Volatility, Spillover, and Herding of the Middle East North African (MENA) region

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Abstract

The first aim of this thesis is to examine the market behaviour of the Middle East North African (MENA) region. This aim is fulfilled by examining the volatility of eight selected markets representing the MENA region using ARCH/GARCH models. Using the volatility estimated using the GJR-GARCH model, the volatility spillover of the MENA region is investigated using the most commonly used index, the Diebold and Yilmaz (henceforth, DY) (2012) index. The sample period from 2003 to 2018 covers several important events that the region experienced, including the Global Financial Crisis, and the Arab Spring. Using monthly data, the spillover is investigated for the full sample, as well as for pre-, during, and post-crisis periods, in order to quantify the effects of different market conditions. Even though the DY framework is the most commonly used approach, one of the criticisms about this approach is its inability to provide the significance levels of the estimates. The second aim of this thesis is to overcome this criticism by implementing the stationary bootstrap technique in order to provide the significance level of the DY estimates. This is important in interpreting the results and increases the reliability of the drawn conclusions. The results show that there are signs of spillover within the MENA region. However, the total spillover is lower than expected given the strong ties between the eight countries, which leads to further analysis of the divided sample to investigate volatility spillover under different market conditions. The 'pre-crisis' subsample contains fewer significant spillover indexes than the full sample, indicating that the spillover is possibly due to the volatile period included in the full sample. In the 'crisis' subsample the crisis has clearly increased spillover, with a greater number of significant spillover indexes. Meanwhile, in the 'post-crisis' subsample the transmissions remain accentuated by the crises experienced within the MENA region.

In addition to the examination of the transmission across the MENA markets, this thesis also sheds light on investors' behaviour in Egypt. The third aim of this thesis is therefore to examine the existence of herding behaviour in the Egyptian stock market. Egypt witnessed the most significant events during the sample period 2005 to 2019. In consideration of the numerous events that took place, the results show evidence of herding originated in first Egyptian revolution period, persisted in the second Egyptian revolution and economic reform period. Surprisingly, no herding is found during the Global Financial Crisis period. Furthermore, as investors may make similar investment decisions as a response to fundamental market information, it becomes necessary to differentiate between intentional and unintentional herding. Using the Fama-French-Carhart risk factors as a representation of the fundamental factors, the results show that, during periods of stress, such as the Arab Spring, the second Egyptian Revolution and the Economic Reform, there is evidence of unintentional herding. After the first Egyptian revolution the investors became more uncertain and continued to herd intentionally and unintentionally during the second Egyptian revolution and economic reform periods.

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Chapter 1

Introduction

1.1 Introduction

Volatility is an important measure of risk for financial assets. Measuring volatility at the individual asset level, the market level and the global level has important implications for investors and analysts alike. Indeed, the occurrences of financial crises are nowadays more common than before, which points out to the necessity for proper risk management in the financial sector. Consequently, in the last few decades, modelling and predicting stock market volatility has been an active field of research in finance (Hamid, 2015). Thessaloniki (2014) argues that most of the research focuses on modelling and forecasting volatility of financial returns in order to generally understand its meaning and protect investing decisions.

Several studies consider political events and test the changes in market volatility during these periods, and find that political uncertainty is closely linked to market volatility (Chau *et al*., 2014). Therefore, modelling volatility in the Middle East North African (MENA) region is significant given the growing events it is experiencing, including the Arab Spring, the Yemen war and the Syrian conflict.

Given the growing importance of understanding the MENA region, there is a pressing need for a rigorous research to examine the effects of the Arab Spring and other events in order to better understand the relationship between political uncertainty and financial volatility. This analysis would be of interest to financial authorities and policymakers who are trying to evaluate the role of major political events in triggering stock price movement. Investors who wish to invest in the MENA stock markets may also be highly interested in how volatility spreads across markets, since emerging economies presented international investors with a new possibility to diversify their portfolios and offer higher returns (Abou-Zaid, 2011).

Furthermore, analysing the volatility spillover of the MENA region markets provides an insight of market efficiency. High level of spillover would be indicative of a low level of efficiency (Bollerslev and Hodrick, 1992), providing information on the dynamics of the examined market. Reszat (2002) states that when one market experiences an economic or political shock, other markets may be affected to various degrees, depending on how strong transmission links are across these markets. Moreover, volatility spillover indicates the level of integration as it measures the extent to which markets are integrated where high interdependence between markets leads to high cross market spillover (Engle and Susmel, 1993).

Examining volatility spillover is considered one of the topical areas in finance, as there are many researchers who focus on testing volatility spillover across different markets and in different market conditions, including Ng (2000), Baele (2005), and Du *et al.* (2011). Given the importance of examining volatility, several methods to analyse spillover have been proposed. Baele (2005) uses the regime-switching volatility spillover model; Hafner and Herwartz (2006) suggest testing for causality in variance based on GARCH models; and Diebold and Yilmaz (2009, 2012) propose the volatility spillover index (the DY index). The DY index is the most widely used by recent research, since it allows to aggregate spillover effects across countries, which distils valuable information into a single measure (Öztürk and Volkan, 2015).

Despite the widespread use of the DY index, one shortcoming is that it does not provide the significance of its output statistics which makes it hard to interpret. The standard errors of the index as well as its sampling distribution is needed in order to determine the significance of the volatility spillover index estimates and to make statistical inference (Choi and Shin, 2018). Therefore, in order to test the significance of these outcomes and to determine the estimates' significance, and given that there are no available statistical methods for the standard errors of the volatility spillover indexes, the bootstrapping method is used in this thesis.

The existence of volatility spillover within the region calls our attention to the probability that investors herd within the market. The link between investor behaviour and market volatility was first mentioned by Friedman (1953), who argue that irrational investors destabilize prices by buying when prices are high and selling when they are low, while rational investors tend to move prices towards their fundamentals, by buying low and selling high. Froot *et al*. (1992) find that investors tend to imitate one another, and that this drives volatility. Later on, Avramov *et al*. (2005) argue that herding has a strong impact on daily volatility.

Furthermore, Gabbori *et al.* (2020) argue that investors most probably herd when they are under stress, which, in turn, leads several researchers to investigate market behaviour during extreme market conditions and crises. In this regard, the scope of the study is narrowed to testing the herding behaviour in the Egyptian stock market. Egypt is considered to be one of the largest developing markets in the MENA region, and one that has experienced the most adverse events in the region (the Global Financial Crisis, the Egyptian Revolution, and the floatation of the Egyptian currency).

Mertzanis and Allam (2018) argue that herding behaviour is found when investors do not follow their own rational thinking and follow other investors' trading behaviour. A distinguishing feature of this study compared to previous studies (Balcilar *et al*., 2014; Rahman *et al.,* 2015; Balcilar *et al.,* 2017) is that it differentiates between intentional herding that results from investors imitating each other, having similar behaviour, and making similar decisions, and unintentional herding that results from investors not imitating others, rather as a result of their own reactions and decisions.

Thus, this thesis fills several gaps. First, although there are several papers that test volatility in the MENA region, this thesis extends previous results by modelling volatility in the MENA region in a wider span of time to be able to test how several crises and events have affected the volatility in these emerging markets. Second, this thesis also extends the results of previous research by testing volatility spillover in the MENA region over different market conditions. We use a rich sample period that captures several up and down periods. Third, contributing to previous research, this thesis tests the significance of the various spillover indices by using a bootstrapping approach which is important to determine the significance of the index estimates and to make statistical inference. Fourth, this thesis investigates the presence of herding behaviour in the Egyptian stock market by separating between intentional and unintentional herding, and testing the presence of herding behaviour under various market conditions. To our knowledge this has not been considered before.

1.2 Research Background

The volatility of stock market returns is of concern to investors who wish to understand the market they want to invest in, and involve volatility in their decisions making. Analysts, brokers and dealers need to understand and analyse the fluctuations in the markets, especially in crisis times. Moreover, policy makers also rely on market estimates of volatility as a barometer of the vulnerability of financial markets (Olowe, 2009). Typically, modelling volatility is used to forecast the absolute magnitude of returns. Such forecasts are used in risk management, derivative pricing and hedging, market making, market timing, portfolio selection and many other financial activities. For example, a portfolio manager wants to sell a stock before it becomes too volatile, or a risk manager wants to know the likelihood that his portfolio's value might decline in the future (Engle and Patton, 2001).

Modelling volatility has become an important activity, especially given the rise of recent world events which affected stock prices and has intrigued financial economists. In times of political and civil unrests, it is common for stock markets to experience increased levels of volatility as the occurrences of major political events signal potential shift in policy which may cause market wide valuation changes (Karolyi, 2006).

With the rise of the Global Financial Crisis in 2008, the consequences of the crisis not only influenced the major capital markets but also the emerging markets. Among the emerging markets, the MENA region also experienced declines in their stock markets, slowdown in foreign capital, and decrease in exports (Öztürk and Volkan, 2015). Another reason for examining the region is that its growth and development indicate one of the major deviation that the current economics literature seeks to resolve, which is how to reconcile the existence of massive natural resources with high unemployment, low growth and the general underdevelopment of the region (Yusoff and Guima, 2015).

Furthermore, the MENA region has issues arising from internal economic policies, unstable investment climate, less developed financial institutions, lack of integration in the world economy, and low human capital development which made the future of the region debatable (Dutt *et al.*, 2008). However, the rest of the world has grown its interest in the MENA region expecting high stock returns, since the newly launched markets in the MENA region led to increased global integration with 55% of foreign direct investment through merger and acquisition during the period of 1991 to 2000 (Ahmed, 2010). Furthermore, the Arab world is an interesting region to study, especially after the most recent event that took place in this region, namely the Arab Spring, which is generally acknowledged to be a turning point in the history of the region.

Although several papers have tested volatility in the MENA region, this thesis covers a longer time span. The sample period goes from 2003 to 2018, which covers several events that the region experienced, such as the Global Financial Crisis and the Arab Spring. The richness of our data allows us to study different market behaviours under different market conditions by dividing the sample period in order to see the pre, during, and post effect of the various events covered by this study.

The existing research has focused on studying volatility dynamics within markets, as well as volatility spillover in different markets over time. The attention drawn to volatility spillover effects arise from the globalization of the world economy and the increased incidence of crises that span regions and continents. As Engle and Susmel (1993) argue, volatility spillover is an indication of the level of market integration. Moreover, volatility spillover has direct implications for financial hedging, portfolio management, and asset allocation. Examining the volatility spillover of the MENA region provides information on the dynamics of its markets, especially for international investors and policy makers (Öztürk and Volkan, 2015).

From the related literature, few studies have focused on investigating the volatility spillover in emerging markets especially the MENA region. Moreover, this is the first study that sheds light on a sample that includes all recent important events within the MENA region.

Volatility spillover can be identified by various techniques. The most commonly used method is the Diebold and Yilmaz (2012), which is adopted in this thesis. The Diebold and Yilmaz (henceforth DY) approach focuses on variance decompositions that are derived from vector autoregressive models which allows us to disaggregate spillover effects across countries. However, despite the widespread use of the DY index, it does not provide the significance of its estimates which makes the spillover percentages hard to interpret. There are no statistical methods for the standard errors of the volatility spillover indexes. To overcome this limitation, this thesis uses bootstrapping techniques to test for the significance of spillover indices.

One of the main factors that affects investors' decision in stock markets is the condition of the market. In stable periods, investors can think rationally when analysing the market, and have enough time to gather adequate information and therefore make informed decisions. Herding behaviour refers to investors' tendency to ignore their information and to follow other investors (the herd). In markets where herding behaviour is found, prices deviate from their equilibrium and market participants' trading activity drives market mispricing. This departure from the fair values leads to increased volatility and pushes risk averse investors to refrain from entering the market (Gabbori *et al*., 2020).

Furthermore, Bikhchandani and Sharma (2000) stress the distinction between unintentional herding and intentional herding behaviour. Unintentional herding is when investors face a similar fundamental-driven information set and thus base their reactions and decisions on public information and similar problems. Intentional herding is when investors intentionally copy the behaviour of others, which is a result of investors imitating others' actions.

Specifically, herding behaviour may be particularly damaging in developing markets. Investor behaviour has the potential to destabilize the financial system, leading some investors to manipulate it. This reflects badly on overall market functioning and integrity (Gabbori *et al*., 2020). However, due to limited data availability, this thesis focuses on testing the presence of herding behaviour in one of the emerging markets of the MENA region, namely the Egyptian stock market. As mentioned earlier, Egypt is a particularly interesting case study.

1.3 Research Aims and Objectives

This thesis is divided into three parts. The first part is devoted to examining spillover in the region using the standard approach of DY. The second part uses bootstrapping methods to find the significance of the spillover results, and to examine if the conclusions drawn from the standard results are impacted. The third part of this thesis focuses on testing the presence of herding behaviour in the Egyptian stock market by testing both intentional and unintentional herding. Given that, the overall aim of this thesis is to:

"Examine volatility and volatility spillover in the MENA region, and investigate the presence of herding behaviour in the Egyptian stock market"

Modelling and forecasting the volatility of stock market returns have become a fertile field for empirical researchers focusing on financial markets. Volatility is an important concept in many economic and financial applications, such as asset pricing, risk management and portfolio allocation. This thesis attempts to exploit different statistical and econometric volatility models in the context of the eight selected MENA region countries. In cross-country studies, Kim and Rogers (1995), Koutmos and Booth (1995), Wei *et al.* (1995), and Chiang and Jiang (1998) find that national stock returns are significantly correlated, and that international stock markets have grown more inter-dependent through time. This is important as it provides more accurate information to aid global portfolio managers in achieving an efficient mean-variance frontier, and to supply policy-makers with a more precise basis on which to formulate appropriate risk management strategies (Chiang and Doong, 2001).

In addition to modelling volatility, the volatility spillover of the MENA countries is investigated. Volatility spillover is an important aspect of volatility in all financial markets, since it explains the volatility transmission process from one financial market to another (Chen *et al*., 2001). Finally, this thesis narrows its scope and investigates the presence of herding behaviour in the Egyptian stock market. The selection of the Egyptian market is due to it being one of the largest developing countries in the region, along with being the market which experienced the most events during the sample period.

This thesis has the following objectives:

1. Provide a comprehensive literature review concerning the different models of volatility in the MENA region.
2. Investigate the volatility spillover among the MENA region markets and highlight the most important spillover cases among the markets.
3. Test spillover over three subsamples that reflect different market conditions to analyse how spillover behaves in different circumstances.
4. Re-evaluate the results of the DY framework and assess whether their conclusions differ when the statistical significance of the estimates is taken into consideration.
5. Reconsider the results of the volatility spillover of the MENA region, and analyse whether the interpretations drawn differ when the statistical significance of the estimated spillover indexes is taken into consideration.
6. Test the presence of herding behaviour in the Egyptian stock market.
7. Test whether herding in Egypt is due to fundamental risk factors or due to non-fundamental factors.
8. Test whether intentional or unintentional herding differ across different market conditions.

After highlighting the main objectives of this thesis, the next section highlights the main research questions that this thesis aims to address and the contribution that each adds to the literature.

1.4 Research Questions and Contribution to Knowledge

The recent world events have had great effects on stock prices and the stability of stock markets (Ghanem and Rosvall, 2015). Numerous studies have focused on specific political events and have investigated the changes in market volatility during these periods and found that political uncertainty is linked to market volatility (Karolyi, 2006; Mei and Guo, 2004). Yilmaz (1999) confirms that volatility is a significant parameter to be studied since understanding the sources and dynamics of volatility in a stock market helps determine the cost of capital and evaluate asset allocation decisions.

Despite the important amount of research on modelling stock market volatility and the contradicting results about whether volatility can be an indication of market performance and what the causes of volatility are, it can be argued that these results depend on the country's economic conditions and more importantly on its political stability (Neaime, 2012). However, little research has been conducted on the impact of political uncertainty arising from civil uprisings, such as the Arab spring, on the stability and efficiency of financial markets.

Since the 1980s, the MENA region has followed a series of financial liberalization reforms that led to reducing restrictions on foreign portfolios investments to gradually open up their financial markets to the world. These financial reforms aimed to improve the efficiency and the development of their financial markets and decision making. However, financial liberalization would also increase the financial connectedness of the MENA markets with international risk factors, thus making these markets vulnerable to potential wild swings and risk contagions. Tran (2017) argues that the degree of equity market openness is the key factor that leads to the formation of speculative bubbles in the stock market. Furthermore, O'Sullivan *et al.* (2012) argue that despite the growing importance of MENA countries in the world economy in terms of both the volume and the value of trade, there is a lack of research on this region.

In this context, Ben Naceur *et al.* (2007) state that it is not clear whether the MENA markets correspond similarly to economic and political shocks as their counterparts in areas outside the MENA region. In this regard, there is high need to examine volatility in the MENA region since it is still witnessing wars, political turmoil and economic instability. However, this lack of academic research can be attributed to the fact that the MENA region is not considered as a major economic power to attract the focus of researchers. Therefore, studying the MENA region volatility contributes to the understanding of the dynamics of the region markets. On the other hand, even though the MENA region markets are considered less developed than the Asian or Latin American emerging markets (Henry and Springborg, 2004), the MENA markets can offer portfolio and fund managers diversification benefits (Neaime, 2012).

Although there are different models that test volatility, the ARCH/GARCH models are considered the most commonly used approaches in identifying volatility. The selection of the appropriate model either symmetric or asymmetric model depends on which model best fits the sample. According to Oskooe and Shamsavari (2011), one of the weaknesses of the GARCH model is that it assumes symmetric responses to both positive and negative shocks as the conditional variance in the basic model is a function of squared lagged residuals regardless of the signs. In order to capture these asymmetric effects in the volatility of stock returns, extensions of GARCH models can be employed such as EGARCH and GJR-GARCH models.

Although many empirical studies test and model volatility of stock return using ARCH-GARCH model specifications and their many extensions, most of these studies focus on developed markets, whereas scant empirical studies for MENA region stock markets are available (Ahmed and Suliman, 2011). According to Abou-Zaid (2011), studying volatilities in MENA markets is very important for both foreign investors looking for high returns and portfolio diversification, and domestic businesses which have become dependent on the stock market to finance their projects. Moreover, O'Sullivan (2012) points out that very few studies explore the effects of the Arab Spring whether economically or politically. This, in turn, constitutes the first research question of this thesis.

Q1: Does the symmetric or the asymmetric modelling of volatility capture the volatility in the MENA region markets? Which GARCH model provides the best way to capture volatility in the region?

