and Tunisia have robust rules through 4 different trading rules, BB, filter, TRB and EMA for Oman, filter, TRB, EMA AND TMA for Qatar. BB, SMA, EMA, TMA for Tunisia, Cyprus, Bahrain and Turkey have robust rules in different trading group each. Saudi Arabia has robust rules in two trading group, EMA and channel rules.

Chapter 6 Conclusion

This chapter has investigate the profitability of trading rules in MENA countries extending Lagoarde-Segot and Lucey (2005, 2008) work on the MENA markets. The paper applies more trading rules and markets comparing to Lagoarde-Segot and Lucey (2005, 2008) research. This paper applies 63468 trading rules in total for each stock market in 14 MENA countries. Furthermore, two performance measurements used, mean return and Sharpe ratio. In order to account for data snooping bias, Hansen (2005)'s superior Predictive Ability (SPA) and Hus et al. (2010)'s Stepwise-SPA test are used. The results in term of mean return show that the best SMA, EMA, TMA, TRB, MACD and filter trading rules is for Turkey with annual return of 9.81%, 9.19%, 9.27%, 9.78%, 3.25 and 17.6% respectively. However, the best BB is for Jordan with annual return of 2.70% and the best Channel trading rules is for Cyprus with annual return of 11.83%. In term of the percentage of the rules that have positive return, Malta has the highest percentage under MA, 91%, and MACD, 50%. Under TRB and channel trading rules, Bahrain has the highest percentage of the rules that have positive return, 62% for both TRB and Channel trading rules. Oman market has the highest percentage under filter trading rule which is 52% and for BB Jordan has the highest percentage, 35%.

In terms of Sharpe ratio, the best TMA, SMA, channel and filter trading rules is for Turkey. However, the best performing rule under EMA, TRB, MACD and BB trading rule is for Qatar, Jordan, Cyprus, and Dubai respectively. In term of percentage, Bahrain has the highest percentage of trading rules that have positive Sharpe ratio under MA trading rules. Turkey has the highest percentage of trading rules that have positive Sharpe ratio under TRB, channel, filter and MACD trading rules. For BB trading rules, Jordan has the highest percentage of rules that have positive Sharpe ratio. However, Malta stock market has highest percentage of significant rules before and after controlling for data snooping bias through SMA, EMA, TMA, filter and channel trading rule classes. These results consistent with Lagoarde-Segot and Lucey (2008) in 3 cases (Turkey, Jordan and Tunisia), Ranter and Leal (1999), Bessembinder and Chan (1995, 1998), Lento (2007), Loh (2007), Chang et al. (2004) in other emerging markets. These results are also in line with Kuan et al. (2014) who got results that show that trading rules outperform a simple buy and hold strategy. Our results also support Shan et al. (2015) results where they find evidence that supports profitability of trading rules when they use data from Shanghai Securities Composite Index.

Finally controlling for data snooping reduces the number of significant rules where there are 18 cases out of 42 for TMA, SMA and EMA trading rules, 10 cases under filter trading rules, 7 cases under TRB trading rules and channel trading rules, 6 cases under BB that have robust rules. However, there is no robust rule under MACD trading rules. This result in line with Metghalchi et al. (2012) and Shan et al. (2015) where they found that trading rules have predictive ability even after accounting for data snooping bias. These results indicate that MENA markets are not efficient. Our results confirm the previous works which argue that MENA markets are not efficient. For example, Walid (2010) examines the EMH in 11 stock markets in MENA and he finds that these markets are not efficient and the efficiency paths do not sufficiently improve towards the first quarter of 2009, except Saudi stock market. Furthermore, their efficiency paths are instable being affected by the contemporaneous crises. Moreover, these markets are highly sensitive to past shocks in that undesirable shocks extend their influence for a long period. Fouad and Eduardo (2015) test EMH in the GCC and they find that GCC stock markets are not individually and collectively weak-form efficient. This inefficiency could be due to the weak degree of foreign participation and the high concentration in the banking and financial sectors. The weak participation of foreign investors in GCC stock markets can be attributed to: the presence of regulatory restrictions on foreign ownership, the relatively low degree of financial market development in the GCC or the presence of information asymmetry caused by the inadequate digital financial disclosure capacity of GCC equity markets. Almost 61% of these firms do not have websites to publish their financial information to investors, leading to the constitution of information asymmetry. The second factor that affects the efficiency is the high concentration in the banking and financial sectors. Since GCC stock markets have a high concentration in banking and financial sectors, and as there are two financial crises in 2006 and 2008, this cause these equity markets to be inefficient. Because of cross-country banking linkages between GCC countries, a banking crisis in one country gets transmitted to another.

Kinga and Graham (2013) find an evidence of changes in the efficiency of the markets over time. The possible reasons for those changes are the US war in Iraq that started in 2003, the US$ crisis of March 2005, the Gulf market's crash and the Israeli-Lebanon war in 2006, the global financial crisis of 2007/2008, the Dubai debt crisis in late 2009 and the European sovereign debt crisis in 2010. Also they argue that in order to rank the emerging markets according to their predictability, it is important to correct the data for thin trading. The results show that the least predictable markets are Turkey, Egypt and Israel, which belong to the largest or most liquid markets in the sample. The least efficient markets are Jordan and Lebanon which implies that they provide the greatest opportunities for investors to earn abnormal returns. Furthermore, the most recent study is done by Lanouar and Karim (2016) and they find that the recent financial shocks such as Arab spring and subprime crises have a significant impact on the time path evolution of market efficiency.

In sum, our results from applying trading rules in MENA markets after controlling for data snooping bias indicate that these markets are not efficient. However, examining the profitability of technical trading rules in MENA markets taking in the account the transaction costs left for possible future studies. Furthermore applying other performance measure such as information ratio, Treynor ratio, Jensen's alpha (Qi and Wu (2006)) and HAC inference (Ledoit and Wolf (2008)) also left for further future works.

Tables

Table (1) this table shows the real GDP growth.

Real GDP growth(percent)						
	2000-10	2011	2012	2013	2014p	2015p
MENA	5.3	4.7	5.8	2.6	3.0	5.2
Developing MENA	4.8	1.1	5.3	0.4	0.7	5.4
Oil Exporters	5.4	5.2	6.4	2.6	3.2	5.6
High income MENA	5.8	7.8	6.2	4.4	4.9	5.1
Bahrain	4.2	2.1	3.4	4.9	4.0	3.0
Kuwait	3.7	6.3	8.3	-0.4	1.4	1.8
Oman	9.1	5.4	3.4	5.2	5.5	5.6
Qatar	11.9	13.0	6.2	6.1	5.9	7.1
Saudi Arabia	5.6	8.5	6.8	4.5	5.3	5.5
United Arab Emirates	5.0	4.9	4.7	5.2	4.7	4.5
Developing Oil Exporters	4.8	0.4	6.7	-0.9	-0.3	6.5
Algeria	3.8	2.8	3.3	2.8	3.0	3.3
Iran	4.4	3.0	-5.8	-1.7	1.5	2.3
Iraq	5.7	10.2	10.3	4.2	-2.7	1.5
Libya	5.8	-62.1	104.5	-10.9	-27.8	54.3
Syrian Arab Republic	5.8	-3.4	-18.9	-18.7	1.8	2.4
Yemen	3.8	-12.7	2.4	4.8	1.9	4.6
Oil Importers	4.8	2.4	2.7	2.7	2.3	3.4
Djibouth	1.6	4.5	4.8	5.0	5.5	5.5
Jordan	5.9	2.6	2.7	2.8	3.0	3.4
Lebanon	4.8	2.0	2.2	0.9	1.5	2.0
Egypt	1.9	1.8	2.2	2.1	2.1	3.1
Morocco	4.5	5.0	2.7	4.4	3.0	4.6
Tunisia	4.9	-1.9	3.7	2.3	2.3	2.7
West Bank and Gaza	6.5	12.4	6.3	1.9	-3.7	4.4

Source: World Bank report, 2013.

This table shows the real GDP growth countries in MENA area from 2000 to 2015 where p refers to predicated value.

Table (2) This table shows the foreign direct investment for MENA countries.

	FDI*
	2013
Jordan	1,798,450,704
Bahrain	988,829,787
Cyprus	607,038,885
Dubai	10,487,950,987
Egypt	5,553,000,000
Kuwait	1,843,369,998
Lebanon	2,832,720,000
Malta	-1,868,526,80
Morocco	3,358,449,825
Oman	1,625,877,491
Qatar	-840,384,615
Saudi Arabia	9,297,693,333
Tunisia	1,095,613,852
Turkey	12,868,000,000
United Kingdom	48,314,454,024
United States	235,867,000,000

*source: Foreign direct investment, net inflows (current US $).

Table (3) Stock market development in MENA markets

	Market Capitalization/ GDP		Listed firms		Value traded		Turnover	
	2010	2012	2010	2012	2010	2012	2010	2012
Jordan	116.8	87.0	277	243	35.7	9.0	30.1	10.3
Bahrain	79.4	52.9	44	43	1.1	1.0	1.5	1.9
Cyprus	29.5	8.8	123	111	2.7	1.3	10.7	12.0
Dubai	26.8	17.7	101	102	9.5	4.6	34.4	25.3
Egypt	37.7	22.1	213	234	17.0	7.7	43.0	37.8
Kuwait	99.7	53.0	215	189	34.9	12.6	38.8	23.2
Lebanon	33.1	23.8	10	10	4.9	0.9	14.7	4.0
Malta	29.4	41.0	20	20	0.3	0.5	1.2	1.2
Morocco	76.2	54.8	73	76	11.8	3.6	16.3	6.2
Oman	34.5	25.7	119	124	5.8	3.4	18.2	13.3
Qatar	97.1	66.5	43	42	14.6	8.1	17.3	12.2
Saudi Arabia	67.1	50.9	146	158	38.6	70.1	60.5	144.4
Tunisia	24.2	19.6	56	59	3.9	2.8	17.2	13.5
Turkey	41.9	39.1	337	405	57.7	44.2	158.4	136.5

Source: World Bank Global Development Database.

Table (4) Summary statistics for daily returns.

	N	Mean	Std.	Skew	Kurtosis	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5
Jordan	5690	0.282	0.010388	-0.22512	60.86529	0.098	0.254	0.073	0.132	0.051
Bahrain	2297	0.0415	0.006131	-0.45102	9.230508	0	0	0	0	0
Cyprus	3020	-0.99	0.023318	0.100808	7.210826	0	0	0	0	0
Dubai	2626	0.475	0.024029	1.220442	473.5369	0.147	0	0	0	0
Egypt	3602	0.405	0.017328	-0.34629	13.16119	0	0	0	0	0
Kuwait	2915	0.685	0.044113	-0.4857	679.9662	0	0	0	0	0
Lebanon	4110	0.0473	0.013575	-0.6973	149.1381	0	0	0	0	0
Malta	4128	0.274	0.007916	1.4157	23.05951	0	0	0	0	0
Morocco	2558	0.44	0.008398	-0.5817	9.599478	0	0	0	0	0
Oman	3914	0.278	0.011714	0.2649	42.8087	0	0	0	0	0
Qatar	3445	0.543	0.027889	-0.5027	509.3112	0	0	0	0	0
Saudi Arabia	3395	0.414	0.015783	-0.5880	15.42946	0	0	0	0	0
Turkey	5690	0.001379	0.027376	-0.0517	7.164047	0	0	0	0	0
Tunisia	3603	0.425	0.005553	-0.0465	15.72957	0	0	0	0	0

Returns are measured as log differences of the level of the stocks. ρ_i is the estimated autocorrelation at lag i.

Table (5) trading rules parameters

	Parameters	Description	Value
Moving Average	M	Short run moving average	1,2,5,10,15,20,25,50,100,150,200,250
	N	Long run moving average	2,5,10,20,25,50,100,200,250,300
	B	Fixed band	0,05,0.001,0.005,0.01,0.05
	D	Number of days for delay filter	0,1,2,3,4,5
	C	Number of months position is held of all other trading signals	0,1,2,5,10,15,20
Channel Rule	E	Evaluation period	1,2,5,10,20,50
	B1	Fixed Band	0.001,0.05,0.01
	B2	Channel size	0.005,0.01,0.05
	D	Number of days for delay filter	0,…,3
	C	Number of months position is held of all other trading signals	0,1,2,5,10
Trading range break	E	Evaluation period	1,2,5,10,15,20,25,50,100,150,200
	B	Fixed band	0,05,0.001,0.005,0.01,0.05
	D	Number of days for delay filter	0,…..,5
	C	Number of months position is held of all other trading signals	0,1,2,5,10,15,20
Filter Rule	E	Evaluation period	1,2,5,10,25,50,100
	B1	Band for buy signals	05, 0.05, 0.1
	B2	Band for sell signals	05, 0.005, 0.1
	D	Number of days for delay filter	0, 1, 2, 3
	C	Number of months position is held of all other trading signals	0,1,2,5,20
Bollinger Band	E	Evaluation period	5,10,15,20
	Nstd	Number of st.dev	2,4
	C	Number of months position is held of all other trading signals	0,1,2

	D	Number of days for delay filter	0,1,2
MACD	C	Number of months position is held of all other trading signals	0,1,2,5,10,15,20,25,30
	D	Number of days for delay filter	0, 1, 2, 3,4,5

Table (6) This table presents the Buy and hold strategy returns and risk free rate for each country.

	Buy-hold Strategy mean return	Buy-hold strategy Sharpe ratio
Jordan	0.066245	-0.193
Bahrain	0.010598	-0.500
Cyprus	-0.25039	-0.174
Egypt	0.103137	-0.125
Kuwait	0.175999	-0.057
Lebanon	0.012313	-0.194
Dubai	0.121899	-0.103
Malta	0.077505	-0.318
Morocco	0.11255	-0.305
Oman	0.071252	-0.213
Qatar	0.137231	-0.077
Saudi Arabia	0.105732	-0.145
Tunisia	0.0109054	-0.354
Turkey	0.352504	-0.035

Table (7) Performance of Best Technical Trading Rules under Mean Return Criterion.

	SMA						EMA						TMA					
	m	n	B	c	D	AR	m	N	b	c	D	AR	m	N	b	c	d	AR
Jordan	1	2	0	0	0	2.99	1	2	0	0	0	2.70	1	2	0	0	0	2.70
Bahrain	1	2	0	0	0	2.07	1	2	0	0	0	1.94	1	2	0	0	0	1.95
Cyprus	1	2	0	0	0	8.03	1	2	0	0	0	7.47	1	2	0	0	0	7.57
Dubai	15	300	0.005	2	1	4.75	1	2	0	0	0	4.44	1	2	0	0	0	4.49
Egypt	5	15	0.005	2	1	1.39	1	2	0	0	0	5.66	1	2	0	0	0	4.90
Kuwait	20	25	0.05	2	3	5.18	150	25	0.05	4	10	4.84	1	2	0	0	0	5.75
Lebanon	1	2	0	0	0	3.63	1	2	0	0	0	3.41	1	2	0	0	0	3.43
Malta	1	2	0	0	0	2.28	1	2	0	0	0	2.13	50	15	0.05	2	1	2.15
Morocco	50	300	0.001	3	5	2.83	10	50	0.001	2	20	2.68	1	2	0	0	0	2.69
Oman	1	2	0	0	0	2.28	150	50	0.05	1	10	2.91	50	15	0.05	2	1	2.99
Qatar	200	250	0.05	4	5	5.21	100	15	0.01	2	10	4.98	100	50	0.05	1	2	5.05
Saudi Arabia	100	300	0.05	3	5	4.35	5	50	0.01	1	2	4.57	1	2	0	0	0	3.97
Tunisia	5	200	0.01	4	10	1.79	100	300	0.005	2	5	1.68	50	25	0.01	3	5	1.71
Turkey	150	300	0.01	5	3	9.81	5	50	0	4	1	9.19	1	2	0	0	0	9.27
average						4.75						3.78						4.32

SMA, arithmetic moving average, EMA exponential moving average, TMA triangular moving average. M and N are the short and long moving average respectively. B, c and d are fixed band, Number of months position is held of all other trading signals and number of days for delay filter respectively. AR donates for annual mean return.

Table (8) Performance of Best Technical Trading Rules under Mean Return Criterion.

	TRB					Filter rule						Channel rule					
	B	c	D	e	AR	b_{sell}	b_{buy}	c	d	e	AR	b	z	c	D	e	AR
Jordan	1	1	5	5	2.84	05	0.05	0	0	1	6.05	0.001	0.005	0	0	1	2.81
Bahrain	0.005	2	5	1	2.04	05	0.05	0	0	1	2.23	0.001	0.005	0	0	1	2.01
Cyprus	0	0	0	1	8.02	05	0.05	0	0	1	12.6	0.001	0.01	0	0	10	11.83
Dubai	0	0	0	1	4.68	05	0.05	0	0	1	9.40	0.001	0.005	0	0	1	4.67
Egypt	0	0	0	1	5.99	05	0.05	0	0	1	6.83	0.001	0.005	0	0	1	5.98
Kuwait	0	0	0	2	5.09	05	0.05	0	0	1	7.17	0.001	0.005	0	0	1	5.08
Lebanon	0	0	0	1	3.59	05	0.05	0	0	1	7.42	0.001	0.005	0	0	1	3.58
Malta	0	0	0	1	2.23	05	0.05	0	0	1	7.08	0.001	0.005	0	0	1	0.93
Morocco	0	0	0	25	2.82	05	0.05	0	0	1	3.14	0.001	0.005	0	0	1	2.70
Oman	0	0	0	100	3.07	0.05	0.05	1	3	1	7.02	0.001	0.005	0	0	1	3.05
Qatar	0	0	0	5	5.24	0.05	05	2	1	1	14.9	0.01	0.05	1	1	5	6.42
Saudi Arabia	0	0	0	100	4.83	05	0.05	1	3	1	10.6	0.001	0.005	0	0	1	4.83
Tunisia	0	0	0	25	1.76	0.05	0.05	2	2	1	2.04	0.001	0.005	0	0	1	1.72
Turkey	0	0	0	2	9.78	05	0.05	0	0	1	17.6	0.001	0.005	0	0	1	9.77
Average					4.42						8.14						4.67

TRB, trade braking rang. B, c, e and d donates fixed band, Number of months position is held of all other trading signals, evaluation periods and number of days for delay filter respectively. b(buy) and b(sell) for filter rule band for buying signals and band for selling signals. C and d same as TRB. AR donates for annual mean return.

Table (9) Performance of Best Technical Trading Rules under Mean Return Criterion.

	Bollinger Band					MACD		
	e	nstd	c	d	AR	c	d	AR
Jordan	5	2	0	0	2.70	0	0	1.04
Bahrain	20	2	0	1	0.45	0	0	0.71
Cyprus	0	0	0	0	0	0	0	2.76
Dubai	5	2	0	0	1.20	0	0	1.53
Egypt	5	2	1	0	1.29	0	0	2.07
Kuwait	0	0	0	0	0	0	0	1.32
Lebanon	0	0	0	0	0	0	0	1.24
Malta	0	0	0	0	0	0	0	1.06
Morocco	0	0	0	0	0	0	0	1.06
Oman	5	2	0	0	1.09	0	0	1.29
Qatar	0	0	0	0	0	0	0	2.20
Saudi Arabia	0	0	0	0	0	0	0	1.65
Tunisia	5	2	0	0	0.55	0	0	0.71
Turkey	0	0	0	0	0	0	0	3.25
Average					0.35			1.60

MACD, moving average convergence divergence. E, nstd, c, and d in Bollinger Band donate evaluation period, standard deviation, Number of month position is held of all other trading signals and number of days for delay filter respectively. AR donates for annual mean return. C and d for MACD is same as Bollinger Band.