Thus, enlightened by the above discussion, to answer the first empirical question this thesis employs both symmetric and asymmetric models to model volatility for the MENA markets. This research question is considered a contribution since the sample period covers several events that took place within the region such as the Global Financial Crisis and the Arab Spring, which are not previously investigated in literature.

In addition, estimating volatility for the MENA region using the symmetric and asymmetric models, and finding the model that best fits the sample contributes to knowledge for the following reasons. First, modelling the volatility is significant since it contributes to understanding the market development and growth, providing a measure of the risk of the asset, and protecting investing decisions in general. Practitioners seek to analyse volatility to quantify the risk associated with several financial assets (Merton, 1980) and evaluate different financial products along with the development of different hedging techniques (Ng, 2000). Second, estimating volatility for the MENA region is of direct interest to investors who wish to invest in the region. Third, examining the region for the given sample period that includes the Arab Spring provides a better understanding of the relationship between political uncertainty and financial volatility. Fourth, the sample period being examined includes several events representing different market conditions, which provides an understanding of the different views of volatility under different market conditions.

Given the increased volatility in the financial market, researchers argue that volatility may not be a consequence of internal market conditions, rather it could be an impact from other markets (Kristinsson, 2014). According to Baele (2005), the volatility of the returns in domestic financial markets can be explained by events that occurs outside the actual country. In addition, globalization makes financial markets more integrated, which facilitates volatility in a given market to spill over to other financial markets. Therefore, sufficient effort has been dedicated to the study of volatility dynamics within markets, as well as, volatility spillover, for example, Ng (2000), Baele (2005), and Du *et al.* (2011).

According to Engle and Susmel (1993), the volatility spillover is an indication of the level of market integration. Volatility spillover plays an important role in investigating the transmission mechanism of information among financial markets (Shafqat, 2017). In addition, investigating the volatility spillover helps policymakers understand the transmission process of volatility across domestic and international financial markets (Becketti and Sellon, 1989).

Although there are many studies that focus on volatility spillover, most of these studies focus on developed markets. For example, Diebold and Yilmaz (2012) examine the spillover between United States stock, bond, foreign exchange, and commodity markets and Barunik *et al.* (2016) examine the volatility spillover of petroleum commodities: crude oil, gasoline, and heating oil. Later on, researchers' focus has shifted towards emerging markets due to globalization and the increased interest of investors on these markets given the high rates of returns that these markets promise (Beirne *et al.*, 2010).

This study examines the MENA region, and investigate the spillover within the region. Spillover is expected to be found within the region for several reasons. First, although there are notable differences among the countries in the MENA region in terms of economic size, population, standards of living, natural resource endowments, external indebtedness, and trade and financial links with the rest of the world (El-Erian *et al.*, 1996), the countries in the region also share similarities in that they are natural resource-abundant economies and their top export items are primary products. Second, the strong linkages between the MENA countries can be related to sharing similar conditions like climate, location, and natural resources, making spillover effects more likely to occur among them (Baysoy and Altug, 2021). Third, according to Aziz (2018) spillover effects may arise from the existence of foreign direct investment, which typically flows to countries that promote property rights and the rule of law.

Yu and Hassan (2008) examine the volatility spillover between the MENA and world stock markets using a multivariate AR-GARCH model and find large and predominantly positive volatility spillover between them. Awartani *et al.* (2013) examine the return volatility spillover from the U.S. and the Saudi market to equity markets in the GCC countries, the results show a clear jump in net transmissions from both markets during the Financial Crisis in 2008. Later on, Maghyereh *et al.* (2015) study the spillover effects between the MENA markets and the U.S market and the results suggest that the pre-crisis relation with the U.S. was weak and negligible, and then the relation witnessed a significant increase after the crisis.

Although recently some studies have started to focus on the MENA region, this thesis aims to extend their work and contribute to knowledge in a number of ways. First, this study examines the volatility spillover from/to the region's markets unlike some of the previous studies that test the spillover from/to the rest of the world. In light of the above mentioned studies, the effect of the political events might affect volatility spillover, and given the major events that took place in the MENA region, it is interesting to investigate the effect of these events on the region's markets. Second, this study aims to examine the political and economic events such as the Arab Spring effect on the region. To our knowledge, this has not yet received enough attention in the literature. Third, this study covers a wide sample size from January 2003 to December 2018 to include different market conditions in order to examine the volatility spillover under different phases.

Furthermore, by the end of 2010, the MENA region was considered to be the third largest emerging market with respect to the level of local and foreign investments (Neaime, 2012). This, in turn, resulted in significant changes in the dynamics of volatility and correlation of equity returns. In this regard, investigating the volatility spillover of the MENA region has implications on the integration of the markets. For instance, are the markets within MENA getting more or less integrated? Which countries might be more, and which might be less, integrated than others? In addition, few studies have focused on examining the effect of the Arab Spring even though it is considered to be a turning point for some countries. Although not all countries within the region have experienced the Arab Spring, its impact is unpredictable and has not yet been examined.

Thus, given the increased support of research for investigating volatility spillover, the first empirical question contribution helps estimate volatility which is then used in investigating the volatility spillover within the region using Diebold and Yilmaz (2009, 2012) approach, the most commonly used spillover framework in recent research. The investigation of the stock market volatility spillover is of interest to investors due to their potential international portfolio diversification benefits (Dovhunova, 2014). This leads to the second empirical question.

Q2: Does volatility spillover exist within the MENA region? Are these markets getting more or less integrated? Have the recent events changed the connectedness across the MENA?

After highlighting the importance of investigating stock market volatility spillover of the MENA region markets, the next step is to implement the most common and popular index for volatility spillover, Diebold and Yilmaz (2012). The DY (2009, 2012) index is a unified framework for conceptualizing and empirically measuring connectedness at various levels.

The volatility used in investigating the volatility spillover is estimated from the first empirical question of modelling volatility. The DY framework provides total spillover which reflects the contribution of spillover of volatility shocks across asset classes to the total forecast error variance. In addition, the framework provides directional volatility spillover received by one of the markets from all other markets. Thus, given the common use of the DY framework, the second set of empirical questions that this thesis aims to answer is whether the MENA markets are more or less integrated, how markets within the region are impacted by the Arab Spring, and how this event change the connectedness in the region?

According to Luciani (2017), in theory, the Arab region should be expected to provide a model of successful regional economic integration since the resources are so unevenly distributed where individual countries within the region face obvious difficulties due to the lack of one or other ingredient in the development recipe, and are thus clearly complementary with each other. Furthermore, with the rise of political events like the Arab Spring, the consequences on stock markets especially on regional stock markets are questionable as the signal they send has unclear implications. Although these revolutions aim to promote democracy and improve economic capabilities, they might influence the behaviour of investors due to the loss of confidence in the local and regional stock markets (Alsharairi and Abubaker, 2016). Uncovering the linkages among the MENA markets is significant for regulators and policymakers seeking the stability of the financial markets through timely responses to the increasing financial interactions across borders and to shocks. With the clarification of the markets dependence especially under different conditions the appropriate policies can be established in order to have optimal asset allocation and risk management for the region (Mensi *et al.* 2018).

Despite its wide use, the Diebold and Yilmaz (2012) framework, is criticized for its inability to carry out statistical inference on the index outcome. Therefore, the standard errors as well as the sampling distribution of the estimated spillover index is required in order to determine the significance of the index estimates and make statistical inference. However, since the volatility spillover index is nonlinear, there is no available statistical properties for such index.

The third contribution of this thesis is to provide a feasible solution to this problem, implementing bootstrapping as a solution for the absence of an analytical statistical solution. Bootstrapping is a commonly used approach in literature for estimating standard errors and confidence intervals of complex statistics (Choi and Shin, 2018). Generally, bootstrapping is a method for estimating the distribution of an estimator or t-statistic by resampling the data or a model estimated from the data (Horowitz, 2001). It simply determines the accuracy to an estimated sample by relying on random sampling with replacement (Chong and Choo, 2011). By finding the statistical significance of the volatility spillover estimates and assessing the precision of these estimates, the interpretations built from these estimates may change. Moreover, applying bootstrapping is important since the conclusions drawn from the outcome of the volatility spillover estimates are used in a wide variety of decisions such as for academics and practitioners understanding whether financial markets become more independent during financial crises (Kenourgios and Padhi, 2012) and generally in decision making. This leads to the third empirical question.

Q3: Does using bootstrapping to estimate the statistical significance of the Diebold and Yilmaz framework change previously drawn interpretations?

Following Choi and Shin (2018) we apply bootstrapping technique to derive confidence intervals for the volatility spillover index estimates. Given that there are several methods of bootstrapping, the most appropriate method is chosen according to the sample being examined. In this thesis the stationary bootstrapping is implemented as this thesis uses time series data, and stationary bootstrapping is suitable for almost any sort of dynamic models and handles heteroscedasticity and serial correlation (Politis and Romano, 1992).

Given the flexibility that bootstrapping offers and the ability to calculate the significance of the spillover index using it, this thesis aims to re-evaluate the results of Diebold and Yilmaz (2012) to identify whether the interpretations of their results can change when the significance of the results is considered. Furthermore, reconsidering the results of the volatility spillover of the MENA region by applying bootstrapping, in order to analyse whether the interpretations drawn differ. Thus, within this context, this thesis aims to estimate the statistical significance of the estimates of the DY results which provides better interpretations about the stock market volatility spillover of the MENA region. Finding the statistical significance of the DY index estimates provides better interpretations of the results and constitutes a significant gap in research that this thesis aims to fill, and leading to institutional and individual investors obtaining a better understanding of the market dynamics for portfolio diversification and efficient allocations.

After measuring the volatility of the MENA region, examining the volatility spillover within it, and assessing the significance of the estimates of the spillover outcome, the results provide an overview of the market behaviour but do not reflect the investor behaviour. One of this thesis's aim is to test the presence of herding behaviour in the Egyptian stock market. The Egyptian stock market is chosen for several reasons. First, the Egyptian market is considered one of the largest developing markets in the MENA region (World Bank, 2020). Second, it is the only market that experienced numerous events during the chosen sample period such as the two Egyptian revolutions and floatation of the Egyptian pound. Third, after investigating the volatility spillover of the MENA region, which includes the Egyptian market, the results provide an overview of the market behaviour but do not reflect the investor behaviour. Consequently, it is interesting to see if the Egyptian market is experiencing any herding behaviour.

Generally, herding behaviour is considered to be the main reason behind periods of high volatility and market instability (Spyrou, 2013). In addition, testing herding behaviour is important in order to understand empirical realities given the fact that individual investors tend to mimic the actions of others. Furthermore, practitioners are keen to examine herding behaviour since it may drive stock prices away from fundamental values and present profitable trading opportunities. As for policymakers, herding may destabilize markets and increase the fragility of financial systems (Christie and Huang, 1995).

Thus, given the importance of testing the presence of herding behaviour, the next empirical question focuses on testing herding behaviour within one specific market in the MENA region, the Egyptian stock market.

Q4: Does herding behaviour exist in the Egyptian stock market? If yes, which kind of herding behaviour exist: intentional or unintentional? Does herding behaviour differ under different market conditions?

By answering this question, we contribute to the literature in the following manner. Most of the studies that test the existence of herding behaviour and differentiated between the different rational and irrational herding (named throughout this thesis unintentional and intentional herding) focus mainly on the US and the European equity markets (Gabbori *et al*., 2020) and there is a dearth in studies that test herding in emerging markets despite the fact that these markets are more vulnerable to behavioural biases. Borensztein and Gelos (2003) study covers about 80% of the dedicated emerging market equity fund worldwide. They conclude that herding is more pronounced in emerging markets than in developed markets. Studies on developing markets, such as Economou *et al.* (2015) who test herding behaviour in frontier markets (Bulgaria and Montenegro), find managers herd significantly in both markets. Indeed, Chang *et al.* (2000) and Demirer *et al.* (2010) examine herding in Taiwan and find strong evidence of herding behaviour. A study focusing on a market from the MENA region is Rahman *et al.* (2015). These authors investigate herding in the Saudi Arabian market and find evidence of pervasive herding among the market participants.

Mertzanis and Allam (2018) examine herding behaviour in the Egyptian stock market from 2003 to 2014, which is a narrower sample period than that of this thesis, and they did not differentiate between intentional and unintentional behaviour. Instead, they examined herding during bull and bear markets, and found that the Egyptian stock market exhibits herding behaviour in general and weak adverse herding in stressful conditions.

This indicates that there is evidence of herding behaviour in Egypt. Hence, it is important to determine whether such herding is intentional or unintentional. On the other hand, El Shiaty and Badawi (2014) test the presence of herding behaviour in the Egyptian stock market using the Christie and Huang (1995) (henceforth, CH) model for a sample period from 2006 to 2010 and find no evidence of herding behaviour in the market.

Given the results of these studies, their methodologies, and their sample period, this thesis aims to extend their results due to the following reasons. First, by using the most common method, the Cross Sectional Absolute Deviation (CSAD), this thesis aims to test the existence of herding behaviour in the Egyptian stock market for a wide sample period from the beginning of 2005 to the mid of 2019.

Second, this thesis aims to test which kind of herding behaviour exists in the market, whether intentional and unintentional herding by using the fundamental factors as a measure of risk. These results of testing herding behaviour helps to comprehend if investors are herding due to fundamental factors where similar reactions take place due to similar information provided or due to non-fundamental factors. Bikhchandani and Sharma (2000) differentiate between intentional herding and unintentional herding behaviour, where herding can be copying the behaviour of other investors either intentionally or unintentionally. Most of the previous empirical studies focused on detecting the existence of herding behaviour. However, there is a scant of research focusing on detecting which kind of herding behaviour exists in the market. Thus, this constitutes a significant gap in research that this thesis aims to fill by detecting which kind of herding behaviour exists in the Egyptian stock market.

In this context, the Fama-French-Carhart risk factors are aiming to be able to explain the cross section of average stock returns. This leads to being able to differentiate between unintentional herding where investors copy the behaviour of others and intentional herding where investors face a similar fundamental-driven information set and thus make similar decisions. Furthermore, unintentional herding is the result of the imitation on investors of others' actions, while with intentional herding investors don't imitate but base their reactions and decisions on public information and similar problems (Bikhchandani and Sharma, 2000).

Third, this thesis aims to focus on whether the different market conditions such as political or economic factors change or affect the behaviour of investors. Despite the significance of the Egyptian stock market, its richness, and the interesting environment to detect the existence of the herding behaviour, there is scant research that tested the period covering all recent events that the market experienced. Overall, not only do we examine herding and determine the type of herding, but we also detect it under different market conditions. In order to do that the thesis divides the selected sample into six subsamples, in order to deeply analyse the different market conditions. The six subsamples are the pre-crisis, the Global Financial Crisis (GFC), the Arab Spring, the second Egyptian Revolution, the Economic Reform, and the post-crisis period.

1.5 Structure of the Thesis

The thesis is organized as follows: after this introduction, Chapter 2 provides a detailed discussion of volatility various definitions and measures. Specifically, it highlights the advantages and disadvantages of each model, sheds light on the significance of the MENA region, and highlights the major political and social events that the region.

Chapter 3 provides a comprehensive overview of volatility spillover importance and different approaches. It discusses the difference between examining developing and developed markets, and pointing out the significance of examining the MENA region. Moreover, highlighting one of the DY index criticism and providing bootstrapping as a solution are included. Then, it discusses the importance of bootstrapping and discusses the various types of bootstrapping. Additionally, it highlights the significance of using bootstrapping in finding the standard errors and confidence interval.

Chapter 4 discusses the concept of herding behaviour along with different ways of examining it. Furthermore, it discusses the fundamental risk factors that are used in order to differentiate between intentional and unintentional herding. The chapter also discusses testing the presence of total, intentional, and unintentional herding behaviour under different market conditions.

Chapter 5 highlights the data description along with main variables used in examining volatility spillover and bootstrapping the DY index. The chapter proceeds by discussing the relevant methodological techniques employed in the first part of this thesis, and discusses the different models of the ARCH/GARCH model. The DY index, its strengths and weaknesses are discussed. We offer arguments for the best bootstrapping method to be used in order to solve the DY index testing problem. Furthermore, the data description and variables are highlighted for the second part of the thesis examining herding behaviour. Specifically, it focuses on the construction of the fundamental factors for the Egyptian stock market.

Chapter 6 provides the descriptive statistics of the stock market return of the MENA region markets. Modelling volatility and providing the results of using symmetric model (GARCH) and the asymmetric models (EGARCH, GJR-GARCH), highlighting GJR-GARCH as the main technique that captures the variation. The study also implements the DY index and provides the results in order to find the volatility spillover among the MENA region. Furthermore, the chapter reports the spillover outcome of dividing the sample into pre-crisis during the crisis, and post-crisis in order to capture the transmission of these events and to be able to see their effect on each market.

Chapter 7 provides the significance of the DY index along with an overview on how the conclusions may have changed when the significance of the estimated spillover indexes is considered. The chapter provides the significant levels of the volatility spillover indexes of the MENA region.

Chapter 8 starts with the descriptive statistics of the Egyptian stock market and the fundamental risk factors. The chapter then discusses the results of the presence of herding behaviour using the cross-sectional absolute deviation. Moreover, it discusses the results of intentional and unintentional herding in the Egyptian market, along with the presence of herding behaviour under different market conditions by dividing the sample into subsamples.

Chapter 9 concludes the thesis and re-addresses the research objectives to determine whether the market conditions, significance and direction of volatility spillover across the MENA markets. Some research and policy implications are discussed on the basis of the main testing results. The chapter also summarises the main results on the presence of intentional and unintentional herding in the Egyptian stock market. Finally, the chapter highlights the main limitations of the thesis and provides recommendations for future research.

Chapter 2

Volatility and MENA: A Review of Literature

2.1 Introduction

One of the main aims of this thesis is to investigate the volatility spillover of the Middle East and North African (MENA) countries (Egypt, Bahrain, Jordan, Turkey, Oman, Saudi Arabia, Kuwait, and United Arabs of Emirates). This aim cannot be fulfilled without examining the stock market volatility of these countries. Generally, developing stock markets are characterized by high average returns and low correlations of returns with developed markets, which provides large yield and diversifications, which attracts foreign investors. However, developing markets are also known by large fluctuations of market returns, which cast doubt to efficiency and accuracy of the valuation of investment opportunities. According to Chiwon Yom (2000), excess volatility in developing markets is greater than that in developed markets. Therefore, in order to identify the problems of financial market instability, and find better possibilities for improving investment climate in the MENA region, investigating stock price volatility within the region is necessary. In addition, exploring and modelling total as well as directional spillover across these countries taking into consideration the political events that have taken place within each country is also important.