Table (10) This table reports the number and percentage of technical trading rules that generate positive return.

		Jordan		Bahrain		Cyprus		Dubai		Egypt		Kuwait		Lebanon	
		N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)
MA	SMA	9416	**47**	13809	**70**	6529	**33**	780	**3**	9707	**49**	184	**1**	1747	**8**
	EMA	10866	**55**	15834	**80**	7074	**35**	340	**1**	10866	**55**	172	**1**	1978	**10**
	TMA	10866	**55**	12319	**62**	6741	**34**	258	**1**	10745	**54**	55	**0**	1477	**7**
TRB		822	**32**	1574	**62**	1023	**40**	202	**8**	1027	**40**	34	**1**	585	**23**
Channel		421	**39**	669	**62**	223	**21**	150	**14**	261	**24**	60	**6**	291	**27**
Filter		122	**13**	226	**25**	210	**23**	49	**5**	176	**19**	21	**2**	93	**10**
Bollinger band		25	**35**	8	**11**	0	**0**	8	**11**	8	**11**	0	**0**	0	**0**
MACD		12	**20**	12	**20**	18	**30**	12	**20**	18	**30**	6	**10**	12	**20**
		Malta		**Morocco**		**Oman**		**Qatar**		**Saudi Arabia**		**Tunisia**		**Turkey**	
		N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)
MA	SMA	18548	**94**	2033	**10**	18690	**95**	1081	**5**	1912	**9**	7359	**37**	1596	**8**
	EMA	16618	**85**	2734	**13**	10279	**52**	1280	**6**	2237	**11**	7293	**37**	1596	**8**
	TMA	18577	**95**	1176	**5**	11247	**57**	1048	**5**	1062	**5**	7933	**40**	507	**3**

TRB	1565	**61**	427	**16**	1461	**57**	184	**7**	350	**13**	823	**32**	272	**10**
Channel	628	**58**	354	**33**	580	**54**	188	**17**	183	**17**	432	**40**	139	**13**
Filter	364	**40**	84	**9**	311	**52**	135	**15**	201	**22**	159	**17**	128	**14**
Bollinger Band	0	**0**	0	**0**	24	**33**	0	**0**	0	**0**	16	**22**	0	**0**
MACD	30	**50**	18	**30**	12	**20**	30	**50**	18	**30**	18	**30**	18	**30**

N refers to the number of trading rules that generate positive return. (%) refer to the percentage of technical trading rules that generate positive return.

Table (11) This table reports the best performing trading rule, chosen with respect to the Sharpe ratio criterion.

	SMA						EMA						TMA					
	m	N	b	c	d	Sharpe ratio	m	n	B	C	d	Sharpe ratio	m	n	b	C	d	Sharpe ratio
Jordan	1	2	0	0	0	0.316	1	2	0	0	0	0.3164	1	2	0	0	0	0.316
Bahrain	1	2	0	0	0	0.127	1	2	0	0	0	0.0795	1	2	0	0	0	0.081
Cyprus	1	2	0	0	0	0.699	1	2	0	0	0	0.6096	1	2	0	0	0	0.627
Dubai	1	2	0	2	1	0.275	1	2	0	0	0	0.251	1	2	0	0	0	0.456
Egypt	1	2	0	2	0	0.703	1	2	0	0	0	0.795	1	2	0	0	0	0.721
Kuwait	1	2	0.05	2	0	0.154	1	2	0	4	0	0.140	1	2	0	0	0	0.145
Lebanon	1	2	0	0	0	0.368	1	2	0	0	0	0.335	1	2	0	0	0	0.335
Malta	1	2	0	0	0	0.154	1	2	0	0	0	0.312	1	5	0	2	0	0.211
Morocco	1	2	0	0	0	0.374	1	2	0	0	0	0.319	1	2	0	0	0	0.144
Oman	1	2	0	0	0	0.305	1	2	0	0	0	0.268	1	2	0	0	0	0.274
Qatar	1	2	0.05	4	0	0.286	1	2	0	0	0	0.861	1	2	0	0	0	0.269
Saudi Arabia	1	2	0	0	0	0.520	1	2	0	0	0	0.456	1	2	0	0	0	0.461
Tunisia	1	2	0	0	0	0.175	1	2	0	0	0	0.134	1	2	0	3	0	0.144
Turkey	1	2	0	3	0	0.842	1	2	0	4	1	0.742	1	2	0	0	0	0.754
Average						0.378						0.401						0.357

SMA, arithmetic moving average, EMA exponential moving average, TMA triangular moving average. M and N are the short and long moving average respectively. B, c and d are fixed band, Number of months position is held of all other trading signals and number of days for delay filter respectively.

Table (12) This table reports the best-performing trading rule chosen with respect to the Sharpe ratio criterion.

	TRB					Filter rule						Channel rule					
	b	C	d	E	Sharpe ratio	b_{sell}	b_{buy}	C	D	e	Sharpe ratio	b	z	c	d	e	Sharpe ratio
Jordan	05	0	0	1	0.346	05	0.05	0	0	1	0.291	0.001	0.005	0	0	1	0.347*
Bahrain	05	1	3	1	0.106	05	0.05	0	0	1	0.042	0.001	0.005	0	0	1	0.106*
Cyprus	0	0	1	1	0.715	05	0.01	0	0	1	0.691	0.001	0.005	0	0	1	0.715*
Dubai	0	0	1	1	0.272	05	0.05	5	0	1	0.247	0.001	0.005	0	0	1	0.272
Egypt	0	1	0	1	0.699	05	0.05	0	0	1	0.616	0.001	0.005	0	0	1	0.700
Kuwait	0	0	1	1	0.154	05	0.01	5	1	1	0.140	0.001	0.005	0	0	1	0.154
Lebanon	0	0	0	1	0.363	05	0.05	0	0	1	0.297	0.001	0.005	0	0	1	0.363
Malta	0	2	0	1	0.256	05	0.05	0	0	1	0.254	0.001	0.005	0	0	1	0.451
Morocco	0.005	0	0	1	0.360	05	0.05	0	1	1	0.259	0.001	0.05	0	0	1	0.360
Oman	05	0	0	1	0.303	05	0.05	0	0	1	0.255	0.001	0.005	0	0	1	0.298
Qatar	05	0	0	1	0.283	05	0.05	2	0	1	0.255	0.001	0.005	0	0	1	0.283*
Saudi Arabia	05	0	0	1	0.515	05	0.01	0	0	1	0.454	0.001	0.005	0	0	1	0.515*
Tunisia	05	0	0	1	0.155	0.05	0.05	0	0	1	0.114	0.001	0.005	0	0	1	0.153
Turkey	05	2	0	1	0.840	05	0.01	0	0	1	0.815	0.001	0.005	0	0	1	0.849*
Average					0.36						0.275						0.36

TRB, trade braking rang. B, c, e and d donates fixed band, Number of months position is held of all other trading signals, evaluation periods and number of days for delay filter respectively. b(buy) and b(sell) for filter rule band for buying signals and band for selling signals. C and d same as TRB.

Table (13) Performance of Best Technical Trading Rules under Sharpe ratio Criterion.

	Bollinger Band					MACD		
	E	nstd	c	d	Sharpe ratio	c	d	Sharpe ratio
Jordan	5	2	0	0	0.53	0	0	0
Bahrain	0	0	0	0	0	0	0	0
Cyprus	0	0	0	0	0	0	0	0.096*
Dubai	5	2	0	0	0.64	0	0	0
Egypt	0	0	0	0	0	0	0	0.082*
Kuwait	0	0	0	0	0	0	0	0
Lebanon	0	0	0	0	0	0	0	0
Malta	0	0	0	0	0	0	0	0
Morocco	0	0	0	0	0	0	0	0
Oman	0	0	0	0	0	0	0	0
Qatar	0	0	0	0	0	0	0	0.054
Saudi Arabia	0	0	0	0	0	0	0	0.29*
Tunisia	0	0	0	0	0	0	0	0
Turkey	0	0	0	0	0	0	0	0.153*
Average				0.58	0.35			0.083

MACD, moving average convergence divergence. E, nstd, c, and d in Bollinger Band donate evaluation period, standard deviation, Number of month position is held of all other trading signals and number of days for delay filter respectively. C and d for MACD is same as Bollinger Band.

We report only the series that have positive Sharpe ratio. * indicates that there are more than one rule but we only report the first one.

Table (14) This table reports the number and percentage of technical trading rules that have positive Sharpe ratio.

		Jordan		Bahrain		Cyprus		Dubai		Egypt		Kuwait		Lebanon	
		N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)
MA	SMA	37	**0**	339	**2**	157	**1**	104	**1**	137	**1**	55	**0**	42	**0**
	EMA	37	**0**	504	**3**	210	**1**	200	**1**	504	**3**	55	**0**	44	**0**
	TMA	17	**0**	330	**2**	134	**1**	60	**0**	100	**1**	35	**0**	39	**0**
TRB		32	**1**	2	**0**	86	**3**	42	**2**	73	**3**	23	**1**	31	**1**
Channel		51	**5**	3	**0**	82	**8**	64	**6**	84	**9**	40	**4**	55	**5**
Filter		16	**2**	2	**0**	63	**7**	20	**2**	20	**2**	36	**3**	15	**2**
Bollinger band		7	**10**	0	**0**	0	**0**	4	**6**	0	**0**	0	**0**	0	**0**
MACD		0	**0**	0	**0**	12	**9**	0	**0**	11	**5**	0	**0**	0	**0**
		Malta		**Morocco**		**Oman**		**Qatar**		**Saudi Arabia**		**Tunisia**		**Turkey**	
		N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)
MA	SMA	31	**0**	11	**0**	60	**0**	63	**0**	70	**0**	11	**0**	276	**1**
	EMA	35	**0**	11	**0**	160	**1**	80	**0**	80	**0**	10	**0**	351	**2**
	TMA	20	**0**	5	**0**	76	**0**	117	**1**	101	**1**	5	**0**	227	**1**
TRB		20	**0**	14	**1**	33	**1**	55	**2**	41	**2**	4	**0**	166	**7**
Channel		2	**0**	27	**3**	50	**5**	70	**6**	64	**6**	4	**0**	108	**10**
Filter		5	**0**	10	**1**	18	**2**	40	**4**	20	**2**	2	**0**	95	**11**
Bollinger Band		0	**0**	0	**0**	0	**0**	0	**0**	0	**0**	0	**0**	0	**0**
MACD		0	**0**	0	**0**	0	**0**	6	**1**	6	**1**	0	**0**	12	**13**

N refers to the number of positive Sharpe ratios and (%) refers to the percentage of technical trading rules that generate Sharpe ratio.