Furthermore, volatility provides a base for examining herding behaviour, which reflects the sixth objective of this thesis to test the presence of herding behaviour. The link between herding and market volatility is noted by Friedman (1953), who argues that irrational investors destabilize prices by buying when prices are high and selling when they are low, while rational investors tend to move prices towards their fundamentals, by buying low and selling high. Later on, Hellwig (1980) and Wang (1993) claim that volatility is driven by uninformed or liquidity trading, given that adjustments arising from uninformed trading tend to revert. Therefore, volatility is required to be understood and examined in order to proceed with the thesis objectives.

This chapter intends to achieve the thesis' aim by providing definitions of volatility, outlining the various approaches to measure volatility along with their merits and discussing the importance of volatility in the literature. Additionally, this chapter highlights the importance of the MENA region and why it is important to be investigated. Finally, this chapter refers to previous studies that investigate volatility and its relation to the stock market which highlights the research gap on the MENA region.

The outline of this chapter is as follows: Section 2.2 provides various definitions of volatility. Section 2.3 elucidates various measures of volatility using different approaches and models, along with understanding the advantages and disadvantages of each model. Section 2.4 highlights the significance of examining volatility. Section 2.5 reviews several previous studies that explored the relation between stock market and volatility. Section 2.6 sheds light on the significance of the MENA region along with major political and social events that shook the region. Section 2.7 concludes.

2.2 Understanding Volatility

Several definitions of volatility have been proposed. Rajhans *et al*. (2015) define volatility as the fluctuation of a variable with respect to time. In other words, volatility does not measure the direction of the trend but only its magnitude. In statistics, volatility is the standard deviation or the variance of a random variable. Moreover, volatility measures the dispersion of asset prices or returns in finance. In other words, it is the variation in the price of a financial instrument over time. As Shafqat (2017) points out, volatility is a measure of risk, which makes it a significant concept in finance. Erdemlioglu *et al*. (2012) mention that volatility process indicates how news affects asset prices, which information is important and how markets process this information.

Since volatility can be explained as the deviation of a measure from its expected value, defining volatility can be derived from various statistical definitions. One definition is based on the moments that characterize a distribution. These moments are the weighted averages of the deviations from the mean, elevated to various powers. The first power gives the expectation or mean, whereas the second power gives the variance. As the second moment that characterizes the dispersion around the mean, it is a convenient measure of risk since it measures the magnitude of possible fluctuations around the mean (Press, 2007). Volatility, therefore, reflects the second moment of distribution of returns or prices.

One of the volatility characteristics is that it is not observable. In financial markets, the prices of instruments and their movements are observable but volatility is latent. For example, in daily frequency, since there is only one observation in a trading day then the daily volatility is not observable from the returns (Tsay, 2005). However, volatility is not observable, it has some characteristics that are commonly found in asset returns. For instance, volatility clusters where some periods are high and some are low, and evolves in a continuous manner. Another characteristic is that volatility does not diverge to infinity, leading to volatility being stationary.

In light of the previous discussion, volatility can be described as a phenomenon which characterizes the changeability of a variable under consideration, and associated with unpredictability and uncertainty. The concept of volatility is simple and intuitive. However, there are some subtleties that make volatility challenging to be analysed and implemented. Since volatility is a standard measure of financial vulnerability, it plays a role in assessing the risk-return trade-off. It is worth noting that literature on stock market reveals that it is synonymous with risk. In particular, excessive volatility, or noise, in the stock market undermines the usefulness of stock prices as a signal of the fundamental value of a firm, a concept that is core to the paradigm of the informational efficiency of markets (Karolyi, 2006).

Although volatility has a long history as a noticeable empirical regularity characterizing high frequency speculative prices, in the financing field, it has only been recently recognized as being important to modelling volatility by researchers. Bollerlev *et al*. (1992) explain that volatility of prices is widely believed to be the cause of changes in economic factors such as interest rates, inflation, variability in speculative market prices, unexpected events such as political unrests and the instability of market performance. The following section provides a thorough explanation of the relation between the stock market returns and volatility looking back to the theoretical background.

2.3 Various Approaches to Measuring Volatility

This section discusses different approaches for modelling volatility. Considering the scope of previous studies, it is very important to correctly model volatility as the estimated volatility will be used subsequently as an input to other applications, such as estimating volatility spillover indexes, or option valuation.

Generally, there are two approaches that the majority of researchers adopt to estimate volatility. The first method is to extract information on the variance of future returns from historical data using the Sample models, Exponentially Weighted Moving Average models, Autoregressive Conditional Heteroscedastic models, Stochastic volatility models, or the Realized volatility. The second method, is to extract market expectations on future volatility from observed option prices, using implied volatility indices (Kambouroudis *et al.*, 2016).

Historical volatility, which is computed from historical prices, utilizes past history to predict the future. Historical volatility is the simplest model for volatility which involves calculating the sample variance or standard deviation of returns in the usual way over some historical period, which becomes the volatility forecast for all future periods. It is traditionally used as the volatility input to options' pricing models although there is a growing body of evidence (Brooks, 2015) suggesting that the use of volatility predicted from more sophisticated time series models will lead to more accurate option valuation. It can also be used as a benchmark for comparing the forecasting ability of a more complex time models (Chu and Freund, 1996).

Given that the sample volatility for time t, and the σ_t is the sample standard deviation of period t returns. If t indexes months with daily data, then σ_t is the sample standard deviation of daily returns in month t. If t indexes days with daily data, then

$$\sigma_t^2 = R_t^2 \tag{2.1}$$

However, with high frequency data, the daily σ_t is derived from cumulating squared intraday returns.

The second model is the exponentially weighted moving average (EWMA) model, which allows recent observations to have a stronger impact on the forecast of volatility than older points. The latest observation has the largest weight and weights associated with previous observations decline exponentially over time. There are two advantages for this model. First, since recent events are more likely to be more relevant, they carry more weight than events further in the past. Second, the effect on volatility of a single given observation declines at an exponential rate as weights attached to recent events fall. It is worth mentioning that there are several approaches to estimate the EWMA. One of the limitation is that the EWMA models are not “mean reverting”. To elaborate, “mean reverting” means that if it is currently at high level relative to historic average, it will tend to fall back towards average level. Alternatively, if it is currently at low level relative to historic average, it will tend to rise towards the average (Brooks, 2015).

The third model is the Autoregressive Conditional Heteroscedasticity (ARCH) model, initially introduced by Engle (1982) to assess the volatility process based on the return series of a financial asset. It assumes a deterministic relationship between the current volatility and its past. The volatility estimate is conditional on the available information set which is named as conditional volatility. The ARCH model for volatility modelling provides a systematic framework of volatility clustering, under which large shocks tend to be followed by another large shock. Bellini *et al.* (2014) state that the ARCH model is among the models that are introduced in order to eliminate some of the limitations of the Black-Scholes model. The ARCH models are considered one of the most popular volatility measures (Bollerslev *et al.*, 1992).

The basic notion of ARCH models is that the mean corrected asset return a_t is serially uncorrelated, but dependent, and the dependence of a_t can be described by a simple quadratic function of its lagged values. ARCH model assumes that:

$$a_t = \sigma_t \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 , \tag{2.2}$$

where ϵ_t is a sequence of independently and identically distributed random variables with mean zero and unit variance, $\alpha_0 > 0$, and $\alpha_i \geq 0$, for $i > 0$. To ensure that the unconditional variance of a_t is finite, the coefficients α_i must satisfy some regularity conditions. For ϵ_t , it is normally assumed to follow the student t-distribution. All coefficients in the conditional variance must be non-negative, $\alpha_0 > 0$ and $\alpha_i \geq 0$.

Before using an ARCH model, one must test whether "ARCH effects" are present in the residuals of the model or not. This test is one of a joint null hypothesis that all lags of the squared residuals have coefficient values that are not significantly different from zero. If the critical value from the χ^2 distribution is smaller than the value of the test statistic, then the null hypothesis is not accepted. This test also works as a test for autocorrelation in the squared residuals, and it is usually applied to raw returns data (Brooks, 2015).

However, there are weaknesses to the ARCH model. The most important is that the model requires many parameters to be able to capture volatility. Also, the model over predicts the volatility due to a slow response to large, isolated shocks to the return series (Tsay, 2010). Previous evidence that used Engle's ARCH model showed that a high ARCH order is needed to capture the dynamic behaviour of conditional variance (Alberg *et al.*, 2008).

The Generalized autoregressive conditional heteroscedasticity (GARCH) model was introduced by Bollerslev (1986) to overcome these limitations. It allows both a longer memory and a more flexible lag, in other words it depends on previous own lags and avoids overfitting (Alberg *et al.*, 2008).

Assuming that the mean equation is described by a simple AR model for the dependent variable r_t (the stock return), the mean equation is given by $r_t = \mu + \alpha r_{t-1} + u_t$, where

$u_t = \sigma_t\, \varepsilon_t$, and ε_t is iid (0,1).

The conditional variance equation for a GARCH (1,1) is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2.3}$$

Under the conditions $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, to ensure that the conditional variance is always positive, and $\alpha_1 + \beta_1 < 1$ is required for stationarity. The conditional variance σ_t^2 is calculated based on any relevant past information. σ_t^2 is interpreted as a weighted function of a long-term average value or the mean of the unconditional variance (dependent on α_0), information about volatility during the previous period ($\alpha_1 u_{t-1}^2$), and the fitted variance from the model during the previous period ($\beta_1 \sigma_{t-1}^2$).

The ARCH/GARCH models have become widespread tools for dealing with time series heteroscedastic models to provide a volatility measure to be used in financial decisions concerning risk analysis, portfolio selection and derivative pricing (Bouoiyour *et al*., 2016).

However, similar to the ARCH model, the GARCH model encounters some common weaknesses. First, both respond equally to positive and negative shocks. Also, the tail behaviour of GARCH models remains too short for high frequency financial time series, even with standardized student-t innovations. Furthermore, several financial time series have nonlinear dependence structure and are nonstationary. Therefore, the GARCH family models may not capture nonlinear patterns in the data and linear approximation approach of those complex time series may not be satisfactory. Additionally, GARCH models assume that the variance equation parameters used for forecasting future volatility does not provide any information of the associated uncertainty (Lahmiri, 2017).

Due to these drawbacks, ARCH/GARCH models have been transformed and developed to more sophisticated models, such as IGARCH, TGARCH, EGARCH, GJR-GARCH and GARCH-M. Different models have different features. Some volatility models are proposed specifically to overcome the limits of GARCH based models (Tsay, 2010). The EGARCH model is developed to capture the asymmetry in volatility induced by big “positive” and “negative” asset returns. TGARCH on the other hand, is created to capture the negative movements of the volatility that usually is bigger than the positive movements. Likewise, the EGARCH allows for unequal changes of the volatility.

A popular alternative is stochastic volatility, which refers to the fact that the volatility of asset prices is not deterministic. The Stochastic volatility model (SV) extends the ARCH model by including randomness in the intertemporal relationship of the volatility process (Hull and White, 1987; Shephard, 1996).

The major difference between SV models and GARCH models is that volatility is not known but rather an unobserved random variable. Whereas, SV models offer a natural economic interpretation of volatility which are easier to connect with continuous time diffusion models with SV and are often found to be more flexible in the modelling of financial returns. However, the classical SV model does not take into account the leverage effect that is the effect that negative news tends to increase volatility more than positive news. To add this effect in the model, a dependence between the two error terms should be introduced. For GARCH models, the predictive density of returns depends on volatility which is simply measured with respect to the information set which is estimated by the maximum likelihood. However, in SV models it cannot be solved analytically and direct numerical methods are infeasible even for large samples. In this case, other techniques have to be employed (Bauwens *et al.*, 2012).

Another model is the realized volatility model, which is a non-parametric measure proposed by Andersen, Bollerslev, and Diebold (2003). Realized volatility is simply measuring over a fixed time interval by summing increasingly finer sampled squared high frequency returns over the relevant time interval. The model uses intra-daily high frequency data to directly measure the volatility under a general semi-martingale model setting using different sub sampling methods (Barndorff-Nielson *et al.*, 2010). This model is a popular measure of volatility since it yields a perfect estimate of volatility in the hypothetical situation where prices are observed in a continuous time and without measurement error. Realized volatility approach uses the intra-daily prices of financial assets where data are sampled at a very high frequency to compute measures of ex-post volatility at a lower frequency. This problem in high frequency financial data complicates the estimation of financial volatility and makes standard estimators less accurate. There are three facts regarding this model: (a) long range dependence, which means it displays significant autocorrelation even at very long lags, (b) leverage effects, where returns are negatively correlated with realized volatility, and (c) jumps, which have a strong positive impact on future volatility and they are unpredictable.

A simpler method, the implied volatility, cannot be calculated from historical prices of the stock, but is rather the by-product of an options pricing model. Moreover, implied volatility is an expression of the market's expectation of the future volatility of the stock price between now and the option's expiration. Also, it is computed from the market's consensus of the fair value for a derivative instrument (Glantz and Kissell, 2014). This approach is often criticized for using a specific model which is based on some assumptions that might not hold in practice (Brooks, 2015).

In a nutshell, Historical volatility is based on actual stock prices from the past, on the one hand, and implied volatility is an estimate of future option volatility based on assumptions that are not necessarily accurate, on the other hand. Subsequently, the next section explains the significance and illustrate the usages of volatility in real world.

2.4 The Significance of examining Volatility

This section elucidates the importance of examining volatility, as well as stating its uses in the real world. As mentioned before, estimating volatility is required in order to fulfil one of this thesis aims, which is investigating the volatility spillover of the MENA region. There are several other reasons behind estimating volatility and it is important to identify them in order to recognize the importance of this estimation. First, volatility is a measure of the risk of the asset. The larger the variance on daily stock price changes, the more a stock market participant stand to gain or to lose in a day. A risk averse investor who is concerned about risk would be less tolerant of participating in the stock market during a period of high rather than low volatility. Second, the value of some financial derivatives depends on the variance of the underlying asset. For the trader to know the price at which to buy or sell, he needs the best available forecasts of future volatility. Third, forecasting variances increases the possibility of accurate forecasted intervals (Stock *et al.*, 2007).

The issue of volatility is not only a regional phenomenon but also an integral part of global risk. Volatility provides more accurate information to aid global portfolios managers in achieving an efficient mean-variance frontier. Moreover, policy-makers are provided with a more definite basis upon which to formulate appropriate risk-management strategy (Chiang and Doong, 2001).

The volatility of stock market returns is of concern to investors, analysts, brokers, dealers and regulators (Glantz and Kissell, 2014). Policy makers rely on market estimates of volatility as a barometer of the vulnerability of financial markets (Olowe, 2009). They are interested in measuring volatility to learn about the market expectations and uncertainty about policy. Modelling volatility is important for portfolio selection and asset management as well as for the pricing of primary and derivative assets. While most researchers agree that volatility is predictable in many asset markets, they dissent on how this volatility predictability should be modelled (Bollerslev *et al*., 1992).

Volatility is used differently among practitioners: traders use volatility to understand potential price movement over the trading day, as input into market impact models, to compute trading costs, and to select algorithms that are used to determine when it is appropriate to accelerate or decelerate trading rates in real time. As for portfolio managers, they use volatility to evaluate overall portfolio risk, as input into optimizers, for value-at-risk calculations, as part of the stock selection process, and to develop hedging strategies. Derivatives desks use volatility to price options and other structures products. In addition, plan sponsors utilize volatility to understand the potential that they will or will not meet their long-term liabilities and financial obligations. Volatility is a very important financial statistic (Glantz and Kissell, 2014).

As mentioned, modelling volatility using any model is an important step in estimating how much risk a particular asset carries, which afterwards can be used in investigating the volatility spillover. In risk management, the volatility level in financial market provides a measure of risk exposure of investors to their investments. Investors and financial analysts are concerned about the uncertainty of the returns on their investment assets, caused by the variability in speculative market prices (and market risk) and the instability of business performance (Alexander, 1999). Therefore, high volatility may create barrier for investing. The understanding of volatility in a stock market can be useful in determining the cost of capital and in evaluating asset allocation decisions (Olowe, 2009).

The variation in the returns provided by the stocks due to fluctuation in prices are volatility. Even if the movements are not bad, it can turn out to be bad if the swings are unusually sharp or rapid in a short time. The increase in the uncertainty here is due to the high fluctuations in prices and therefore the risk as well increases. Then if the market performance is unstable, investors cannot rely on predicting the future which then results in further uncertainty about future movements in that market. Thus, it can be concluded that uncertainty about the future may prevent investors to take risk and fund investment. Such volatile market makes it difficult for companies to raise funds in the capital markets. Investor confidence is then lost as uncertainty increases especially when making investment and leverage decision (Ding, 2013).

For policy makers and market practitioners understanding the origins of stock market, volatility is of great importance. Policymakers try to understand the main determinants of stock market volatility and its spillover effects to the real economy. This knowledge is meaningful when policymakers formulate policies that ensure financial and macroeconomic stability. For investment bankers and fund managers, this knowledge is interesting since stock market volatility affects asset pricing and risk, empowering them to formulate hedging strategies (Corradi *et al.*, 2006).

This section provides the reasons why examining volatility is important, or precisely stock market volatility, which underlined the importance of the study. At this point, one can understand that estimating stock market volatility is important. However, several previous studies have done it using different measures and techniques and applied their study on different countries. The following section mentions some of the previous studies of modelling the relationship of stock market and volatility in order to provide support to this study.

2.5 Previous Studies Modelling Stock Market Volatility

This section discusses some previous studies on modelling the relationship between stock market and volatility whether on developed or developing countries. Mentioning the previous studies have two main benefits, initially it shows how different researches modelled volatility, different techniques, and different findings. Second, it shows the first literature gap that this study aims to fulfil.

The attention of many investors and financial analysts around the relationship between stock market and volatility can be traced back to 1987 stock market collapse. This contributed to an increase in volatility of interest rates and exchange rates. Different studies show different results about the relationship between stock market and volatility, either positive, negative, or found no relation. For instance, Léon (2007) argues that a positive relationship should exist between stock return and volatility for the risk averse investor. He also mentions that investors are compensated by higher risk premium if the volatility is high in the stock market. In addition, French *et al.* (1987) examine the relationship between volatility and returns for the U.S market and evidence showed that the market risk premium is positively related to volatility of stock returns. Likewise, French *et al*. (1987) use daily and monthly returns on the NYSE stock index and found that there is a positive relation between the risk and volatility of stock return. Confirming these results, Chou (1988) finds a positive relation between stock market and volatility and Baillie and DeGennaro (1990), using GARCH in mean models and estimating a variety of models from daily and monthly portfolio return data, conclude that most asset pricing models postulate positive relationship between stock portfolio's expected returns and risk, which is often modelled by the variance of the asset price. Similarly, Duffee and Huang (1985) examine the Brazilian stocks and find a positive relationship between stock returns and volatility. Later on, Nelson (1991) tests this relationship using his EGARCH model and find that there is a strong relationship between stock returns and current volatility. Sabri (2004) examines emerging market indexes in five regions and found that stock price changes are positively correlated with the stock trading volume and the exchange rate. Using the backward multiple regression technique, trading volume and exchange rates are found to be more predictable variables than inflation of emerging stock price volatility.

Conversely, Cheung and Ng (1992) investigate the relationship between stock price dynamics and firm size, their evidence show a negative relation between the conditional future volatility of equity returns and the level of stock price and the effect is stronger for small firms and firms with higher financial leverage. Likewise, Mougoné and Whyte (1996) study the equity markets to see the relation between stock returns and volatility, and find insignificant relation. Glosten *et al*. (1993) as well use the NYSE and find a negative relation between stock market return and volatility. Later, Bekaert and Wu (2000) report asymmetric volatility in the stock market and negative correlation between return and conditional volatility.

On the other hand, Theodossiou and Lee (1995) investigate 10 developing countries using GARCH in mean model testing for the conditional variance and expected market return relationship. They find no significant relationship between conditional volatility and expected return for any of these countries. Similarly, Engle *et al.* (1987) introduce the GARCH in mean model that is applied afterwards in several studies to investigate the relationship between stock return and volatility like French *et al*. (1987), Gloston *et al*. (1993), Leon (2007), and others. Mixed results are found by each author.

In light of the aforementioned discussion, one can conclude that the relationship between stock market returns and volatility is not clear, it can be either positive, negative, or no relation can be found. Some of these studies adopt the same methods of analysing and some do not, along with investigating different developed and developing countries and markets. Different results reflect the different economic and political conditions that each country has (Ben Naceur *et al.*, 2007). Since analysing the developed and developing markets is different, a comparison between studies that focused on each is needed.

Looking at two countries from the MENA region, Butler and Malaikah (1992) investigate the Kuwait and Saudi Arabian stock markets and find market inefficiency in both markets. Similarly considering the same region but three different countries, Darrat and Hakim (1997) examine Amman, Cairo, and Casablanca markets and find that there is integration within the region but not on the international level. Later on, Lagoarde-Segot and Lucey (2007) focus on potential diversification in the MENA region using local currency and dollar, he argues that according to their study MENA markets should attract more portfolio flows in the future.

Furthermore, Hammoudeh and Li (2008) investigate the sudden changes in volatility for five Arab stock markets, and find that these countries are more sensitive to major global events than to local regional factors. Alsubaie and Najand (2009) investigate the market indices and firm level of firms listed in Saudi stock market from 1993 to 2005 trying to see the effect of trading volume on volatility persistence on the volatility model. The results show that with the inclusion of trading volume the persistence level decreased for some of the market indices but not all, while the firm level data showed persistence level decreased highly for all firms.

Considering other regions, Hussain and Uppal (1997) examine the Pakistani equity market for stock returns volatility, and find strong evidence of persistence in the variance of returns. This implies that shocks to volatility continue for a long period. Later on, Batra (2004) examines the time variation in volatility in the Indian stock market and finds that the most volatile period in the stock market is where the crisis of economic reforms in India took place. Sudden shifts in the stock return volatility in India are more likely to be a consequence of major policy changes. Xu and Fung (2002) examine China stocks flow of information that are dual listed on exchanges in Hong Kong and New York using GARCH model. Their results indicate that stocks in the domestic market (Hong Kong) appear to play a more significant role of information transmission in the pricing process, whereas stocks listed in the offshore market (NYSE) play a bigger role in volatility spillover. Beer *et al.* (2006) investigate the asymmetric effects on Shanghai market using the T-GARCH (1,1) model and find that volatility is persistent.

Moreover, Thiripal Raju and Rajesh (2010) study attempt to model volatility of two Indian stock markets, the results show volatility clustering in the daily returns of the indices. They used different GARCH models, the GARCH (1,1) with MA (1) in the mean equation is found to fit the best. This study is interesting since its aim is similar to this thesis in that it estimated volatility in order to then test the spillover effect between the benchmark indices of the two Indian markets. In order to test the possibility of transmission within a country and between the two exchanges.

After considering several previous studies mentioned above, one can conclude that the relationship between stock market returns and volatility is an interesting topic and has attracted the attention of investors and analysts lately. Since there are fewer studies that examine the MENA region. In the next section, an overview of the MENA region, mentioning the significance of examining it and highlighting major events that aid in understanding the empirical findings of this study.

2.6 Significance of the MENA region

This section provides an overview of the importance of political uncertainty and its impact on market volatility, specifically in the MENA region. The section additionally discusses the events that took place recently.

Uncertainty is central to much of modern finance theory (Bollerslev *et al.*, 1992). Over the past years, there have been huge fluctuations (ups and downs) in the stock prices for several markets, including developed and developing markets across the world. Investors and financial analysts became concerned about high or sharp up-down movements of asset prices and the effect of uncertainty of returns on their investments. After the financial crises it became more important for financial institutions to capture the movements of financial asset prices. These movements are usually measured by volatility (Chau *et al.*, 2014).

World events have had great effects on stock prices for decades especially after the great dramatic shocks that happened in recent years. In times of political and civil unrest, it is common for stock markets to experience increased levels of volatility as the occurrences of major political events signal potential shift in policy which causes market valuation changes. Numerous studies consider specific political events and investigate the changes in market volatility during these periods and find that political uncertainty is linked to market volatility (Karolyi, 2006). Brooks *et al.* (1997) study a significant political change in South Africa and finds comparable results indicating that stock market volatility is closely linked to political instability. Furthermore, huge change in excess returns happens as political risk increases or decreases, according to Perotti and Oijen's (2001) study on a number of emerging markets.

Despite the fact that most of the previous studies focused on political events such as elections, wars, and terrorist attacks, little research is conducted on the impact of political uncertainty arising from civil uprisings such as the Arab spring, on the stability and efficiency of financial markets. Even though, the growing importance of MENA countries in the world economy in terms of both the volume and the value of trade, there is a lack of research, according to O'Sullivan *et al.* (2012).

According to Ben Naceur *et al*. (2007), it is not clear whether MENA emerging markets react to economic and political shocks in a similar way to other emerging or developed markets. There is a high need to examine volatility in the MENA region since it is still witnessing, wars, political turmoil and economic instability. However, the MENA countries have not yet emerged as economic powers, which explains the lack of academic research on MENA capital markets.

The region's main economic development process went through several eras. Between the 1950s and the late 1970s, the MENA region economic structure was characterized as an import substituting regime including strict controls on international trade, overhead exchange rates and rationing foreign exchange and credit market. The MENA region countries began to liberalize their stock markets in the 1990s, but very scant studies took into consideration such reform as a theoretical and empirical literature. These reforms started the development of stock markets in other countries of the MENA region, and aimed to increase private investment and protect investors, and develop new capital markets (Yusoff and Guima, 2015).

The MENA region has issues arising from internal economic policies, unstable investment climate, less developed financial institutions, lack of integration in the world economy, and low human capital development which made the region debatable (Dutt *et al.*, 2008).

Ahmed (2011) states that the new markets in the MENA region led to increase global integration with 55% of Foreign Direct Investment (FDI) by merger and acquisition between 1991 and 2000. One of the reasons behind the development in the MENA region is the petroleum prices (Dahi, 2011).

Neaime (2012) argues that the MENA capital markets are less developed than the Asian or Latin American emerging markets but offer portfolio and fund managers outstanding diversification benefits. The openness of the MENA markets to local and foreign investors made it the third largest emerging market by the end of 2010, which resulted in affecting the dynamics of the volatility and correlation of equity returns. However, over the recent years the region has been rather unpredictable. This can be gathered by the numerous events that the region witnessed such as the blockade against Qatar, regional tensions with Iran, the oil collapse and the Arab Spring.

It may be informative to look at three countries in the MENA region, namely Egypt, Saudi Arabia, and Tunisia, and comparing the events that took place and their effects. By the 1990s, the Egyptian and Saudi markets were relatively developed with the Egyptian market having witnessed stronger momentum. It is worth mentioning that the Tunisian market had also been developing strongly and actively in the early 1990s, but stepped back in 1997 due to the Far East crisis. However, the Egypt and Saudi markets were not affected.

With the start of the Millennium, in the first decade Saudi and Egyptian markets showed major jumps in activity, but Tunisia continued in depression. In the Second decade and up to 2012, the Egyptian and Saudi markets slowed down due to the global financial crisis in 2008, suffering from a decline in FDI and low oil prices. However, the global crisis had a positive effect on Tunisia until the start of the political instability in 2010 (Yusoff and Guima, 2015). Since then, political instability took place in various countries in the MENA region.

From the early 2000s, the region saw a remarkable economic growth and evolved into a vibrant as well as important economic financial block. This was thanks to liberalization, privatization and globalization policies adopted by most of the MENA countries. Nevertheless, the MENA countries remain relatively smaller and less liquid than the major world financial markets (Domowitz *et al.*, 1998). They exhibit weak efficiency and capital market fragmentation due to poor-quality information and low competition (Assaf, 2009).

Countries within the MENA region have relatively close economic, institutional, regulatory, political and cultural links that may sometimes function differently from developed economies. These conditions may contribute to different return, volatility, and correlation behaviour than those observed in developed markets (Assaf, 2009).

Seeing the MENA region as an attractive sample to study, one must be aware of the most recent and popular events that took place in this region such as the Arab Spring. This is considered a turning point in the history of the MENA region.

2.6.1 The Arab Spring

The purpose of this section is to explain the most important event that took place in the MENA region in recent years. The Arab Spring started in December 2010 in Tunisia, when a tragic suicide of a young vegetables seller from a small town occurred. The political turmoil in certain Arab countries quickly spread into other neighbouring countries. Later on, the Arab spring arose in Egypt leading to the removal of President Hosni Mubarak, followed by the election of Mohamed Morsi in 2012. Finally, the defence minister at that time, Abdel Fattah El Sisi, took over power in 2013.

In Libya, Muammar Gaddafi was overthrown in 2011 during a violent civil war. Likewise, Syria's civil war due to the Arab spring lasted for several years which led to many citizens leaving the country to seek refuge in other countries. Morocco was spared, but the protests led to constitutional changes in 2011 (BBC News, 2018).

The Arab Spring long-term impact remains unpredictable even though it is a historic moment in the politics of the MENA region. The economic condition of most of the Arab countries are under a challenge of increasing food and energy prices, high unemployment and corruption rates, weak economic reforms, and other challenges which is the reason behind the political unrest that accentuated the existing tensions in the region. Some countries are thought to be the cause of this unrest like, Tunisia, Egypt, Libya, Yemen, Syria, and Bahrain which are more involved in revolutions and conflicts. However, the effect spread to other countries in the region as well as wealthy countries too. Speaking of the Stock exchange of the MENA region countries, it had been affected previously by the global financial crisis of 2007-2009 then with the start of the Arab Spring, the region market indices started to fall. Foreign direct investment fell due to the uncertainty from the ongoing unrests (Chau *et al*., 2014).

Still, much is not studied for this controversial region which produces one third of the world's oil and represents one of the most diverse and interesting mixture of political and economic configurations (Luciani, 2017). The Arab Spring makes the MENA region, a fertile ground for informative and instrumental research. There are two sides for this event. The first side is that the revolutionary movements leads to MENA countries establishing accountable, effective and transparent governance. The second side is this political uncertainty that may or can cause economic fluctuations in stock market cycles and volatile reactions leading to shaking investor's confidence in the region's markets. The MENA region political system is rich with a variety of market and financial arrangements like conventional and Islamic ones (Franke and Wand, 2014). All these reasons make the MENA region a very rich and interesting region to be examined.

2.7 Conclusion

This chapter provides a discussion of volatility, stock market, and the MENA region. It builds on an extensive literature review of the theory and evidence of volatility measurements and models, in addition to the importance of stock market and specifically the MENA region. According to Yilmaz (1999), studies confirm that modelling volatility is an important issue to be examined since understanding the sources and dynamics of volatility in a stock market helps determine the cost of capital and evaluate asset allocation decisions. Despite the large amount of research on modelling stock market volatility and the contradicting results, it can be concluded that these results depend on the country's economic conditions and more importantly on its political stability (Neaime, 2012).

The MENA region is not given the appropriate attention from researchers especially after the Arab Spring. There is therefore a need for analysts and researchers to provide suitable discussions of the unrests and assess the future of these countries. According to Abou-Zaid (2011), studying volatilities in MENA markets is very important for both foreign investors looking for high returns and portfolio diversification, and domestic businesses which have become dependent on the stock market to finance their projects. Moreover, O'Sullivan (2012) points out that very few studies have explored the effects of the Arab Spring. Taking this into consideration, one can see that the Arab Spring rose in various countries after 2012, which is a great motivation for researchers to analyse this phenomenon.

This chapter covers the discussion about the relationship between stock market return and volatility, which is the first part of the thesis analysis. After estimating volatility, the second part of the thesis aims can be considered which is investigating the total and directional volatility spillover across countries taking into consideration the political events that took place within each country. The next chapter provides more details about spillover in order to be able to understand its importance and be able to analyse it.

Chapter 3

Spillover and Bootstrapping: A Review of the Literature

3.1 Introduction

The analysis of volatility spillover is central for investors, financial institutions and governments alike. Excessive volatility affects the financial stability of financial markets and, consequently, economic performance. Financial market volatility has increased over time (Reszat, 2002), which is a major concern for policymakers. Therefore, considerable effort has been dedicated to the study of volatility dynamics within markets, as well as volatility spillover in different markets over time, particularly, during financial crisis where markets show a sharp increase in volatility and spillover across markets (Aslam *et al.*, 2020). The attention drawn to volatility spillover effects arises from the globalization of the world economy and the increased incidence of crises that span regions and continents (Katusiime, 2018).

With globalization, financial markets have become more integrated, which allows volatility in a given market to spill over to other financial markets. Therefore, several studies have focused on volatility spillover, for example, Ng (2000), Yang and Doong (2004), Baele (2005), and Du *et al.* (2011). The importance of volatility spillover stems from the notion of market efficiency. Higher levels of spillover indicate lower levels of efficiency (Bollerslev and Hodrick, 1992). Also volatility spillover indicates the level of market integration (Engle and Susmel, 1993).

The previous chapter provides an extensive literature review of volatility, a review of volatility measurements and models, and a discussion of the importance of examining volatility in the MENA region. This chapter provides some literature review for another aim of this thesis, which is to investigate volatility spillover across eight selected Middle East and North African (MENA) countries. One important task is to explore the total and directional spillover across these countries taking into consideration the political events that took place within each country. Of particular importance is the transmission of shocks from one market to another. When one market experiences an economic or political shock, other markets may be affected to various degrees, depending on how strong transmission links are across these markets. The study of spillover is an essential tool for understanding how shocks are transmitted across markets whether total or directional spillover. Beirne *et al.* (2013) argue that research on volatility on financial markets has become focused on how the volatility of one asset transmits to the volatility of another asset, hence, volatility spillover.

Furthermore, the chapter draws on the importance of examining volatility spillover in the MENA region, and proposes several methods that can be used. Importantly, the most common method of measuring spillover is criticized, and a solution is proposed.

This chapter is organized as follows. Section 3.2 defines volatility spillover, while Section 3.3 discusses stock market spillover and its importance. Section 3.4 sheds light on previous studies of developed and developing countries specially MENA region countries and points out its significance. Section 3.5 discusses different measurement approaches of spillover and its criticism. Section 3.6 explains the significance of bootstrapping methods as solution for the DY index limitation. Section 3.7 discusses bootstrap standard errors and confidence interval. Section 3.8 explains the various types of bootstrapping. Finally, section 3.9 concludes the chapter.

3.2 Defining Volatility Spillover

This section aims to discuss various aspects relating to volatility spillover. Pugel (2016) claims that financial integration makes volatility in one market react to innovations in other markets. The author argues that the interdependency between countries and the speedy growth in cross border volatility spillover has become more central. More precisely, spillover effects are externalities of economic activities or processes that affect those who are not directly involved. Spillover usually exhibits linkages between two or more economic variables.

According to Yilmaz (2010), cross-country shock transmission became more prominent after the Global financial crisis in 2008. This turmoil led to a sharp increase in the stock market volatility which spread quickly across markets. Furthermore, Dovhunova (2014) explains volatility spillover as one of the major interests for researchers, practitioners as well as policy makers. He argues that studying the mechanism of volatility transmission requires determining the degree of market interconnectedness and its exposure to the distress in the other markets.

Rigobón (2019) argues that spillover is present during all phases of the market whether good or bad conditions to measure the interdependence within the market. Moreover, Wegener *et al.* (2018) introduce the concept of spillover of explosive regimes to highlight the migration process between crises, such that one crisis generates another one. Volatility connectedness quantifies the dynamic and directional characterization of volatility spillover among various assets or across markets (Diebold and Yilmaz, 2015). As mentioned earlier, financial integration causes volatility in one market to react to innovations in other markets. Recently, studies that emphasize financial crises, such as Gallo's *et al.* (2012), focus on the sources of the crisis, and asked whether the crisis that started in one market and spilled over to other markets was the result of the spillover effect or an interdependent reaction to some common shock.

According to Diebold and Yilmaz (2009), spillover is observed in returns and volatility, and is usually associated with risk. Later on, Bekaert *et al*. (2014) indicate that it is a shock transmission that cannot be explained by fundamentals. Meanwhile, Konstantina (2014) mentions that spillover effects are defined as externalities of economic activity or processes that affect those who are not directly involved, exploring and exhibiting the linkages between two or more economic variables. Correspondingly, Shafqat (2017) simply argues that volatility spillover is when shocks arising in one market are transmitted to the other markets, this effect can either bring positive change or negative change.

In addition, Cornes and Sandler (1986) state that spillover is not intentionally provided, rather they are incidental extras that are spilled over to others. The concept of volatility spillover is drawn from the work of Engle *et al.* (1990), they define volatility spillover as the causality in variance between markets. They indicate that domestic returns could be significantly influenced by foreign returns. The authors state two theoretical foundations for own and cross type spillover. The heat wave hypothesis, which represents own spillover, states that the current volatility of a market is a function of past volatility of the same market (volatility clustering). On the other hand, the meteor shower hypothesis, which represents cross spillover, states that the current volatility of a market is a function of both past volatilities of the same market and past volatility from other markets (volatility transmission). Empirically, strong evidence by Engle and Susmel (1993) favor the own spillover hypothesis where all stock markets display heat wave type phenomenon.