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Table (15) This table presents the performance of the robust trading rule.

	SMA		EMA		TMA	
	SPA p-value	SSPA	SPA p-value	SSPA	SPA p-value	SSPA
Jordan	0.87	0	0	1978	0	1598
Bahrain	0.97	0	0.95	0	0.980	0
Cyprus	0.608	0	0.57	0	0.100	0
Dubai	0.106	0	0.132	0	0.504	0
Egypt	0.998	0	0.996	0	0.970	0
Kuwait	0.38	0	0.288	0	0.400	0
Lebanon	0.166	0	0	1512	0	1301
Malta	0	4524	0	3018	0	4045
Morocco	0	1908	0	2658	0.002	1098
Oman	1.00	0	0	9915	0.998	0
Qatar	0.89	0	0	1789	0.364	0
Saudi Arabia	0.732	0	0	2011	0	1032
Tunisia	0	4487	0	4058	0	5001
Turkey	0.992	0	0.926	0	0	486

The table shows the SPA p-value for each index and the number of robust rules identified by SSPA Test.

Table (16) This table presents the performance of the robust trading rule.

	TRB		Filter		Channel	
	SPA p-value	SSPA	SPA p-value	SSPA	SPA p-value	SSPA
Jordan	0.602	0	0	96	0	367
Bahrain	0.836	0	0	220	0	597
Cyprus	0	365	0	168	0	184
Dubai	0.154	0	0.104	0	0.110	0
Egypt	0	154	0	145	0	220
Kuwait	0.450	0	0.262	0	0.280	0
Lebanon	0	348	0.004	84	0.080	0
Malta	0	401	0	301	0	608
Morocco	0.980	0	0	71	0	274
Oman	0	1442	0	188	0.120	0
Qatar	0	120	0	78	0.908	0
Saudi Arabia	0.052	0	0.646	0	0	181
Tunisia	0.928	0	0.962	0	0.246	0
Turkey	0	198	0	119	0.548	0

The table shows the SPA p-value for each stock and the number of robust rules identified by SSPA Test.

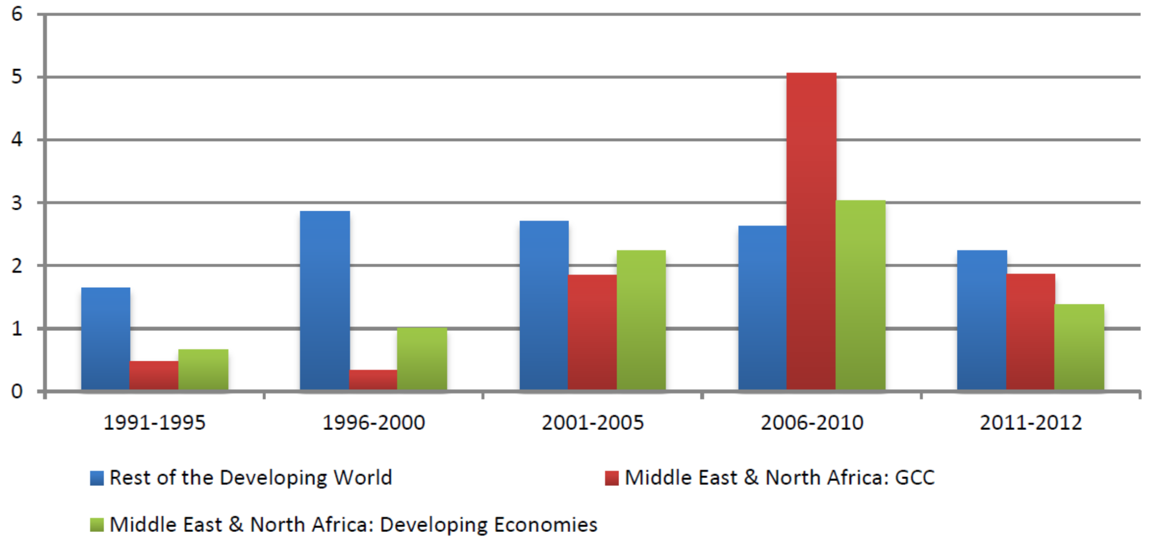
Table (17) This table presents the performance of the robust trading rule.

	BB		MACD	
	SPA p-value	SSPA	SPA p-value	SSPA
Jordan	0.900	9	0.76	0
Bahrain	0	7	0.766	0
Cyprus	0	11	0.81	0
Dubai	0.028	11	0.916	0
Egypt	0	9	0.758	0
Kuwait	0.820	0	0.36	0
Lebanon	0.004	10	1.00	0
Malta	0.80	0	0.704	0
Morocco	0.32	0	0.808	0
Oman	0	17	0.578	0
Qatar	0.25	0	0.704	0
Saudi Arabia	0.74	0	0.710	0
Tunisia	0.58	12	0.852	0
Turkey	0.21	0	0.72	0

The table show the SPA p-value for each stock and the number of robust rules identified by SSPA Test.

Graphs

Figure (1) Net FDI inflows to MENA and other developing countries (% of GDP)



Source: UNCTAD data. GCC=Gulf Cooperation Council.

Figure (2) Inflation

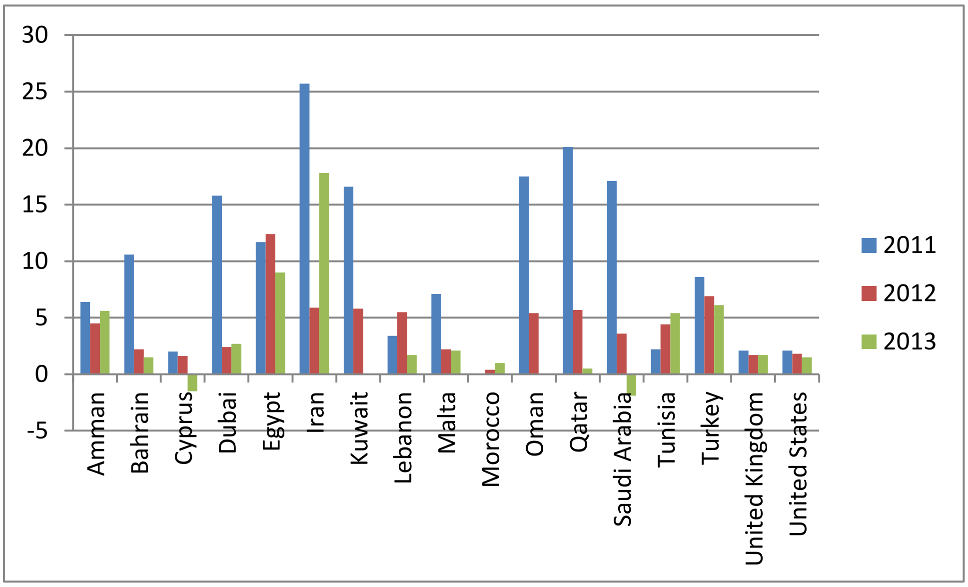
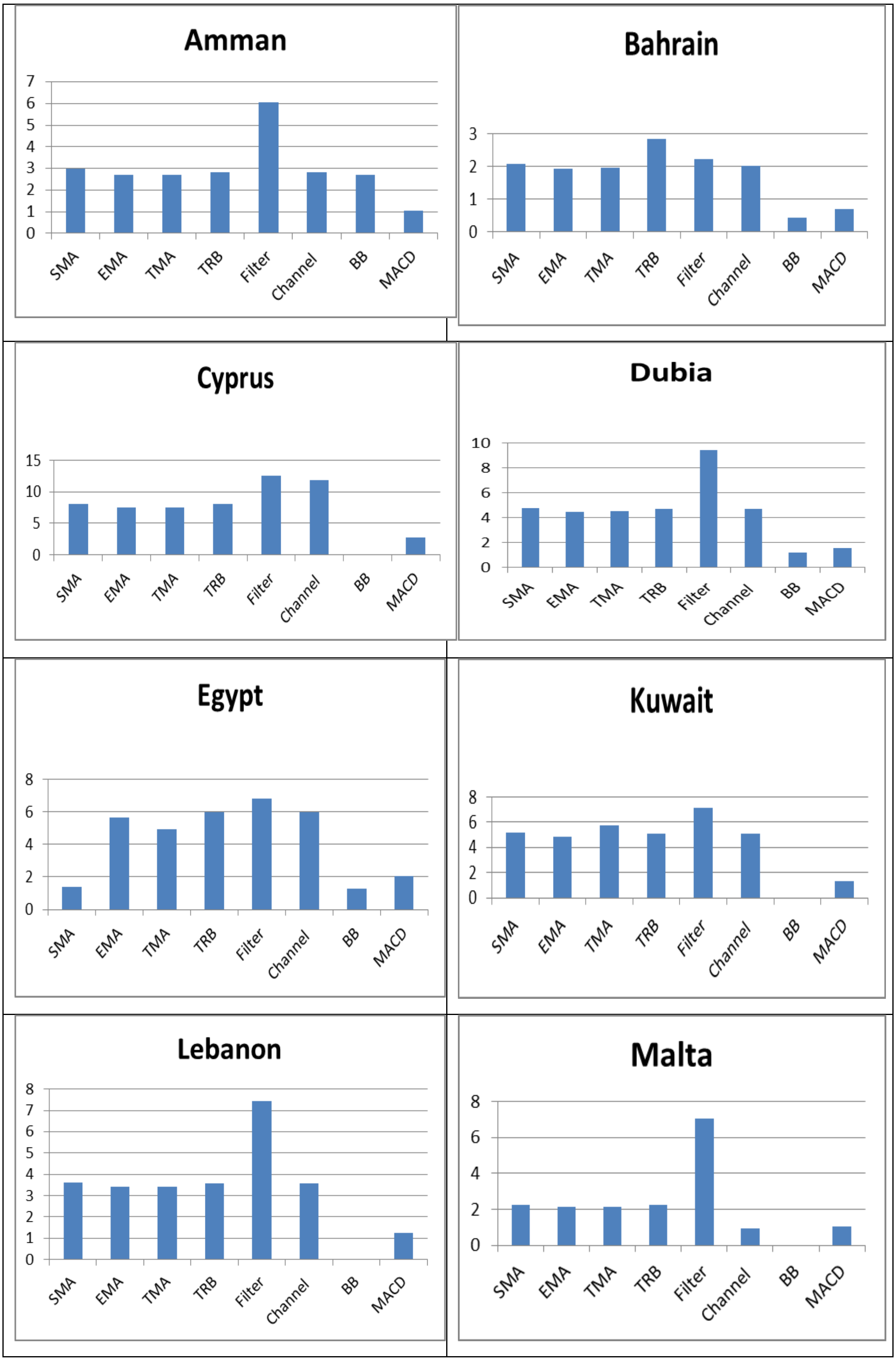
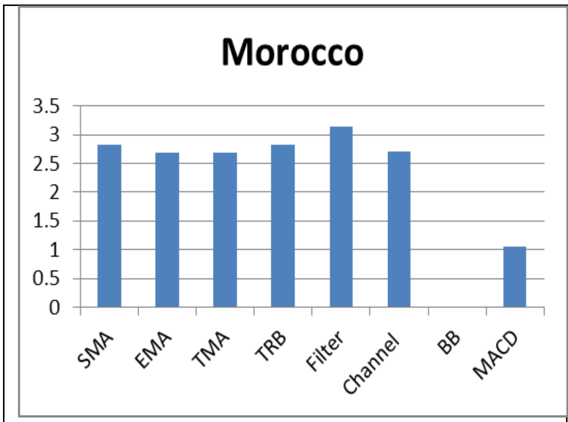