Diebold and Yilmaz (2015) argue that volatility connectedness quantifies the dynamic and directional characterization of volatility spillover among various assets or across markets. Moreover, Wu (2001) claims that volatility spillovers across markets are larger when market interdependence is high. Simultaneously, market returns tend to be more correlated when volatility increases and key periods of high volatility are linked with market crashes. As Diebold and Yilmaz (2012) mention, market volatility associated with crisis development is most probably a sign of the existence of spill across markets.

Since volatility is transferred across markets through spillover, it can be said that volatility spillover exhibits asymmetries as well. Which means that, just like volatility exhibits asymmetry, the spillover of volatility also exhibits asymmetry depending on the type of news. Bad news seems to have severe effect on spillover both own and cross as compared to good news. Therefore, both volatility and its spillover can be a good informative measure for risk valuation and portfolio diversification strategies (Garcia and Tsafack, 2011). Bartram *et al*. (2012) argue that examining asymmetry helps differentiate whether the volatility is originally of bad or good type, which can exhibit distinctively different impacts on asset prices (Segal *et al.*, 2015).

3.3 Stock Market Spillover

This section discusses stock market spillover, its measurement and its significance. Generally, studying volatility spillover can help understand how information is transmitted across markets. The examination of spillover has increased recently (Kumar and Pandey, 2011; Mukherjee and Mishra, 2010; and Beirne *et al.*, 2010). An important issue is whether financial markets become more dependent during financial crises. This issue acquired great importance among academics and practitioners especially after the rise of several crises in the past few decades (Kenourgios and Padhi, 2012).

Shafqat (2017) argues that volatility spillover plays an important role in investigating the transmission mechanism of information among financial markets. As explained before, if there are two markets that are integrated to some degree, a shock in one market will automatically transmit to the other market proportionately to their level of integration. Additionally, the author argues that it is clear that integrated markets have more shock effects than non-integrated markets, but commonly volatility spillover effect is higher in financial markets during crises. According to Becketti and Sellon (1989), studying spillover is significant because it helps policymakers understand the transmission process of volatility across domestic and international financial markets.

As Dovhunova (2014) states, the evolution of volatility spillover and the development of linkages among stock markets is of interest to investors due to their potential international portfolio diversification benefits. Correspondingly, BenSaïda *et al.* (2018) argue that studying volatility spillover gives direct implications on designing optimal portfolios and building policies to prevent harmful shock transmission.

As Stoica and Diaconasu (2012) argue, the knowledge of spillover is used for example in forming a portfolio, hedging, pricing derivatives or other assets, in risk management or in preparation of regulatory policy of financial markets. Bekaert, Harvey, and Ng (2002) indicate that studying volatility spillover is interesting from the perspective of portfolio diversification and hedging.

Several market factors other than the market price contribute to the uncertainty on the future returns generated by a risky asset such as a change in interest rates, exchange rates, and other economic variables. This uncertainty leads to risk when one holds assets over a given period of time. Therefore, estimating the price or expected returns of a risky asset is derived at least partially from the knowledge of volatility. However, the most popular variable investigated in previous studies is the stock market spillover.

According to Hammoudeh and Choi (2007), it is important to consider an economic variable such as a stock return in terms of its permanent component and its transitory component in order to determine the volatility. An interesting link for investigation that is discussed by Stoica and Diaconasu (2012) is the relation between monetary policy and stock markets. Stoica and Diaconasu argue that stock prices give a good implication for financial stability since speculative bubbles may degenerate into a financial crisis.

Assenmacher-Wesche and Gerlach (2008) argue that central banks should not take into consideration asset prices developments, since the setting the monetary policy's response to asset price movements can generate higher losses than those resulting from a possible explosion of asset bubbles. Similarly, Illing *et al.* (2006) stated that central banks intervention in stock markets through injecting liquidity may increase financial instability.

Hussain (2010) argues that monetary policy decisions have a significant influence on volatility and stock market index returns in both European and US markets. Similarly, Farka (2009) state that volatility depends on the type and timing of monetary policy shocks. Bjorland and Leitamo (2009) find interdependence between interest rate and stock prices in US market.

Demirer *et al.* (2017) examine the high-dimensional network linking the publicly traded subset of the world's top 150 banks from 2003 to 2014. Demirer *et al.* elucidate that global bank equity connectedness has a strong geographic component, whereas country sovereign bond connectedness does not. Also, they find that equity connectedness increases during crises, with clear peaks during the Great Financial Crisis and each wave of the subsequent European Debt Crisis, and with movements coming mostly from changes in cross-country as opposed to within-country bank linkages.

Looking at the abovementioned studies, stock market volatility seems to be one of the most popular economic variables used in cross-market connectedness research. As Markowitz (1952) claims, the correlation between variables help to understand the dependency of variables on each other. The lower the degree of correlation between economies, the more the benefit of diversification will be. This phenomenon made the market participants start to diversify the risk of their portfolio by taking positions in less correlated markets. Volatility spillover has comprehensively been discussed in the finance literature for equity market spillover (Engle *et al*., 2013), for bond market spillover (Claeys and Vasicek, 2012) and for currency market spillover (Antonakakis, 2012). As Becketti and Sellon (1989) argue, studying spillover is significant because volatility can bring unexpected variability in portfolio return and destabilize the financial and economic system. Hence, policymakers are always concerned with the transmission process of volatility across domestic as well as international financial markets.

Recently a booming literature has emerged on the volatility spillover between developed and emerging stock markets, and between emerging or developed markets belonging to the same region (Alshbiel and Al-Zeaud, 2012). To this end, the next section reviews prior studies of developed and developing countries.

3.4 Previous Studies of Volatility Spillover

This section refers to the existing studies of volatility spillover in developed and developing countries. Early studies of spillover across national stock markets primarily covered advanced economies. Stimulated by the October 1987 stock market crash in the US, Hamao *et al*. (1990), King and Wadhwani (1990) and Schwert (1990) investigate spillover across major markets before and after the crash. Engle and Susmel (1993) expand the analysis of advanced market links by examining spillover between New York and London equity markets in high frequency hourly data using the ARCH model. They find minimal evidence of volatility spillover between the two markets and have duration which lasts only one hour.

Lin *et al.* (1994) investigate the volatility spillover between the US and Japanese stock markets. They report that contemporaneous correlations of returns between the two markets tend to increase when volatility is high and conclude that the results support the informational efficiency hypothesis. Bekaert and Harvey (1997), Ng (2000), and Bekaert *et al.* (2005) investigate volatility-spillover effects on various equity markets using volatility-spillover models. They all find evidence of volatility-spillover effects. Ng (2000) finds evidence of volatility-spillover effects to various Pacific Basin stock markets from Japan (regional effects) and the US (global effects). Baele (2005) investigates the volatility-spillover effects from the US (global effects) and aggregate European (regional effects) stock markets into various individual European stock markets.

Zhou, Zhang, and Zhang (2012) investigate both regional and total volatility spillover from 1996 to 2009 between eleven major individual markets like Japan, Taiwan, Hong Kong, US, UK, and Chinese market. They use Generalized Vector Autoregressive structure where the forecast error of variable ordering is invariant to variance decompositions. The results showed that before 2005 the Chinese market was rarely affecting others but after 2005 the Chinese market had a great influence on the other markets. The study also finds that the spillover among the Japanese, Indian and Chinese markets is different than among the US, UK and Chinese stock markets, which further shows that the correlation among Asian equity market has increased in recent years.

Jan and Jebran (2015) examine the volatility spillover effect from G5 equity market (France, Japan, US, Germany, and UK) to Karachi stock market by using weekly data from 2004 to 2013. They apply the co-integration analysis of Johansen and Juselius (1992) and GARCH (1,1). The results show that there is a long run relation between the G5 stock market and the Karachi stock market, and there is volatility spillover between G5 stock market to Karachi stock market. Furthermore, results show that France, UK, Japan, and Germany stock market increase the volatility of Karachi stock market while US market decreases the volatility of Karachi stock market. Therefore, it is not favorable for Karachi investors to invest in the G5 equity markets to diversify their portfolio, and investors of the G5 stock market cannot take any benefit by investing in the Karachi market.

Gamba-Santamaria *et al.* (2017) investigate the volatility spillover among major global stock market index (Germany, UK, China, Australia, Canada, Japan, and US) from 2001 to 2016. Their study is an extension of Diebold and Yilmaz (2012) who consider the time varying framework of their covariance and calculates spillover directly from the return series. The study uses DCC-GARCH for representing the relationship of multivariate of volatility among the stock market. The results show that the net transmitters are always US, Germany, UK and Canada while Japan, Canada and China are the net receivers. The study concludes that during the crisis period the spillover significantly increases.

Barunik *et al.* (2017) examine the volatility spillover of the foreign exchange future contracts of six currencies (Australian Dollar, British Pound, Canadian Dollar, Euro, Japanese Yen, and Swiss Franc) over the period 2007 to 2015 using 5-minutes intraday data. They use the combined approach of Diebold and Yilmaz index and the realized semi variance general framework and found that the bad spillover was dominating the good. The results show that negative spillover is tied to the crisis in Europe while positive spillover is correlated with the subprime crisis, different monetary policies among key world central banks, and developments on commodities markets. Positive asymmetries are the result of monetary and real-economy events, while fiscal factors are linked with negative spillover.

In light of the above discussion, the majority of existing studies have attempted to quantify developed market interrelationships and volatility spillover. Research into cross-border links in emerging stock markets has increased, thanks to globalization and the opening of these markets to foreign investment (Beirne *et al.*, 2010). Nevertheless, these issues are less known in the emerging markets of the Middle East and North African (MENA) region (Bouri and Azzi, 2014).

The markets in the MENA region are typically much smaller, less liquid and more volatile than developed and globally integrated financial markets (Domowitz *et al.*, 1998). Additionally, there is an indication that the emerging markets may be less informationally efficient and their structure is often quite different from developed economies. Therefore, these conditions should lead us to expect a different behaviour in the MENA stock markets (Eissa *et al.* 2010).

Bekaert and Harvey (1997) investigate the volatility of 20 emerging stock markets. They use time series and cross sectional models to analyse the reasons why volatility is different across emerging markets. They found that capital market liberalization often increases the correlation between local market returns and the world market but does not drive up local market volatility. Darrat and Hakim (1997) examine price linkages among three Arab stock markets (Amman, Cairo and Casablanca) and their integration with international markets. They find that these markets are integrated within the region but not on an international level.

Hammoudeh and Choi (2007) use univariate GARCH approach with Markov switching to study the volatility behaviour for the transitory and permanent components of the individuals Gulf Cooperation Council (GCC) market indices. The results suggest that there is a significant high volatility regime for all GCC stock markets and oil markets but low correlation between the countries. Malik and Hammoudeh (2007) use trivariate GARCH models, including one individual GCC market index, the WTI oil price and the

S&P 500 index to analyse return volatility transmission for the three GCC markets. They only involve one GCC market per system. In all cases, Gulf equity markets receive volatility from the oil market except for Saudi Arabia; the volatility spillover is from the Saudi market to the oil market.

Hammoudeh and Li (2008) test the sudden changes in volatility for five Gulf area Arab stock markets and analyse their impacts on the estimated persistence of volatility using GARCH models. They find that most of the Gulf Arab stock markets are more sensitive to major global events than to local regional factors. Lagoarde-Segot and Lucey (2008) examine the efficiency in the MENA stock markets, analysing the impact of market development, corporate governance and economic liberalization. The study concludes that heterogeneous levels of efficiency in the MENA stock markets, and their efficiency index seem to be affected mostly by market depth and corporate control.

Zarour and Siriopoulos (2008) use the univariate CGARCH model to investigate the existence of volatility decomposition into short run and long run components. They analyse nine emerging markets. Their results show the existence of a component structure of volatility, namely the existence of a transitory component to volatility and a permanent volatility that decays over a much longer horizon in three markets (Jordan, Oman and Saudi Arabia). Nikkinen *et al.* (2008) examine the impact of the September 11 attack on markets' returns and volatility including the MENA equity markets. They find that the impact of the attack has a significant increase in volatility across regions and over the study period. Nevertheless, stock returns experience significant negative returns in the short run but recovered quickly afterwards.

Yu and Hassan (2008) use a multivariate AR-GARCH model to examine the international transmission of stock returns and volatility between MENA region and developed countries. The study indicates that there are large positive volatility spillover and volatility persistence in conditional volatility between MENA and the world stock markets. Own volatility spillover were higher than cross volatility spillover for almost all the markets. Hammoudeh *et al.* (2009) investigate the volatility spillover between service, banking and industrial sectors in Kuwait, Qatar, Saudi Arabia and UAE. Eissa *et al.* (2010) examine the presence of volatility spillover between stock returns and exchange rates' changes in Egypt, Morocco and Turkey. Mohanty *et al.* (2011) examine the link between oil price shocks and stock returns at the industry level, the results show a significant positive exposure in twelve out of twenty industries investigated in the GCC. Awartani *et al.* (2013) explore the dynamic spillover of return and volatility between oil and equities in the GCC countries using the Diebold and Yilmaz spillover index. The results indicate that return and volatility transmissions are bidirectional, where oil market gives other markets more than it receives in terms of returns and volatilities.

Beirne *et al.* (2013) model volatility spillover from mature to emerging stock markets to test the changes in the transmission during turbulences in mature markets and examine the implications for conditional correlations between mature and emerging market returns. The study uses tri-variate GARCH-BEKK models of returns in mature, regional and local emerging markets for 41 emerging markets. Results suggest that mature market volatility affects conditional variances in many emerging markets. Also, spillover parameters change during turbulent episodes and that conditional correlations between local and mature markets increase during these episodes. While conditional variances in local markets increase, volatility in mature markets increases more, which is the reason behind the increase in conditional correlations.

Bouri and Azzi (2014) use a multivariate model to show the dynamic mean and volatility interdependence across the markets of Morocco, Tunisia, Egypt, Lebanon, Jordan, Kuwait, Bahrain, Qatar, United Arabic Emirates, Saudi Arabia and Oman from 2005 to 2012. The results show that the Arab Middle East and North African equity markets are interconnected by their volatilities and not by their returns, which makes risk reduction possible. They also found evidence of significant volatility spillover from small to larger markets. Bouri (2015) finds weak unidirectional volatility spillover from oil prices to the Lebanese stock market.

Bouri and Demirer (2016) argue that there is a unidirectional volatility transmission from oil prices to emerging stock markets, especially the net exporting nations of Kuwait, Saudi Arabia and UAE. Maghyereh *et al.* (2016) use a new implied volatility indexes that depends on DY framework to examine the directional connectedness between oil and equities in eleven major stock exchanges around the globe from 2008 to 2015. The results across the sample countries show that connectedness between oil and equity is established by bi-directional information spillover between the two markets. Again the results indicate that the major transmission is from the oil market to equity markets and not vice versa. Basher and Sadorsky (2016) investigate the link between oil and gold and emerging markets equities represented by the MSCI emerging market index. Once more the results indicate that oil is the best asset to hedge emerging market stock prices.

Maghyereh *et al.* (2017) investigate the return and volatility spillover between crude oil, gold and equities, and examine the usefulness of the two commodities in hedging equity portfolios. They use daily data from January 2004 to May 2016 for GCC countries and estimate dynamic correlations and hedge ratios by DCC-GARCH model. Again, the results confirm significant spillover from oil to equities and the dependence of the local economies on oil, while spillover of gold on the stock markets are insignificant.

To sum up, it is clear that examining developed countries is different from examining developing countries. However, different techniques are implemented to examine spillover. The next section discusses the different approaches of measuring spillover.

3.5 Approaches to the measurement of spillover

This section discusses various approaches for measuring spillover. The advantages and limitations of each approach are also provided. Several methods have been suggested for analysing the connectedness, link or relation between markets or countries. For example, some studies focused on spillover of volatility from one market to another (Lee and Kim, 1993), while others considered the shocks to volatility in a GARCH framework (Engle *et al.*, 1990).

These studies can be divided into two categories. The first category concentrates on the relevance of different variables, and employs methods like cointegration test and Granger causality, correlation coefficients, Baba, Engle, Kraft and Kroner generalized autoregressive conditional heteroscedastic (BEKK-GARCH) models, principal-components analysis, and others. Also, it characterizes the structure of interrelationships across markets where GARCH models by Engle *et al.* (1990) allow to see whether conditional variances are affected by additional information in the form of squared innovations occurring in other markets (Gallo *et al.*, 2012). The second category emphasizes the risk spillover measurement and the contribution of individual institutions to systematic risk. Methods like marginal expected shortfall (MES) and the conditional value at risk (CoVaR) are used. Both categories are based on market data and have advantages and disadvantages. More precisely, there are two limitations. First, the lack of a unified framework that considers the relevance of different dimensions, like correlation-based methods are limited to the correlation between variables without taking into account the importance of the entire system. The second limitation is that most of these methods only show correlation levels and not the directions of the connectedness (Xiao *et al.*, 2010).

An approach suggested by Billio and Pelizzon (2003) analyses shock spillover using switching regime models. They argue that there are several reasons why regime switching models represent a good approach to analysing volatility spillover. First, it is possible to see the shifts between high and low states of volatility and correlations due to changes in the economic and financial context. Second, it reduces the persistence in second moments. Therefore, the underestimation of volatility problem in high volatility state or the one of overestimated volatility in the low volatility state is overcome. Lastly, it allows for the fact that the time varying character of conditional correlations is due to regime switches in the spillover parameters. For the link between stock markets, the general switching regime models are used for a better description and understanding of these relations (Billio and Pelizzon, 2003).

Other studies adopt the same framework in their analysis such as Psaradakis's *et al*. (2005) study. The authors apply the same framework to analyse the changes in the Granger causality. Beckmann's *et al*. (2014) employ the advanced Markov switching vector error correction model (VECM) with shifts in the adjustment coefficients and the variance covariance matrix by applying a Gibbs sampler to analyse the relationship between global liquidity and commodity prices. The main limitation of these studies is that the analysis of spillover on bivariate cases due to the complexity of their designs even when applied to multiple dependent variables, the transmission mechanism is still investigated for one pair of variables at a time (Bensaïda *et al*., 2018). Leung *et al*. (2017) try to avoid the complexity of the models by adding a dummy variable in a simple regression framework to analyse possible changes of volatility spillover during crises. Nevertheless, in order to examine this model, crises periods must be defined in advance, excluding any shocks or burst that may follow major events.