Figure (3) Annual return for best trading rules.

These figures show the average return for each trading rule across all countries.




Morocco
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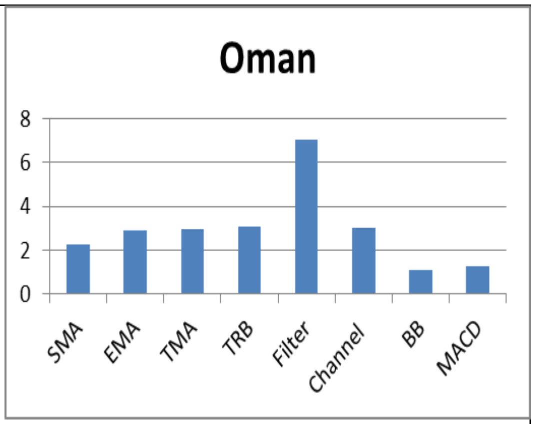
3
2.5
2
1.5
1
0.5
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD


Oman
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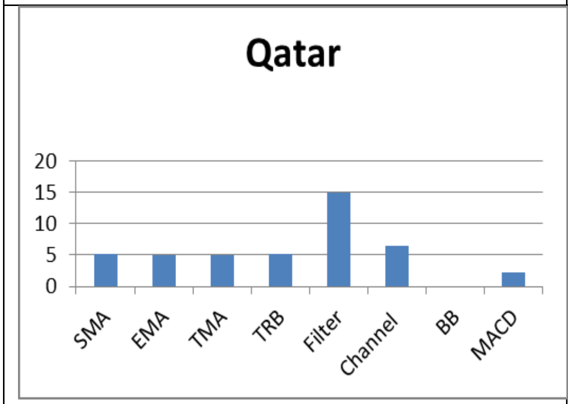
6
4
2
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD


Qatar
20
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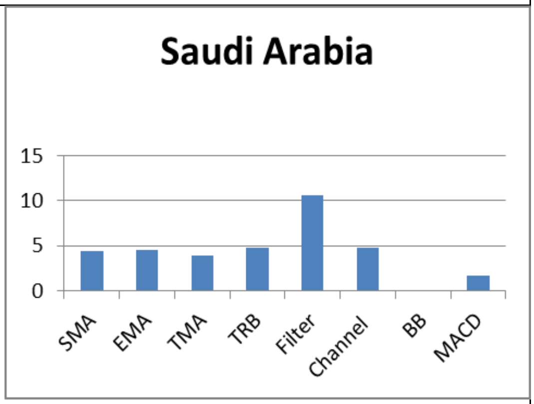
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD


Saudi Arabia
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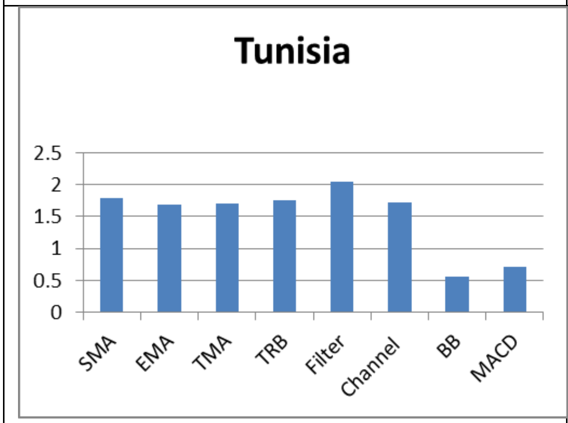
MACD


Tunisia
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2
1.5
1
0.5
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD

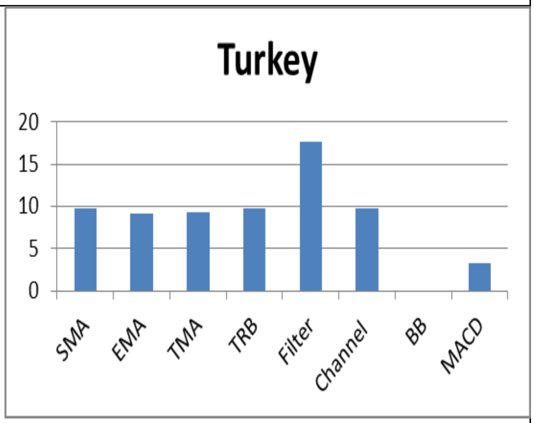

Turkey
20
15
10
5
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD

Figure (4) Annual return for SAM, EMA and TMA trading rules.

This figure presents the annual return for best SAM, EMA and TMA trading rule for each country and compared them with buy-hold strategy.

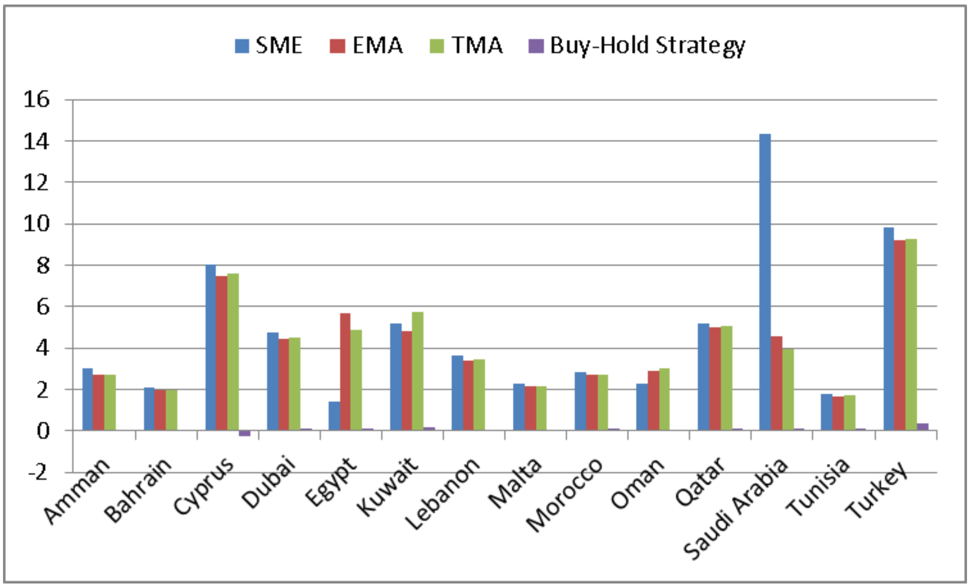


Figure (5) Annual return for TRB, Filter, Channel, MACD and Bollinger Bands trading rule. This figure presents the annual return for best TRB, Filter, MACD, Channel and Bollinger Band trading rule for each country and compared them with buy-hold strategy.

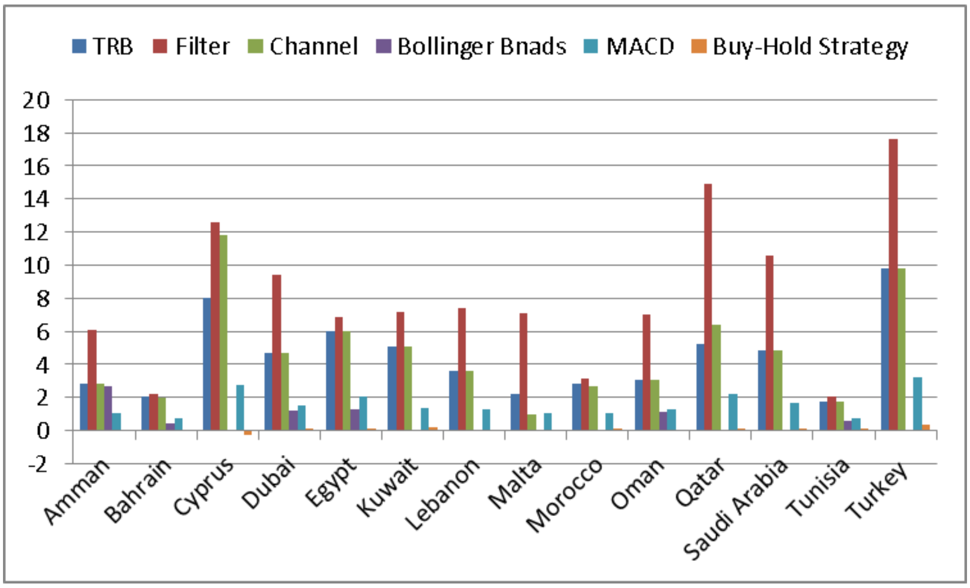


Figure (6) The annual return for all trading rules

This figure presents the annual return for all rules for all countries.

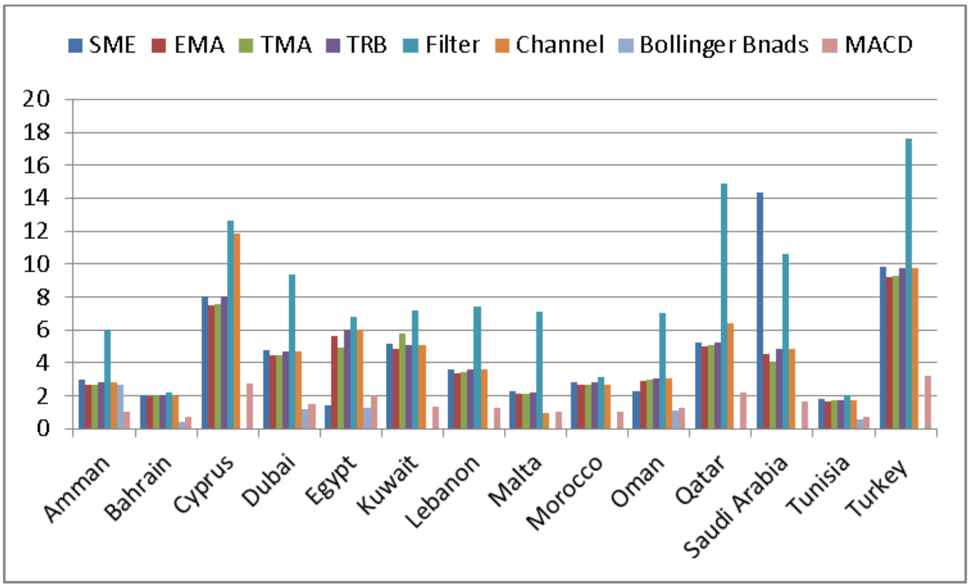
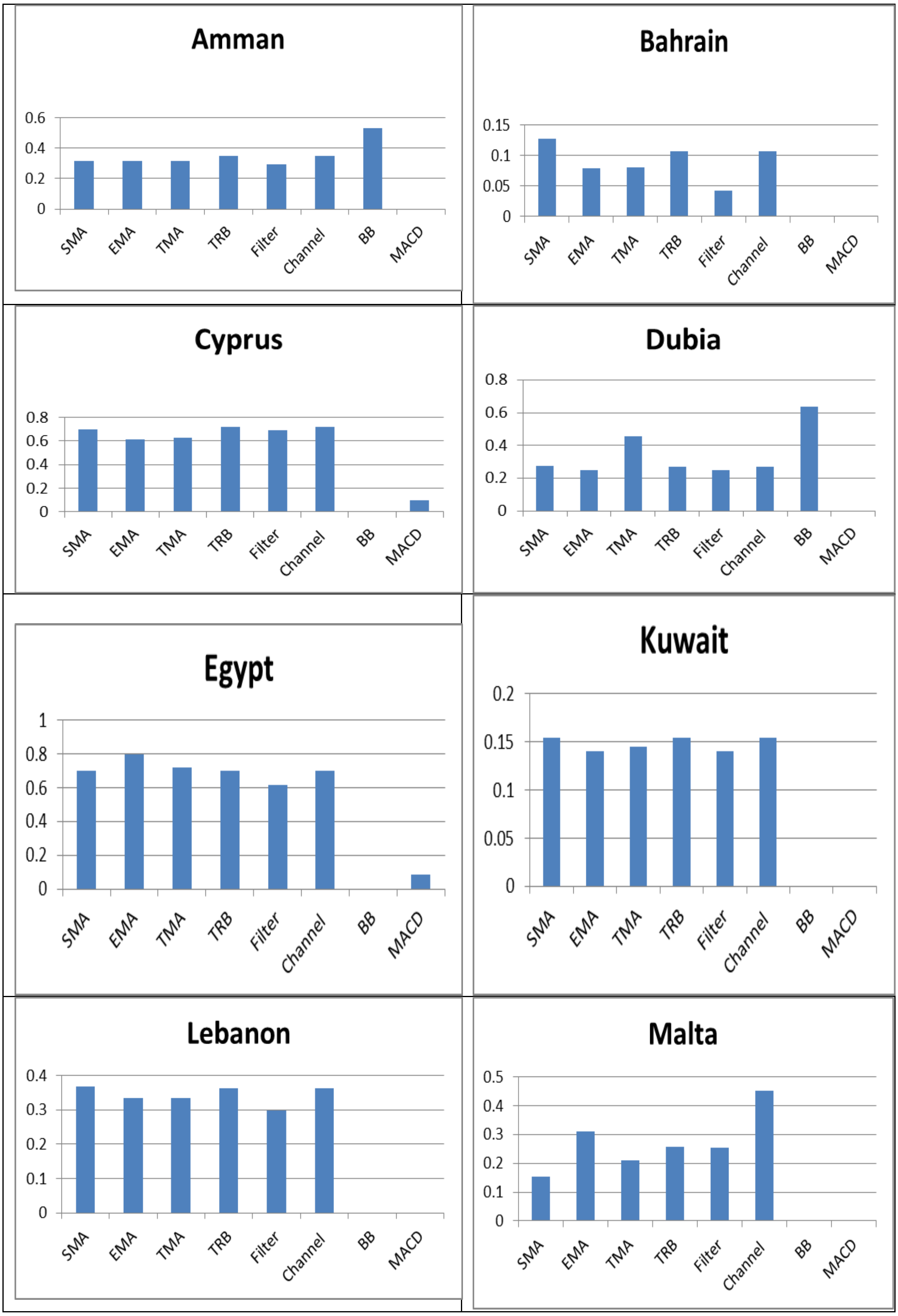


Figure (7) Sharpe ratio values for best trading rules.

These figures show the values of Sharpe ratio for each trading rule across all countries.



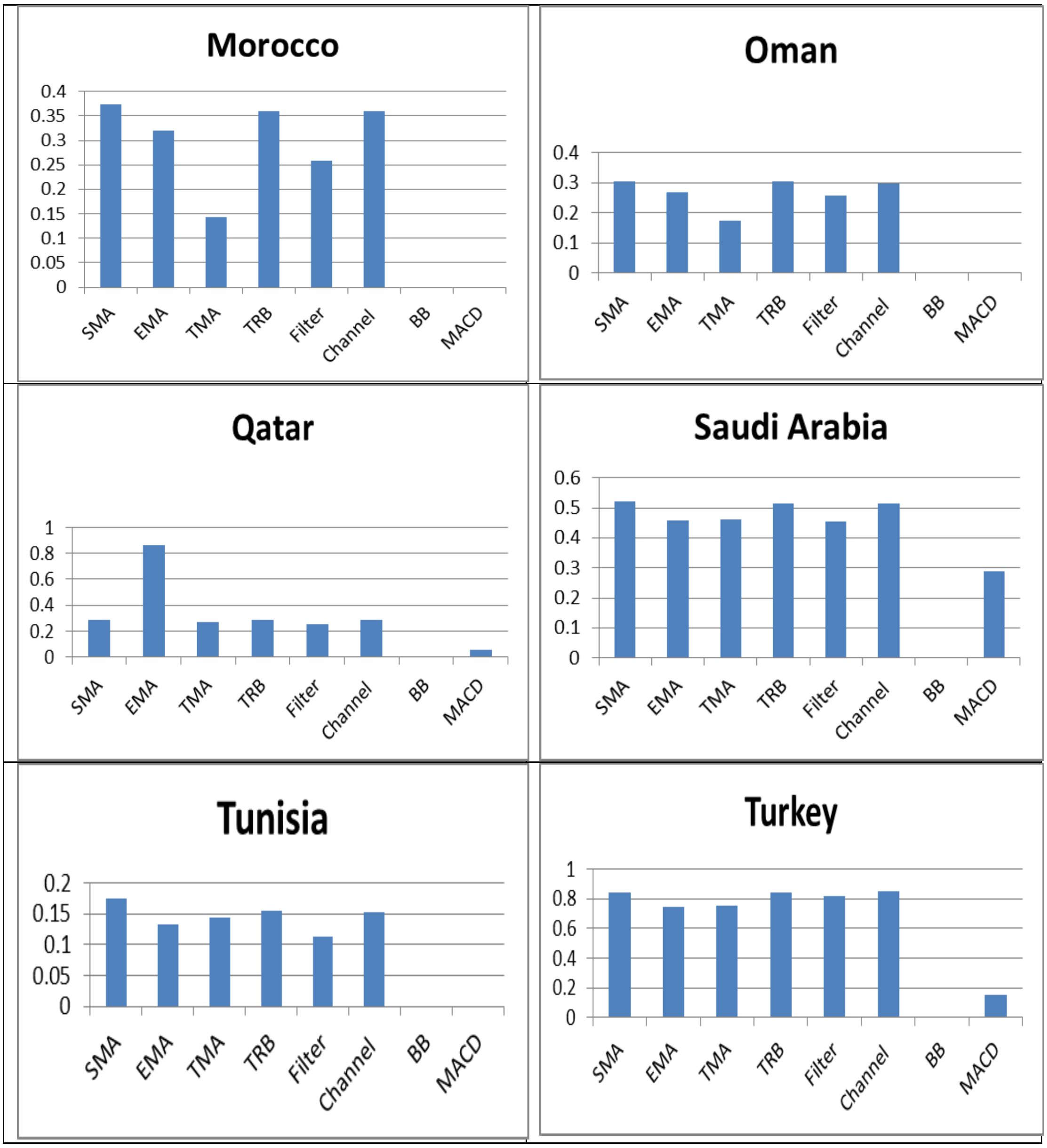

Morocco
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD
Oman
0.4
0.3
0.2
0.1
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD
Qatar
1
0.8
0.6
0.4
0.2
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD
Saudi Arabia
0.6
0.5
0.4
0.3
0.2
0.1
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD
Tunisia
0.2
0.15
0.1
0.05
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD
Turkey
1
0.8
0.6
0.4
0.2
0
SMA
EMA
TMA
TRB
Filter
Channel
BB
MACD

Figure (8) Sharpe ratio for SAM, EMA and TMA trading rules.