The Global Vector Autoregressions approach (GVARs) study cross country spillover across financial and macroeconomic variables by taking into account international linkages. It is worth noting that this approach provides a global consistency framework for a system of country level time series analysis that exploits cross sectional relationships. GVAR models simply accommodate spillover from the global economy in a systematic and transparent manner. It consists of a single country models that are stacked to yield a comprehensive representation of the world economy (Cuaresma *et al.*, 2016). According to Chudik *et al.* (2013), this approach is proven to be very useful in analysing interactions in the global macro economy and other data networks where both the cross section and the time dimensions are large. Several studies adopt this framework, such as Dées *et al.*

(2007). The results of their study show that equity and bond market in the US and the euro area follow each other quite closely, while monetary policy shocks in US have insignificant effects on the output and inflation in the euro area.

Some studies on volatility spillover employ versions of the GARCH model (Li and Giles, 2013; Lin, 2013). However, the ability to measure spillover by those type of models is limited in their lack of spillover dynamics, therefore recent developments introduced a new way to capture volatility spillover more effectively.

In an attempt to mitigate the above problems, Diebold and Yilmaz (2009) develop and apply a unified framework for conceptualizing and empirically measuring connectedness at various levels. First, they come up with a simple measure of interdependence of asset returns and volatilities that is based on the forecast error variance decomposition from the vector autoregressive models (VARs) of Engle *et al.* (1990). For the Diebold and Yilmaz framework (DY), they set each asset as i then add the shares of its forecast error variance coming from shocks to asset j, for all $j \neq i$, and then add across all $i = 1, \dots . N$. In order to minimize notational clutter, consider a covariance stationary first-order two-variable VAR,

$$x_t = \Phi x_{t-1} + \varepsilon_t, \tag{3.1}$$

where $x_t = (x_{1t}, x_{2t})$ and Φ is a 2×2 parameter matrix. So, here x_t will be a vector of stock return volatilities. The moving average representation of the VAR will be:

$$x_t = \Theta(L)\varepsilon_t, \tag{3.2}$$

where $\Theta(L) = (I - \Phi \mathrm{L})^{-1}$. Rewriting the moving average as $x_t = A(L)u_t$, where $A(L) = \Theta(L)Q_t^{-1}$, $u_t = Q_t\varepsilon_t$, $E(u_t u_t') = I$, and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ε_t. If considering 1-step ahead forecasting, $x_{t+1,t} = \Phi x_t$, with corresponding 1-step ahead error vector:

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \tag{3.3}$$

which has covariance matrix

$$E\left(e_{t+1,t}e_{t+1,t}'\right) = A_0 A_0' \tag{3.4}$$

Therefore, the variance of the 1-step ahead error in forecasting x_{1t} is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the 1-step-ahead error in forecasting x_{2t} is $a_{0,21}^2 + a_{0,22}^2$. If we take a simple 2 variable example: x_{1t} shocks that affect the forecast error variance of x_{2t} with contribution $a_{0,21}^2$, and x_{2t} shocks that affect the forecast error variance of x_{1t} with contribution $a_{0,12}^2$, then the total spillover is $a_{0,21}^2 + a_{0,22}^2$. The total forecast error will be $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = trace(A_0 A_0)$. The spillover index is:

$$S = \frac{a_{0,21}^2 + a_{0,22}^2}{trace(A_0 A_0)} \times 100 \tag{3.5}$$

For the general p^{th} order N-variable VAR, using H-step-ahead forecast the spillover index is:

$$S = \frac{\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{h,ij}^{2}}{\sum_{h=0}^{H-1} trace(A_0 A_0)} \tag{3.6}$$

However, this approach depends on the Cholesky-factor identification of the VARs where the results are dependent on the ordering of variables. Therefore, Diebold and Yilmaz (2012) introduce an extension method of measuring total and directional spillover in a generalized VAR framework in which the results are invariant to ordering of variables.

Diebold and Yilmaz (2012) base their extension on Pesaran and Shin (1998) making the spillover metric invariant to order by using a generalized impulse response function that does not require orthogonalization by Cholesky decomposition and construct directional indices. The new DY index measures both total and directional volatility spillover. They solve the previous DY problem by exploiting the GVAR framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), known as the KPPS that produces variance decompositions invariant to ordering. This approach allows correlated shocks but accounts for them appropriately using the historically observed distribution of the errors. Since each variable shock is not orthogonalized, the sum of contributions to the variance of forecast error is not necessary equal to one. Denote the KPPS H-step-ahead forecast error variance decompositions by $\theta_{ij}^{g}(H)$, for H = 1,2,….. Then, we have

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)^2} \tag{3.7}$$

where $\sum$ is the variance matrix for the error vector ε, σ_{ii} is the standard deviation of the error term for the ith equation and e_i is the selection vector with one as the ith element and zeros otherwise. Using the information available in the variance decomposition matrix in the calculation of the spillover index, we normalize each entry of the variance decomposition matrix by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3.7}$$

By using the KPPS variance decomposition, the total volatility spillover index is given by

$$S^{g}(H) = \frac{\sum_{i,j=1\ i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1\ i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3.8}$$

The total spillover index measures the contribution of spillover of volatility shocks across asset classes to the total forecast error variance. After calculating total spillover, we then look at the directional volatility spillover. Directional volatility spillover received by market i from all other markets is given by

$$S_{i\cdot}^{g}(H) = \frac{\sum_{i,j=1\ i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{3.9}$$

Directional volatility spillover transmitted by market i to all other markets is given by

$$S_{\cdot i}^{g}(H) = \frac{\sum_{i,j=1\ i\neq j}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 \tag{3.10}$$

Even though the new extension is more flexible, it does not distinguish the potential asymmetry in spillover that originate due to bad and good volatility. Another limitation is that both DY frameworks use daily or weekly range based volatility of Garman and Klass (1980) to compute spillover. Range based estimators give an efficient way of estimating volatility but high frequency data can further improve the understanding of the transmission mechanism.

One of the main criticism for the DY framework is that it does not identify whether or not the spillover from one market to another is significantly different from zero. Thus, in order to determine the significance of this estimated spillover index, the standard errors of the estimated index as well as its sampling distribution are required. Despite the importance of identifying the significance of spillover estimates, there are no available statistical methods for the standard errors of the volatility spillover indexes.

Choi and Shin (2018) suggest applying bootstrapping to estimate standard errors and confidence interval estimations of the Diebold and Yilmaz index as it is considered as one of the commonly used approaches in the literature to estimate standard errors and confidence interval of the results better than the usual methods. The next section defines bootstrapping and provide more details about the approach.

3.6 Bootstrapping

Generally, hypothesis testing is basically comparing the observed value of a test statistic with the distribution that it would follow if the null hypothesis was true. The null is then rejected if the test statistic is sufficiently extreme relative to this distribution. There are two scenarios for the test statistic and distribution. The primary scenario is where the distribution is known. The standard t or F tests on the coefficients of a linear regression model with exogenous repressors and normal errors can then be performed. The second scenario, which is often encountered by econometricians is where the distribution of the test statistic is not known. As a result, we need to compare the observed value of the test statistic with a distribution that is only approximately correct. Usually, these approximations are based on asymptotic theory (MacKinnon, 2009). Asymptotic theory typically derives the properties of estimators and tests in the limit as the sample size grows infinitely (Robinson and White, 1988).

A useful alternative is bootstrapping (MacKinnon, 2009) which generates a large number of simulated values of the test statistic and compares the observed value of the test statistic with the empirical distribution function of the simulated ones. It is becoming more common to use the bootstrap to perform hypothesis tests in econometrics. The bootstrap usage is encouraged by Horowitz (1994, 1997), Davidson and MacKinnon (1999) and several others.

Bootstrapping is a method for estimating the distribution of an estimator or t-statistic by resampling the data or a model estimated from the data (Horowitz, 2001). Bootstrapping is close to simulation but the difference is that the simulation of the data is constructed completely artificially, while bootstrapping obtains a description of the properties of empirical estimators by using the sample data points themselves and sampling repeatedly with replacement using the sample data themselves (Godfrey, 2009). As Davidson and MacKinnon (2000) mention, bootstrap is a statistical technique that is usually implemented by simulation. However, simulation is not a necessary element of the bootstrap. Generally, bootstrapping determines the accuracy to an estimated sample by relying on random sampling with replacement. It can be categorized under the resampling methods. Basically, bootstrapping is the inference about a population from sample data that is modelled by resampling the sample data and performing inference about a sample from resampled data (Chong and Choo, 2011). In bootstrap resamples the population is the sample and the quality of inference of the true sample from resampled data is measurable. It treats the data as if it is a population in order to evaluate the distribution of interest (Horowitz, 2001).

The term "bootstrap" started to appear around the eighteenth century in the stories of The Adventures of Baron Munchausen by Rudolph Erich. Where the Baron apparently falls to the bottom of a deep lake and he seemed that he lost everything. Then, he saves himself by picking himself up by his own bootstraps (Davison and Hinkley, 1997). Stout *et al.* (1999) argues that the bootstrap methods are commonly used by statistics professionals, algebra-based statistics texts and several others.

Efron (1979) introduced the term "bootstrap" but it did not become popular until the late 1990s, where most of the theories and methods of bootstrapping developed during this period. Horowitz (2003) defines "bootstrapping" as a method for estimating the distribution of an estimator or test statistic by resampling the data from the sample data. The author explains that the bootstrap gives an approximation to the distribution of an estimator or test statistic that is at least as accurate as and often more accurate than the approximation obtained from first order asymptotic theory.

Based on the bootstrapping sample, a statistic is estimated and recorded, then this process is repeated by another bootstrap sample in which a statistic is calculated and recorded.

This process is usually repeated several times such that the number of bootstrap samples are large, for example 1000 times. Generally, bootstrapping is used to get a general approach to understanding the characteristics of a population by using the statistics that were calculated on each of the bootstrap samples. Bootstrapping for most of the cases is accurate, but it can be inaccurate and misleading if it is used incorrectly. For example, when it includes inference about a parameter that is on the boundary of the parameter set, inference about the maximum or minimum of random variables, and inference in the presence of weak instruments (Davidson and MacKinnon, 2000). As Johnson (2001) argues that bootstrap methods are more flexible than classical methods which may be analytically intractable or unusable because of a lack of the appropriate assumptions being satisfied. The next section provides the advantages and disadvantages of bootstrapping along with the situations where bootstrapping is ineffective.

3.6.1 Advantages and Disadvantages

The major advantage of bootstrapping is its simplicity. It derives estimates of standard errors and confidence intervals for complex estimators of complex parameters of the distribution such as the correlation coefficient. Another advantage is providing a way to control and check the stability and accuracy of the results. It is more accurate than the standard intervals obtained using sample variance and assumptions of normality. This advantage is actually the reason behind using bootstrapping in this thesis. Furthermore, bootstrapping avoids repeating the study in case of experiments, getting another group of sample data which excludes additional costs. Another advantage of bootstrapping over the use of analytical results is allowing the researcher to make inferences without making strong distributional assumptions, since the employed distribution will be that of the actual data. It empirically involves estimating the sampling distribution by looking at the variation of the statistic within a sample (Brooks, 2015).

On the other hand, there are disadvantages for bootstrapping. Bootstrapping does not provide finite sample guarantees where the results depend on the representative sample. Another disadvantage is that it can be time consuming but this can be solved by the software that can calculate it automatically. The number of bootstrap applications in finance and in econometrics have recently increased which added power and speed to it (Brooks, 2015). While bootstrapping has extensively been discussed in the popular press (e.g., Harnish, 2002; Gendron, 1999), it does not widely appear in the academic literature in the form of prescriptive work, theoretical development, qualitative studies, or empirical analyses (Winborg and Landström, 2001).

3.7 Bootstrap Standard Errors and Confidence Interval

Originally, the bootstrap was proposed to as a method for computing standard errors (Erfan, 1979). This is valuable when there are no other methods to compute the standard error which is the case here with estimating the standard error of the DY framework. If $\hat{\theta}$ is a parameter estimate, $\hat{\theta}_j^*$ is the corresponding estimate for the j^{th} bootstrap replication, and $\bar{\theta}^*$ is the mean of the series $\hat{\theta}_1^*, \ldots, \hat{\theta}_B^*$, then the bootstrap standard error is:

$$s^*(\hat{\theta}) = \left(\frac{1}{B-1}\sum_{j=1}^{B}(\hat{\theta}_j^* - \bar{\theta}^*)^2\right)^{1/2} \tag{3.11}$$

This is simply the standard deviation of the $\hat{\theta}_j^*$'s. We can use $s^*(\hat{\theta})$ in the same way as we use any other asymptotically valid standard error to construct asymptotic confidence interval or perform asymptotic tests. However, there are cases where bootstrap standard errors are not useful, for example in the ordinary least squares it makes no sense to use bootstrap standard errors (Mackinnon, 2006).

Furthermore, statisticians have written extensive literature on different ways to construct bootstrap confidence intervals. An overview of this literature is provided by Davison and Hinkley (1997). The simplest approach is to calculate the bootstrap standard error in equation 4.8 and to use it to construct a confidence interval based on the normal distribution:

$$\hat{\theta} - s^*(\hat{\theta})\, z_{\frac{1-\alpha}{2}}, \qquad \hat{\theta} + s^*(\hat{\theta})\, z_{\frac{1-\alpha}{2}} \tag{3.12}$$

Here $z_{\frac{1-\alpha}{2}}$ denotes the $\frac{1-\alpha}{2}$ quantile of the standard normal distribution. If $\alpha = 0.05$, this is equal to 1.96. It is not proven that this simple bootstrap interval is better or worse than any other interval based on asymptotic theory. However, it is used when there is no way to calculate a standard error analytically or when asymptotic standard errors are unreliable.

In theory, the percentile t method also known as bootstrap t and Studentized bootstrap has better properties than the simple bootstrap interval advocated by Hall (1992). A percentile t confidence interval for θ at level $1-\alpha$ is

$$\hat{\theta} - s(\hat{\theta})\, t^*_{\frac{1-\alpha}{2}}, \qquad \hat{\theta} - \hat{s}(\hat{\theta})\, t^*_{\frac{\alpha}{2}} \tag{3.13}$$

where $s(\hat{\theta})$ is the standard error of $\hat{\theta}$, and t^*_{δ} is the δ quantile of the bootstrap t statistics

$$t_j^* = \frac{\hat{\theta}_j^* - \hat{\theta}}{s(\hat{\theta}_j^*)} \tag{3.14}$$

For example, if $\alpha = 0.05$ and $B = 999$, $t_{\frac{1-\alpha}{2}}^*$ will be number 975, and $t_{\frac{\alpha}{2}}^*$ will be number 25 in the sorted list of the t_j^*. In order for the quantiles of the distribution of the t_j^* to be estimated accurately, then the value should be large. As with the bootstrap the B should be chosen in a way that $\alpha(B+1)$ is an integer. This method cannot be used if $s(\hat{\theta})$ cannot be calculated. It should not be used if $s(\hat{\theta})$ is unreliable or strongly dependent on $\hat{\theta}$ (MacKinnon, 2006). The following section discusses different bootstrapping methods.

3.8 Bootstrapping Methods

Highlighting the light on bootstrap is incomplete without mentioning the different bootstrap methods. The first and hardest step is deciding on what method of bootstrap to use in any situation. There are a variety of different bootstrap methods and applications. A bootstrap method works well in some settings, while it does not work well in other settings. Conditional on the choice of bootstrap, there are then a number of other substantive decisions to be made. Since it is exhaustive to provide a review of all different bootstrap methods, a focus on the most commonly used methods and that can be applicable to our study.

There are types of bootstrap where the bootstrap samples involve a random number generator which is called bootstrap data generating process (DGP). The bootstrap DGP is for regression models with uncorrelated error terms. Since the error terms are independent, the bootstrap residuals are also independent. However, the residual bootstrap is not applicable if the error terms are not independently and identically distributed.

On the other hand, there are other types of bootstrap that can handle models with dependent errors. The most popular methods are block bootstrap and stationary bootstrap. The former resamples blocks of consecutive observations instead of individual observations, while the latter is similar to block bootstrap with random block lengths (Härdle *et al*, 2003). The block bootstrap is the most general method to improve the accuracy of bootstrap for time series data. These blocks can be overlapping or non-overlapping, and may be fixed or variable in length care then resampled. The accuracy of the block bootstrap is sensitive to the block length chosen and the optimal block length depends on the sample size, the data generating process, and the statistic considered. One of the advantages of the block of blocks bootstrap is that it can be used with almost any sort of dynamic model and that it handles heteroscedasticity and serial correlation (MacKinnon, 2006).

3.9 Conclusion

This chapter explains volatility spillover, and discusses various computational and technical aspects of measuring and modelling market connectedness, and offers an extensive review of prior literature. The significance of studying stock market volatility spillover is highlighted. According to Bouri and Azzi (2014), analysing and gathering information about the risk of equity markets are important components of financial decision making. Thus, the degree of interdependence between the volatility of markets is the key variable to risk and portfolio managers.

Some studies (Neaime and Colton, 2005; Yu and Hassan, 2008) attempt to study market interrelationships, return co-movements and volatility spillover. Others have examined the return and univariate analysis of volatility in selected MENA markets (Neaime, 2006; Nikkinen *et al.*, 2008). However, few studies have focused on the interdependence between volatility of returns in MENA markets. Therefore, studying the volatility spillover in the MENA region sheds light on the dynamics and degree of volatility transmissions across the MENA markets, which would help policymakers, regulators and risk managers make their decisions.

The different approaches of examining volatility spillover are discussed and the most common approach (Diebold and Yilmaz framework) is highlighted, providing its significance as well as its limitations. One of the main criticisms of this approach is not identifying whether or not the spillover from one market to another is significantly different from zero. Following the steps of Choi and Shin (2018), bootstrapping is applied to estimate standard errors and confidence interval estimations of the Diebold and Yilmaz index as it is considered as one of the most commonly used approaches in the literature to estimate standard errors and confidence interval of the results.

Chapter 4

Herding Behaviour

4.1 Introduction

The empirical analysis of herding behaviour has received considerable attention in the recent finance literature (Zhou and Anderson, 2013). The notion of herding is found in different settings from neurology and zoology to sociology, psychology, economics and finance. With regards to economics and finance, herding refers to the process where economic agents are imitating each other's actions and base their decisions upon the actions of others (Spyrou, 2013). In its simplest form, herding is the result of buying and selling the same stocks in the same period. It is based on the fact that less informed investors copy others because they believe that other investors are more informed and have better access to information than them (Medhioub and Chaffai, 2019).