This figure presents the Sharpe ratio for best SAM, EMA and TMA trading rule for each country and compared them with buy-hold strategy.

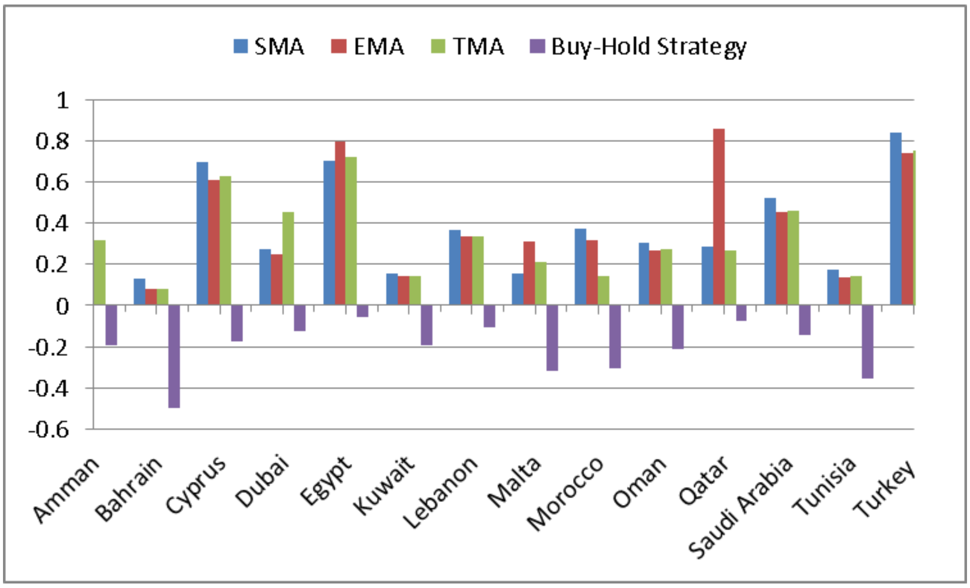


Figure (9). Sharpe ratio for TRB, Filter, Channel, MACD and Bollinger Bands trading rule. This figure presents the annual return for best TRB, Filter, MACD, Channel and Bollinger Band trading rule for each country and compared them with buy-hold strategy.

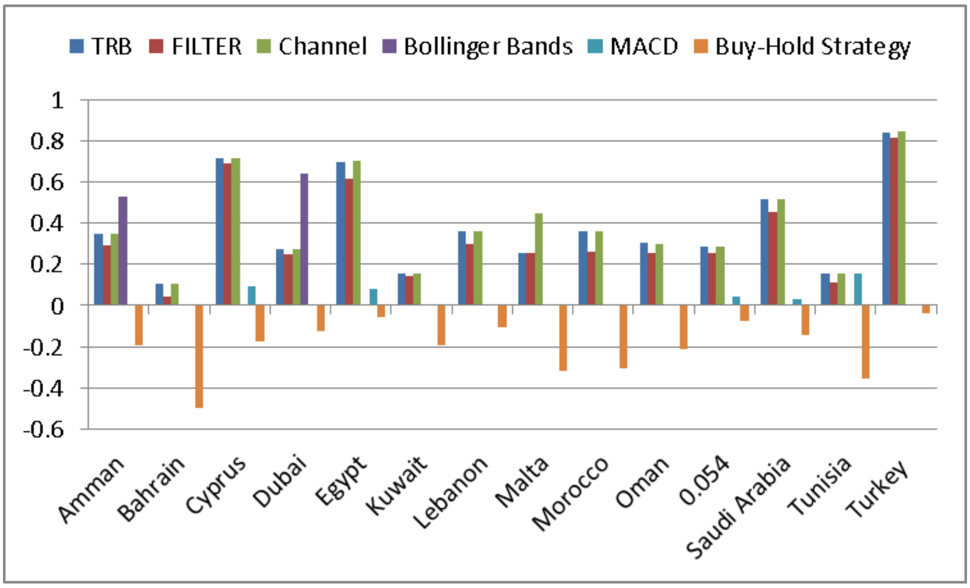


Figure (10) The annual return for all trading rules

This figure presents the annual return for all rules for all countries.

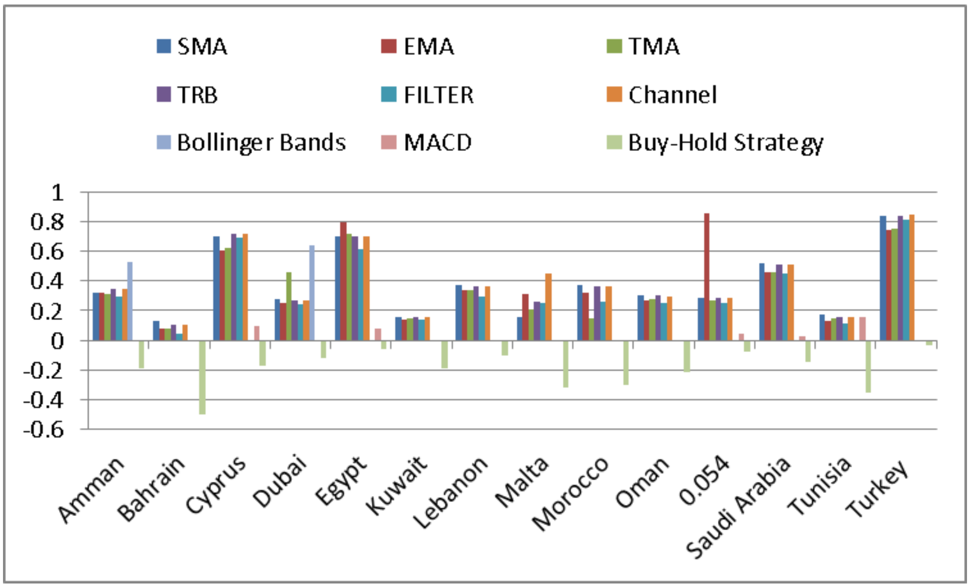


Figure (11). The market capitalazation for each country for 2004 and 2010.

This figure present the market capitalazation for each MENA stock market for 2004 and 2010.