This chapter aims to discuss the different definitions of herding, how herding differs with different market conditions, different types of herding, and different methods of measuring herding behaviour in markets respectively. Section 4.2 explains herding from different point of views and provide several definitions. Section 4.3 points out the importance of herding. As for Section 4.4, it tackles the different measuring approaches of herding behaviour. Section 4.5 provides the several methods of measuring herding. Section 4.6 shed the light on previous studies that examined herding behaviour. Finally, Section 4.7 summarizes the most important points.

4.2 Defining Herding

According to Banerjee (1992, pp.798), herding behaviour is defined as “doing what everyone else is doing, even when one’s private information suggests doing something else.” Moreover, Nofsinger and Sias (1999) state that herding is defined as a group of investors trading in the same direction over a period of time. The understanding of investors’ behaviour in stock market is one of the issues that puzzled researchers and practitioners (Ramadan, 2015). The efficient market hypothesis assumes that markets are efficient and that asset prices fully reflect all available information. This implies that the investment decisions of investors are entirely based on the set of information they hold. However, recently behavioural analysts in finance, observed the propensity of investors to ignore their own beliefs and prior information over market consensus when trading in assets (Galariotis *et al.*, 2015; Holmes *et al*., 2013). Following Bernales *et al.* (2016), this behaviour has significant implications where it not only causes asset prices to deviate from their fundamental values, but also aggravates volatility, destabilizes markets, and increases the vulnerability of the financial system. Bikhchandani and Sharma (2000) claim that investors in financial markets herd when they suppress their personal decisions in favour of the collective view of the market even when they do not think that this view is right. In a similar vein, Cote and Sanders (1997) define herding as individuals alter their private beliefs to correspond more closely with the publicly expressed opinions of others.

It is worth noting that the concept of herding is located between classical and behavioural finance (Filip *et al.*, 2015). The theory of market efficiency assume that a stock market is efficient if prices reflect all the information available at the time and thus investors have rational expectations about the evolution of the future prices. The hypothesis of market efficiency has been disputed by both theoreticians and practitioners and its main weaknesses are highlighted in the literature (Poterba and Summers, 1986). The answer to all the anomalies that could not be explained by traditional financial models is in behavioural finance. Therefore, the herding behaviour became a common explanation for the excess market volatility, which causes deviations of the stock prices from their fundamental values, hence, taking into account the human component and try to find a link between the individuals' psychology and the variations of stock prices (Filip *et al.*, 2015).

Banerjee and Padhan (2017) argue that herding behaviour has drawn extensive attention in behavioural finance literature recently. They define herding behaviour as convergence behaviour, where market participants tend to suppress personal beliefs to follow the bandwagon in trading assets. They also argue that this behaviour is considered to be unlikely rational in view of personal preferences in portfolio building, returns expectations and investment horizon; resulting in driving away assets prices from its intrinsic value and this divergence in pricing results in creating arbitrage opportunities to earn abnormal profits. The long term herding is harmful since it leads to inefficient and destabilized markets, given the fact that since assets fail to converge to its fundamental value as herding persists in market segments.

In light with the above discussion, the concept of herding is used in several different spectrums, like neurology, zoology, sociology, psychology, economics and finance. Specifically, the term "herding" or "herd behaviour" refers to the process where economic agents are imitating each other actions basing their decisions upon the actions of others.

There are several reasons behind the herding action regardless to the fact that the market participants infer information from previous participants, investors being irrational due to psychological or social conventions, reacting to the arrival of fundamental information, or analysts herding to protect reputation (Spyrou, 2013).

4.3 Importance of Herding

Examining herding behaviour is vital to academia, practitioners, and policymakers. For academics, herding contradicts the rational asset pricing theory which accentuates the importance of fundamentals on stock pricing and thus has important theoretical implications for asset pricing and asset pricing models. With regards to practitioners, herding may drive stock prices away from fundamental values and present profitable trading opportunities. For policymakers, herding may destabilize markets and increase the fragility of financial systems (Christie and Huang, 1995). As Welch (2000, p.370) puts it: "herding in financial markets, in particular, is often presumed to be pervasive, even though the extant empirical evidence is surprisingly sparse". Similarly, Christie and Huang (1995) argue that herding has become of particular interest in order to understand empirical realities given the fact that individual investors tend to mimic the actions of others.

Even though earlier studies established a logical link between market volatility and herd behaviour (Bikhchandani *et al.*, 1992), few studies in the literature have empirically examined the relative roles of a market's own volatility and external factors in driving market states where herd behaviour is observed. The previous literature reveals that herding in the stock market measured by dispersion around market return is found during periods of significant changes in stock prices (Caparrelli *et al.*, 2004). According to

Christie and Huang (1995), herding is more likely to occur under conditions of market stress where individual investors tend to suppress their own beliefs and follow the market consensus, which makes it very informative to analyse these periods.

The market efficiency concern arose from the empirical findings that asset prices display more volatility than predicted by expected returns or fundamentals (Lux, 1995). Hence, in order to provide an explanation for these observed facts, Christie and Huang (1995) state that the influence of herding behaviour in the financial market is the most frequently used explanation. It is worth mentioning that the herding behaviour has become an exciting topic in literature post the financial crisis. This is due to the fact that excess volatility destabilizes financial markets and increases the fragility of financial systems. Therefore, herding behaviour may lead to incorrect assessment of stock prices, and investors may depart from rationality through the subjective influence of expectations regarding the future evolution of risk and cash flows.

The academic literature consists of several models of herd behaviour in financial markets. For instance, Froot *et al.* (1992) propose a model in which managers ignore their own private information and herd on the investment decisions of others. Trueman (1992) demonstrates that individual analysts may herd towards earnings forecasts issued by other analysts. Bikhchandani *et al*. (1992) use a model that attempts to explain conformity and short-lived phenomena such as fads and fashions. Meanwhile, Banerjee (1992) develops a model of herd behaviour that is not affected by the incentive problems inherent in principal-agent relationships. Welch (1992) implements a model to explain how sequential issues of the initial public offerings (new security) can lead investors to ignore their private information and herd on the decisions of earlier investors.

Other studies, such as Economou *et al.* (2011), postulate that market prices may deviate from fundamental values due to liquidity constraints and information asymmetries during financial crises. Also, Lin's *et al*. (2013) examine the relationships between herding of various investor groups and trading noise in the Taiwan stock market. The results suggest that rational herding is taken by institutional investors while irrational herding is taken by individuals. Herding of foreign institutions reduces trading noise in the subsequent periods during both the crisis period and the non-crisis period, whereas individual herding results in persistently high trading noise. Furthermore, the study also reveals that although domestic institutions present informational herding, they cannot acquire information as well as foreign institutions, where their herding increases subsequent trading noise during the non-crisis period. Moreover, the study emphasizes the fact that institutional investors' buy or sell herding predicts future upward or downward price movements, while individual investors' buy or sell herding negatively correlates with future returns. Hence, supporting the view that institutional investors are informed traders while individuals are uninformed.

The herd behaviour is common between investors and is considered a main reason behind periods of high volatility and market instability. Economists suggest that herding may lead to destabilizing prices and lead to bubble-like episodes in financial markets (Spyrou, 2013). According to Christie and Huang (1995) and Chang *et al.* (2000), investors will be more likely to suppress their own beliefs and copy the behaviour of others during periods of market stress. Thus, market volatility is an important factor that may cause herding. Likewise, Balcilar *et al.* (2013) associate the market conditions during the herd behaviour with crashes and extreme volatility periods. On the same token, Kodres and Pritsker

(2002) argue that bad news and financial crises contribute to market volatility and herd behaviour in extreme market movements. Thus, there is evidence on the link between market volatility and herd behaviour, with the relationship displaying an asymmetric pattern relative to the sign of the market direction (Balcilar *et al*., 2014).

It is also important to focus on the causes driving investors to cluster their trades. Different causes of herding may result in distinct effects on financial markets. In addition, it is important to ascertain whether the investor herd behaviour is rational or irrational, and to distinguish information-based from non-information-based herding (Lin *et al*. 2013). More details of the categories of herding are discussed in the next section.

4.4 Categories of Herding

The herding behaviour literature can be divided into two categories: theoretical and empirical studies. In light of achieving an overview of theoretical and empirical frameworks about herding of investors from stock markets, Bikhchandani and Sharma (2000) emphasize the distinction between intentional herding and unintentional herding behaviour. Herding can be simply defined as copying the behaviour of other investors intentionally or unintentionally. Although it may lead to market inefficiencies, for investors, herding behaviour can be rational. Intentional herding behaviour refers to the clear intention of the investors to imitate the behaviour of other participants in the market. With regard to false herding behaviour, it is based on the situation where a group of investors face the same information and expectation in taking an investment decision and then take similar trading decisions. For example, a change in regulation often leads fund managers to take similar decisions.

Moreover, the existing theoretical studies have focused on the causes and implications of herding. Herding is mainly interpreted as either being a rational or irrational form of investment behaviours. Early studies argued that herding is rational when a group of investors assume that other investors are more informed (Bikhchandani *et al.*, 1992) or when portfolio managers, -despite suspecting the over inflation of asset prices- follow the herd to protect their reputation (Graham, 1999). Similarly, herd behaviour can be a rational choice if investors do not have long horizons. As Froot *et al.* (1992) show, if speculators have short horizons, they may herd on the same information trying to learn what other informed investors know.

Bikhchandani and Sharma (2000) argue that the rational view concentrate on the principal-agent problem in which investors mimic the actions of others and completely ignore their own private information to maintain their reputational capital in the market. They identified three potential causes of rational herding behaviour. First imperfect information is the most frequent, also known as herding due to informational cascade. Consider the case where 10 investors are faced with a dilemma of whether or not to invest in a certain stock. After each of investors evaluate the potential investment on the stock market independently, three of the investors consider that the stock is profitable while the other seven consider that it is not. When the investors from the first group enter to invest on that stock, some individuals from the second group may change their opinion since they believe that the investors from the first group hold privileged information regarding the profitability of the investment, information that is reflected by their actions. Second, a potential cause is the concern of reputation which occurs when a manager and his employees are not sure about the manager's ability to select suitable assets for investments. Hence, the manager then could adopt a behaviour consistent with other professionals which leads to the occurrence of herding behaviour. The third potential cause is the compensatory structures of the fund managers which exist when a manger remuneration depends on his performance compared with the performance of the other managers, or with the performance of a benchmark index. Manager may be tempted to follow the benchmark, hence herding behaviour occurs.

Furthermore, Devenow and Welch (1996) differentiate between rational and irrational herding. They argue that rational herding is information, that is, rational investors with similar stock preferences adopt the same response to similar information about the company characteristics or fundamentals. In rational herding, prices move toward the fundamental value of assets, and price movement is not likely to reverse. On the other hand, irrational herding occurs when investors with insufficient information and inadequate risk evaluation disregard their prior beliefs and blindly follow other investors' actions. The non-rational herd behaviour can arise as the consequence of psychological stimuli and restraints, such as pressure from social circles and/or social conventions. Hung *et al.* (2010) argue that the non-information based herding might lead to market inefficiencies, drive asset prices away from fundamental values and cause asset mispricing.

Keynes (1936) argues that investors are affected by sociological factors that may drive market participants to imitate the actions of others during periods of uncertainty. It is vital to emphasize that herding is irrational when some short-term noise investors tend to be spontaneous and their trading decisions are based on irrational excitement, fear, or greed. Typically, these noise investors follow informed investors and market trends and react to good and bad news (Cipriani and Guarino, 2005). Baddeley *et al.* (2004) show that even experts may resort to herd behaviour, given information scarcity, asymmetry and the employment of common heuristic rules.

On a different note, empirical studies are mostly concentrated on detecting the existence of herding behaviours. Generally, the empirical support is mixed. Shiller *et al.* (1989) provide evidence survey on herding among institutional investors finding them placing significant weight on the advice of other professionals on their buy and sell decisions in volatile stocks. Lakonishok *et al*. (1992) find weak evidence of herding among small stocks and no evidence of herding among large stocks.

There are two main streams of empirical studies, the group-wide herding and the market-wide herding. The group-wide herding is herding activities among certain groups of investors, such as mutual fund managers and financial analysts which require detailed records of investors' trading activities. The market-wide herding is the collective behaviours of all investors towards the market view which may cause mispricing of individual assets. This is usually examined using the cross-sectional dispersion of stock returns where the dispersion is expected to decline upon the occurrence of herding causing the individual stock returns to cluster around the overall market return. Therefore, investigating the relation between dispersion and market return provides insights for the existence of herding (Zhou and Anderson, 2013).

Moreover, Filip *et al.* (2015) argue that there is a seamless connection between the theoretical background and the empirical evidence because the theoretical models are more often abstract. The majority of the empirical studies does not test the specific theoretical models but they only verify the occurrence of simultaneous decisions on the stock market or in a particular group of investors.

Furthermore, Bikhchandani and Sharma (2000) differentiate between ‘spurious’ (unintentional) herding where investors face a similar fundamental-driven information set and thus make similar decisions and ‘true’ (intentional) herding where investors intentionally copy the behaviour of others. The ‘spurious’ herding may lead to an efficient outcome, whereas, the ‘true’ herding may not lead to efficient outcome but may lead to fragile markets, excess volatility, and systemic risk. Intentional herding is the result of the imitation on investors of others’ actions, while with unintentional herding investors don’t imitate but base their reactions and decisions on public information and similar problems. However, it is impossible to differentiate between the two since investment decisions depend on a multitude of factors (Bikhchandani and Sharma, 2000).

4.5 Measures of Herding

An important question is why some investors disregard market fundamentals in equity markets and follow what others do (Borensztein and Gelos, 2003). Despite the evidence in the literature, there remains an open discussion about the type of investment behaviour especially in developing markets rather than advanced ones. Theories and empirical research on herding do not seem to settle on a unified accepted norm and computation. Also, Hwang and Salmon (2007) argue that there is no accepted method that separates investor behaviour due to herding or reaction to fundamentals.

There are different approaches of measuring herding behaviour. Some of the empirical methodologies for herd behaviour can be classified into two main categories. The first category focuses on explaining the behaviour of investors whether institutional or private in following the actions of others. This phenomenon can be classified as rational when such investors are following the majority or group of investors who may be perceived to have access to better information (Puckett and Yan, 2007).

Concerning the second category, it relies on aggregate price and market activity data to investigate herding towards the market consensus which employs a “market-wide” approach. The most two common measures for the first category are proposed by Lakonishok *et al*. (1992) and Sias (2004) and the most two commonly used measures for the second category are proposed by Christie and Huang (1995) and Chang *et al.* (2000).

The former common metric proposed by Lakonishok *et al.* (1992) is known as the LSV. The LSV measure is simple. Specifically, if there is a tendency of money managers to disproportionately buy an individual stock, then it can be concluded that there is herding at the same level of individual stocks. This is computed by the proportion of net buyers (money managers who increase their holdings in a stock during a given quarter) relative to the total money managers who trade that stock minus an adjustment factor that declines as the number of money managers active in that stock rises. Herding is detected if there is a significant cross-sectional variation in the measure, while no herding is present if the expected value did not vary from period to period. The LSV herding measure, H, is calculated as:

$$H(i) = \left|\frac{B(i)}{B(i)+S(i)} - p(t)\right| - AF(i) \tag{4.1}$$

where $B(i)$ is the number of money managers who are not net buyers, $S(i)$ is the number of money managers who are net sellers, $p(t)$ is the expected proportion of money managers buying in that quarter relative to the number active, and the adjustment factor, $AF(i)$, is the expected value of $\left|\frac{B}{B+S} - p\right|$ under the null hypothesis of no herding. For any stock, AF declines as the number of money managers active in that stock rises (Lakonishok *et al.*, 1992, pp.29-30).

Similarly, Sias (2004) argues that the proportion of institutional investors buying this quarter will covary across assets with the proportion of institutional investors buying last quarter. If the institutional investors herd, then herding can be evaluated by estimating the cross-sectional correlation between demand for an asset by institutional investors last quarter and demand for the asset by institutional investors this quarter. Sias (2004) estimates every institutional investor's position in every asset as a fraction of the asset's shares outstanding at both the beginning and the end of each quarter. When the institutional investor increases ownership in the stock, then the investor is a buyer and for each stock quarter the portion of investors that are buyers is estimated. The ratio denoted as "raw fraction of institutions buying" and estimated as:

$$Raw\Delta_{k,t} = \frac{BI_{k,t}}{BI_{k,t} + SI_{k,t}} \tag{4.2}$$

where BI is the number of institutions buying asset k during quarter t, and SI is the number of institutions selling asset k during quarter t. Sias (2004) standardizes the fraction of institutional investors buying asset k in quarter t in order to allow aggregation over time and comparison for different market capitalizations and investor types.

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_{k,t}}}{\sigma(Raw\Delta_{k,t})} \tag{4.3}$$

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \tag{4.4}$$

Following this pattern of estimation, Sias (2004, p.172) argues that "if the institutional investors follow each other into and out of the same securities (herd), or if individual institutional investors follow their own last quarter trades, then the fraction of institutions buying in the current quarter will be positively correlated with the fraction of institutions buying in the previous quarter". Therefore, the difference between LSV and Sias measures are that LSV tests indirectly for cross-sectional temporal dependence within periods, whereas Sias is a direct test of whether institutional investors follow each other's trades during the following periods.

Additionally, there is another approach proposed by Christie and Huang (1995) that measures investor herding towards the market consensus. This type of herding is market-based, referring to subgroups of investors behaving alike and simultaneously buying and selling the same assets. This approach intends to detect herding in special periods of extreme movements in returns. However, herding does not always occur during turmoil periods only. Christie and Huang's study suggest that herding can be analysed using cross-sectional methods for asset returns, where a smaller cross-sectional dispersion of returns indicates parallel movements with the cross-sectional mean return. They used this method to detect herding in special periods of extreme upward and downward movements in returns.