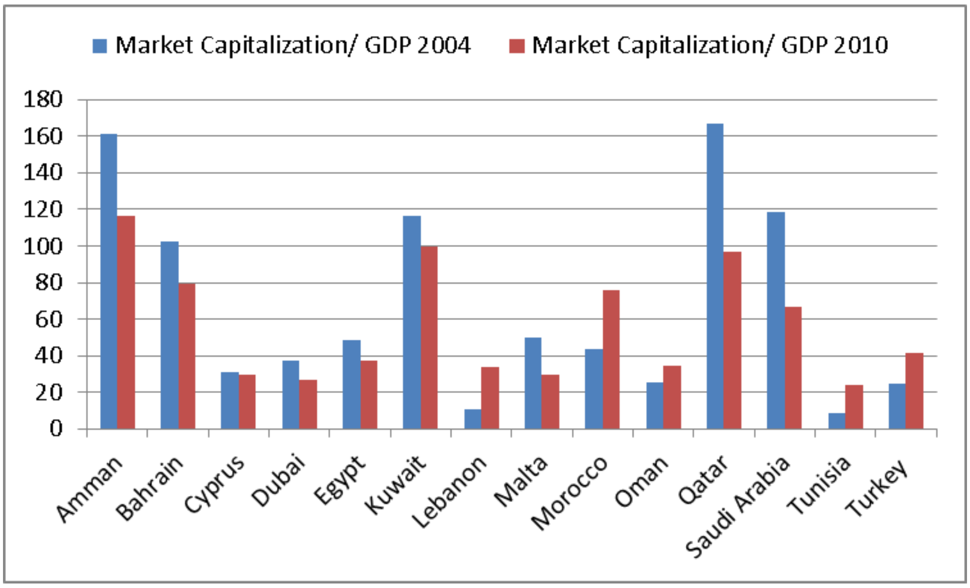
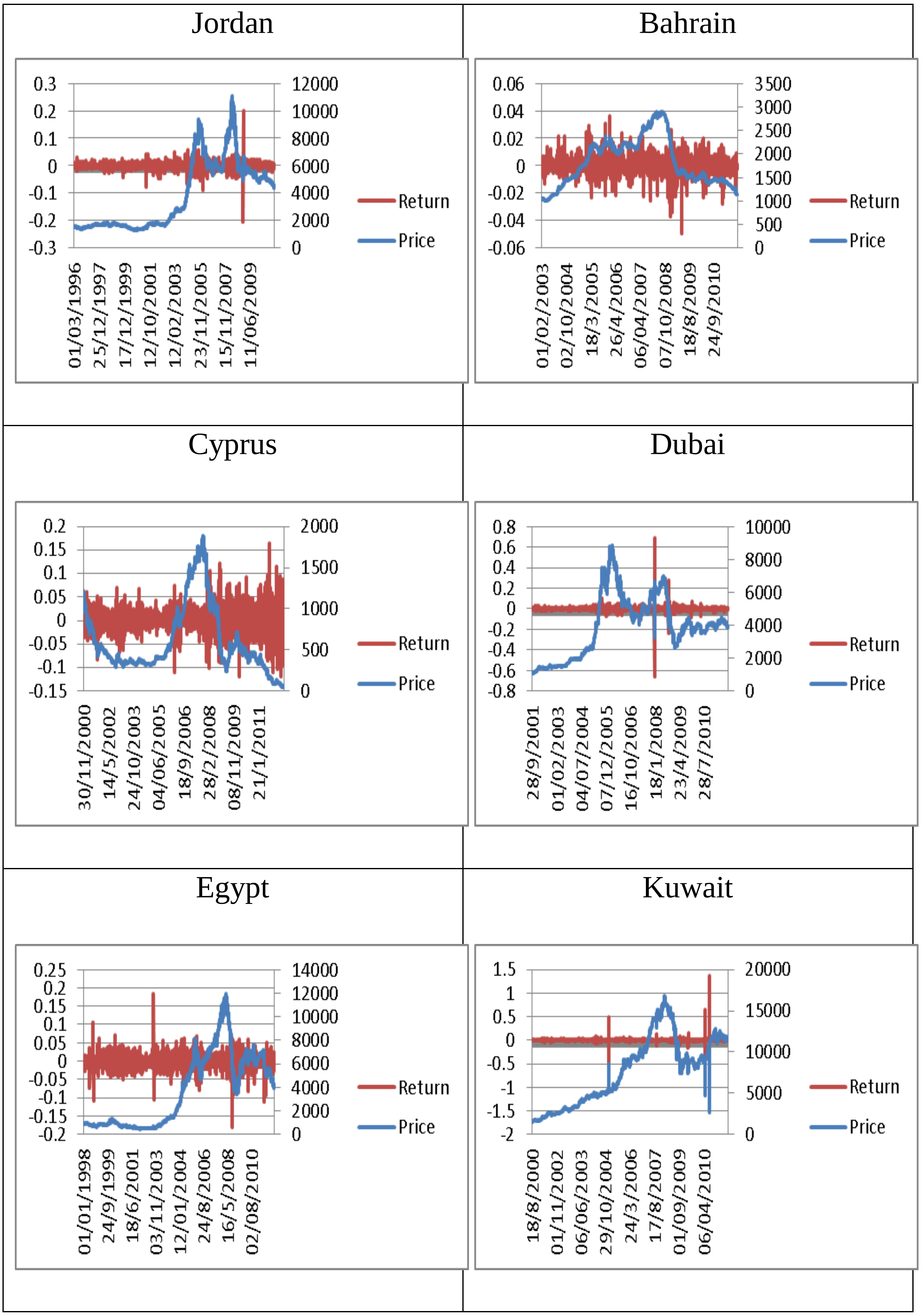
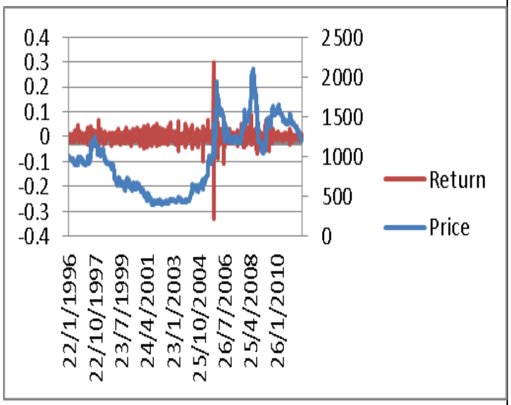


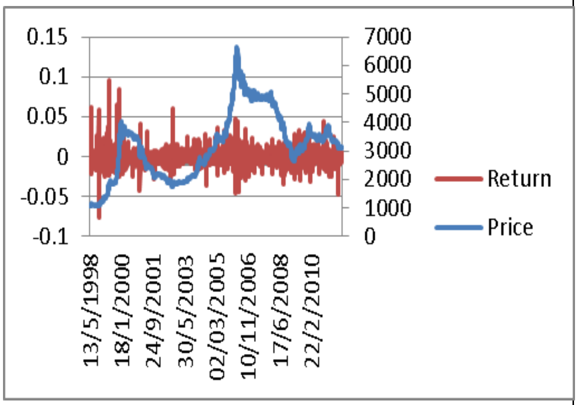
Figure (12). The graphs for price and returns series.



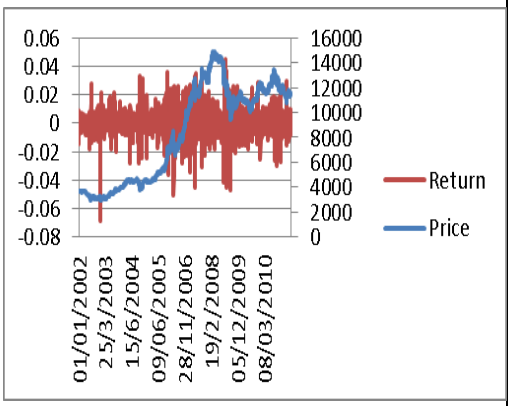
Lebanon



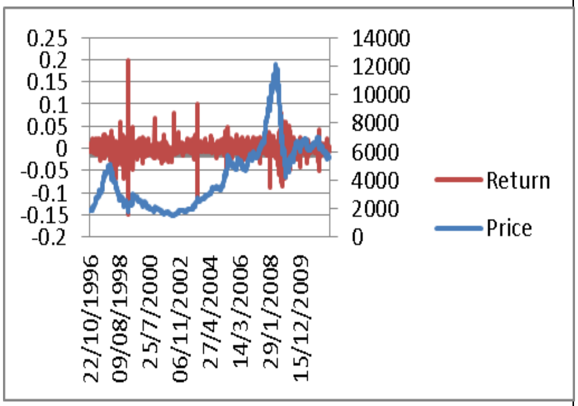
Malta



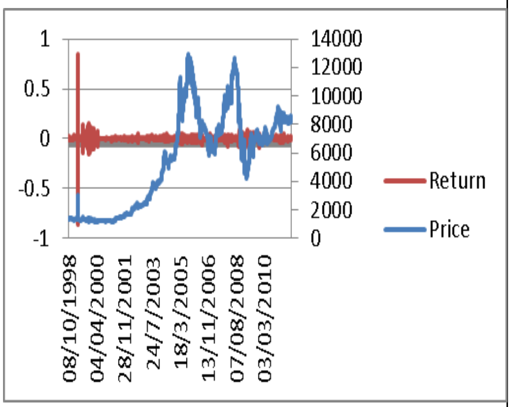
Morocco



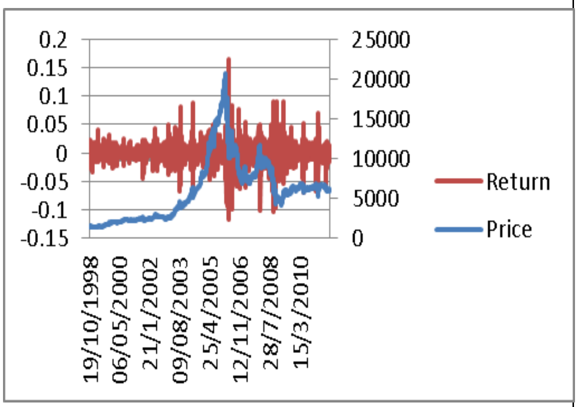
Oman



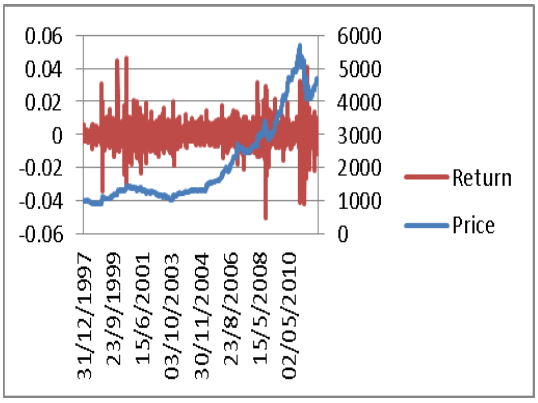
Qatar



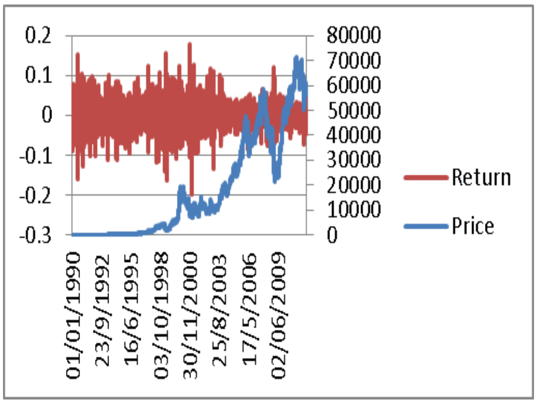
Saudi Arabia



Tunisia



Turkey



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Appendix

	From	To
Jordan stock market	1996	2012
Bahrain stock market	2003	
Kuwait stock market	2000	
Lebanon stock market	1996	
Maltese stock market	1998	
Morocco stock market	2002	
Oman stock market	2002	
Qatar stock market	1998	
Saudi Arabian stock market	1998	
Tunisia stock market	1997	
Istanbul stock market	1991	
United Arab Emirates stock	2001	
Cyprus stock market	2000	
Egypt stock market	1998	