Christie and Huang (1995) estimate the cross-sectional standard deviation (CSSD) of single stock returns with respect to market returns, which is expressed as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}} \tag{4.5}$$

where $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is the cross-sectional average return of the N returns in the market portfolio at time t, and N is the number of stocks in the market portfolio. Afterwards, the CSSD of returns is regressed against a constant and two dummies in order to identify the extreme market phases. First, $D^L = 1$ if the market return on day t lies in the extreme 1% and 5% lower tail of the distribution of market returns (and zero otherwise). Second, $D^U = 1$ if it lies in the extreme 1% and 5% upper tail of the same distribution (and zero otherwise):

$$CSSD_t = \alpha + b_1 D_t^L + b_2 D_t^U + e_t \tag{4.6}$$

where the α coefficient denotes the average dispersion of the sample excluding the regions corresponding to the two dummy variables. To indicate the presence of herd behaviour, the b_1 and b_2 should show statistically significant negative values. However, the cross-sectional standard deviation of returns can be considerably affected by the existence of outliers. That is why Chang *et al*. (2000) propose the use of the cross-sectional absolute deviation (CSAD) as a better measure of dispersion:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{4.7}$$

where $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is the cross-sectional average return of N stocks in the portfolio at time t, and N is the number of stocks in the portfolio. The equation for the CSAD corresponds to equation (4.6) in order to identify extreme market phases:

$$CSAD_t = a + b_1 D_t^L + b_2 D_t^U + e_t \tag{4.8}$$

The aforementioned discussion concludes that CSAD is a quantity that describes how asset returns tend to rise and fall with market returns and accordingly its relationship with the market returns can detect herding behaviour. Chang *et al*. (2000) argue that herding violates the linearity of the relationship and that herding is indicated of the dispersion measure increases with market returns in a non-linear way at a decreasing rate. Consequently, an appropriate specification that may be used to detect the herding behaviour in financial markets is:

$$CSAD_t = \beta_0 + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + e_t \tag{4.9}$$

The relationship between $CSAD_t$ and $R_{m,t}$ is used to detect herd behaviour. If herding behaviour exists, then the relationship between $CSAD_t$ and the average market return is non-linear. When the coefficient β_2 is significant and negative, then herding behaviour is deemed to be present. The reason is that with an increase in the correlation among individual asset returns, the dispersion among asset returns will either decrease or increase at a decreasing rate. Paradoxically, the relationship is linear and increasing in the absence of herding, where the dispersion increases proportionately with the increasing returns of the market. Meanwhile, for herding during volatile periods, there should be a less proportional increase (or decrease) in the CSAD measure (Chang *et al*., 2000). Moreover, herding behaviour is not always due to investors following other investors within the same market; it may be triggered from information originating from other related markets. Galariotis *et al*. (2015) state that the co-movement of shares in a market or across markets may arise due to similar investment styles or due to a flow of fundamental information.

Investor behaviour can be influenced by various factors, such as market conditions, economic and political conditions, fear of mistake, forecasts and other investors' actions (mimicking). It is also influenced by rumors, observed actions, or imperfect information (Mertzanis and Allam, 2018). Gabbori's *et al*. (2020) recent study reveals that investors may make similar investment decisions whether individually or independently, as a response to fundamental market information. They argue that prior research has not accounted for market co-movement of similar style investors may be incorrectly interpreted as herding, which possibly leads to over reporting of herding tendency in financial markets by the reported inferences on herding. Therefore, they suggest subtracting the Fama-French-Carhart investment styles/risk factors from the CSAD. Representing the actual herding behaviour in the market from the relation between squared market returns with the remaining dispersion. Intentional herding arises as investors respond similarly to fundamentals. Regressing the CSAD part related to investor styles on four risk/style factors can be seen as follows:

$$CSAD_t = \beta_0 + \beta_1\left(R_{m,t} - R_f\right) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + e_t \qquad (4.10)$$

The three factors in the model are the Fama and French (1993) style (risk) factors, and the Carhart's (1997) momentum factor. Where $R_{m,t} - R_f$ is a market-oriented investment style which establishes exposure to the general market. The HML_t factor is the return on the portfolio that longs the high book to market value stocks and shorts the low book to market companies. The SMB_t factor is the return on the portfolio that invests in small companies and sells large ones, which is expected to capture small-cap investment style. The MOM_t (momentum) factor (Carhart, 1997) represents the return on a portfolio that buys previous winners and sells previous losers. The next section explains the factors in depth.

4.5.1 Fundamental Factors

The previous challenge in fundamental models is to constitute mimicking or hedging portfolios able to capture the marginal returns associated with a unit of exposure to each attribute. At first, Fama and MacBeth (1973) perform a type of regression on the risk fundamentals aiming to extract unit-beta portfolios. Likewise, Robotti and Balduzzi (2005) argue that this construction of portfolios can be done by aggregating assets according to their correlations with the fundamentals. Later, Fama and French (1993) develop a standard in constructing fundamental risk factors by mimicking portfolios for size and book to market risks. For stocks, portfolios are constructed to mimic risk factors related to size and capture strong common variation in returns, no matter what else is in the time series regressions. This is an evidence that size and book-to-market equity indeed proxy for sensitivity to common risk factors in stock returns. Where the market factor and risk factors related to size and book-to-market equity are able to explain the cross section of average stock returns. Hence, the size and book-to-market factors are able to explain the differences in average returns across stocks. However, these factors alone cannot explain the difference between the average returns on stocks and one-month t-bills, which is left for the market factor. In other words, it can be related to economic fundamentals. Then, Fama and French (1993) argue that the two mimicking portfolios of SMB and HML are created to capture the return premium that small firms receive over large firms, and the return premium that high book-to-market firms receive over low book-to-market firms respectively.

Fama and French (1993) consider two ways to scale stocks: a sort on market equity and a sort on book to market. In addition, they construct four value weighted two-dimensional portfolios at the intersections of the rankings. The model postulates that the expected return on a portfolio in excess of the risk free rate can be explained by the sensitivity of returns to three main factors. First, the excess return on the broad market portfolio, second the difference between the returns on a portfolio of small stocks and a portfolio of large stocks (SMB), third the difference between the returns on a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks (HML) (Fama and French, 1996).

The market factor in stock returns is the excess market return, $RM - RF$, where RM is the return on the value weighted portfolio of the stocks, less the return on the risk free asset, RF is the one-month bill rate. The SMB portfolio aims to mimic the risk factor in returns related to size, it is the difference between the simple average of returns on the two small stock portfolios (S/L and S/H) and the simple average of the returns on the two big-stock portfolios (B/L and B/H). The size factor measures the return differential between the returns on small and big stock portfolios with about the same weighted average book to market equity. Size rankings are based on market capitalisation and book-to-market rankings are based on the ratio of book equity to market equity. The size effect is when the small firms' stocks have higher returns than the large firms' stocks, which leads to a wide array of explanations that emerged to justify why stocks of small firms have higher returns than those of large ones. The HML portfolio aims to mimic the risk factor in returns related to book to market equity.

For the size and value factors, firms are ranked in December of year $t-1$ and are placed into four or six portfolios from January to December of year t, either (2x2) or (2x3) portfolios is formed. If it is the (2x2) portfolio, then four portfolios are formed from the intersection of the two size and the two book-to-market groups: S/L, S/H, B/L, and B/H. If it is the (2x3) portfolio, then six portfolios are formed from the intersection of the two size and the three book-to-market groups: S/L, S/M, S/H, B/L, B/M and B/H. Proceeding the explanation with the (2x2) portfolios, the SMB (Small minus Big) is the difference between the simple average of the value-weighted returns on the two small firm portfolios (S/L and S/H) and the simple average of the value-weighted returns on the two big firm portfolios (B/L and B/H). HML (High minus Low) is the difference between the simple average of the value weighted returns on the two high book-to-market portfolios (S/H, B/H) and the simple average of the value-weighted returns on the two book-to-market portfolios (S/L, B/L).

Chan *et al*. (1985) argue that higher average returns of small firms are mainly compensation for the additional risks borne in efficient market. Accordingly, Chan and Chen (1991) attempt to identify why small firms are riskier than big ones. Indicating that small firms tend to be firms with weak financial performance and therefore they are firms that are not efficiently run and have higher financial leverage. Implying that small firms are riskier than larger firms and this risk cannot be captured by a market index heavily weighted towards large firms.

However, Jegadeesh and Titman (1993) state that the model fails to accommodate the momentum in stock returns. Similar to long-term losers, short-term losers appear to have high loadings on the SMB and the HML factors compared to winners which predict reversal rather than continuation in stock returns. Therefore, Fama and French find that one of the main challenges for their model is the momentum in stock returns. They explain the failure of their model to capture the momentum in stock returns by arguing that momentum in stock returns is mainly due to data snooping. However, there are empirical evidence indicating that momentum exists in developed and emerging markets which rules out their argument about data snooping concerns. Another argument by Fama and French is that the momentum can be due to investor irrationality. However, in order to explain the tendency to underreact to some news and overreact to others, this requires behavioural finance since investors underreact to short-term past information resulting in a continuation of stock returns, but they overreact to long-term past information which leads to the observed return reversal. Fama and French also argue that the three-factor model is just a model that represents a mere approximation of the reality and thus it should not be expected to fully represent the real world. Therefore, the momentum stock returns can be considered one of the shortcoming of the model, hence this motivates researchers to search for richer models that can accommodate this puzzling anomaly by including additional risk factors.

To solve this shortcoming of the three factor model, Carhart (1997) suggest a similar method that reflects the return differential between the highest and the lowest prior-return portfolios, the momentum factor. Carhart is considered as the first author to raise a criticism to the Fama and French approach. The momentum factor is obtained by defining the (2x3) sorts and the yearly rebalancing of the Fama and French into a (3x3) sorts and a rebalancing on a monthly basis. A while later, Cremers *et al.* (2008) express direct criticism showing that the Fama and French's model does not consistently price passive index factors and does not even consistently price portfolios sorted on size and book-to-market.

Fama and French study reveals that the three risk factors capture strong common variation in stock returns by recording a high R^2 statistics of more than 90% for almost all of the portfolios tested. In order to build on previous literature and be aware of the previous studies that implemented different approaches to examine herding, the next section provides some of the previous studies of herding behaviour.

4.6 Previous Studies of Herding

Empirical studies on herding have increased rapidly since the 1990s (Bahadar *et al*., 2019). Looking at the major contributions to this area, Banerjee (1992) proposed the first model of sequential decision, which implies that an investor takes his investment decisions according to prior actions of other (crowd) investors. He argues that these (crowd) investors hold information that is important for an investor who is in a position to take an investment decision.

Several studies attempted to understand herding behaviour in financial markets, including Bikhchandani *et al*. (1992) and Welch (1992). These studies report that market participants mimic each other's actions or engage in herding disregarding personal information (Cipriani and Guarino, 2007). Hwang and Salmon (2007) argue that herding violates the propositions of the efficient market theory, and drives asset prices away from equilibrium as considered by traditional finance theory. In other words, prices no longer reflect the true valuation of firms, potentially resulting in a behaviour which may cause financial bubbles in stock markets (Banerjee, 1992).

Bahadar *et al.* (2019) argue that herding behaviour varies with different market conditions such as increasing or decreasing market return and volatility. Some previous studies support the same finding. For instance, Chiang and Zheng (2010) investigate herding behaviour in eighteen countries. Evidence of herding is found in advanced stock markets except for the United States during periods of negative market returns. Moreover, Chang *et al*. (2000) argue that cross-sectional convergence or divergence of returns, under extreme market conditions, assumes implicitly that investors' behaviour is based on total risk, market risk as well as firm-specific risks.

Economou *et al.* (2015) examine the Bulgarian and Montenegrin markets and find that herding is significantly stronger during periods of positive market performance and high volume. Likewise, Tan *et al.* (2008) investigate the Chinese stock markets where herding occurs in both rising and falling market conditions. Surprisingly, the Shanghai market herding was more pronounced under conditions of rising markets, high trading volumes and high volatility. As for the period of major events like during financial crisis, Hwang and Salmon (2004) examine the stock markets of the United States and South Korea and found less herding. However, Mobarek *et al.* (2014) study the herding behaviour among European markets and they elucidate that herding is not significant during normal times while significant herding during crisis and in regimes of different extreme market conditions.

Most of the empirical studies focus on herding behaviour and its implications for the investors from developed markets. Christie and Huang's (1995) study examines the presence of herd behaviour on the part of investors during periods of market stress using daily and monthly data for the stock market of NYSE and Amex firms from 1962 to 1988. The results of both daily and monthly returns are inconsistent with the presence of herding during periods of large price movements. When herding is expected to be most prevalent during down markets, the magnitude of the increase in the dispersion of actual returns is mirrored by the increase in the dispersion of predicted returns that are estimated from rational asset pricing model.

According to Chang *et al*. (2000), there is evidence of herding in the U.S equity market. However, herding was found in some other equity markets such as Europe, Latin America, Australia and most Asian markets (Chiang and Zheng, 2010; Economou *et al*., 2015; Galariotis *et al*., 2015; Mobarek *et al*., 2014).

There is a paucity of literature on testing herding behaviour in emerging markets. It should be noted that these markets are fast integrating into the global financial system (Banerjee and Padhan, 2017). In other words, the presence of herding behaviour in the developing markets is becoming more relevant on a global scale. Not only might the herd behaviour contribute to market volatility and pricing inefficiencies (Nofsinger and Sias, 1999) but provides additional examination of the relative roles of domestic market volatility and external factors in developing stock markets that can provide additional valuable insight to policy makers regarding the development of market mechanisms to mitigate the negative effects resulting from herd behaviour (Blasco *et al*., 2012).

Similarly, Borensztein and Gelos (2003) argue that herding is found to be more pronounced in emerging markets than in developed markets. There are several reasons behind this, including low trust in available information, information blockage, government intervention, weak regulation, forecasting difficulties, high market volatility, low disclosure requirements, and less educated investors (El-Erian and Kumar, 1995). For example, the Middle East has been experiencing major political instability since the Arab Spring in 2011. Markets within the region cannot possibly escape the possible impacts of the turmoil brought about by political and social events such as the Syrian Civil War, the Egyptian military intervention, the ongoing unrest within Iraqi borders, as well as the volatility of oil prices that are vitally important for the regions' economies. Furthermore, Middle Eastern stock markets are becoming more and more integrated with international markets this is because those markets are relatively new, not fully open, shallower and smaller in size in terms of market capitalization relative to fully developed global markets. Investors within the region either seem to be sceptical about, or isolated from the social and political unrest, or lack information about significant events due to the policies intentionally pursued to keep markets away from shocks which may have destabilizing consequences.

With regard to transparency and interdependency within the MENA region, Lagoarde-Segot and Lucey (2007) examine the market emergence in the region, including the size, depth, activity, and transparency of the market, as well as the factors leading to market emergence. They conclude that the MENA markets are beginning to move towards international financial markets. Moreover, the authors point out that, in the region, Israel and Turkey are the most promising markets, followed by Egypt and Jordan. In 2008, they state that the MENA markets are more noticeably emerging markets than the markets of other emerging regions such as Latin American and Eastern Europe. Another study by Assaf (2003) finds that GCC stock markets are interdependent and that Bahrain plays an exceptional dominant role, in addition to the markets that are not being fully efficient in processing regional news especially asymmetric information. So, it is plausible that the MENA markets have all these specifications that inspire examining herding behaviour in the region.

Balcilar *et al.* (2017) examine the effect of crude oil prices on herding behaviour among investors in the GCC stock markets using firm level data. They examine equity return dispersions within industry portfolios and test the presence of herd in these markets. Their findings reveal significant herding behaviour in all GCC equity markets with the exception of Oman and Qatar, and more consistently during periods of market losses. In addition, the study discloses that significant oil price effects on herd behaviour in those markets especially in extreme positive changes in oil prices periods. They concluded that the developments in oil market significantly affect the investors' tendency to herd.

Balcilar *et al*. (2013), examine that GCC stock markets using dynamic herding approach that takes into account herding under different market regimes. The results show the presence of three market regimes (low, high, and extreme or crash volatility) in those markets, suggesting that these markets have different structure than developed markets. They found evidence of herding behaviour under the crash regime for all markets except for Qatar which herds under high volatility regimes. They also conclude that herding behaviour in these markets can be explained by global financial systematic risks.

Overall, previous studies reveal that the MENA region suffer from an information asymmetry problem, restrictions on foreign capital, issues with tax status, and sharp reversals in oil prices (Andrikopoulos *et al*., 2016). Therefore, it can be deduced that market fundamentals are ignored regardless of investor awareness. Shedding light on one of the largest emerging market in the MENA region, Ezzat's (2012) study finds that the Egyptian stock market is considered an inefficient market nowadays due to the lack of sufficient public information, weak market awareness among investors and low market liquidity. The next section gives a brief conclusion of the main points discussed in this chapter.

4.7 Conclusion

This chapter discusses one of the most interesting topics recently in behavioural finance, namely herding. The first part of this chapter deals with the various definitions of herding, along with clearly identifying the different point of views. As Welch (2000, p.370) points out "herding in financial markets, in particular, is often presumed to be pervasive, even though the extant empirical evidence is surprisingly sparse". Accordingly, this chapter argues for the importance of studying herding behaviour especially in stock markets. Christie and Huang (1995) argue that herding has become of particular interest in order to understand empirical realities given the fact that individual investors tend to mimic the actions of other's. Moreover, Bikhchandani and Sharma (2000) claim that investors in financial markets herd when they suppress their personal decisions in favour of the collective view of the market even when they do not think that this view is right.

There are sufficient theoretical and empirical evidence of examining herding behaviour, which are highlighted in the chapter. Furthermore, highlighting the advantages and limitations of the different approaches that can be used. Despite the variety of studies implemented on developed countries, there is a paucity in studies on developing countries especially the Middle East. As Borensztein and Gelos (2003) argue that despite the evidence in the literature, there remains an open discussion about the type of investment behaviour especially in developing markets rather than advanced ones. Theories and empirical research on herding do not seem to settle on a unified accepted norm and computation, Hwang and Salmon (2007) argue that there is no accepted method that separates investor behaviour due to herding or reaction to fundamentals.

However, Bikhchandani and Sharma (2000) emphasize the distinction between intentional herding and false herding behaviour. Herding can be simply defined as copying the behaviour of other investors intentionally or unintentionally. Intentional herding behaviour refers to the clear intention of the investors to imitate the behaviour of other participants in the market. False herding behaviour, on the other hand, is based on the situation where a group of investors face the same set of information and consequently take similar investment or trading decisions.

Chapter 5

Research Methodology

5.1 Introduction

This chapter aims to highlight the main approaches used throughout this thesis. The first approach deals with modelling volatility in the MENA region few studies have examined the volatility spillover across the countries in the region, especially after the rise of the Arab Spring. The second approach deals with testing the significance of the spillover index statistics using bootstrapping. Finally, the third approach deals with examining the question of herding in the Egyptian stock market. Egypt is considered one of largest developing countries in the region and is particularly prone to herding given the number and scale of political crises it has witnessed in the last decade.

The outline of this chapter is as follows. Section 5.2 defines the variables and sample used to model volatility in the MENA region, and outlines the approach taken in finding the best model that fits the sample. Section 5.3 investigates volatility spillover using the most commonly approach used in the literature, namely, the Diebold and Yilmaz (2012) index. Section 5.4 highlights the steps employed to test the significance of the DY index using the bootstrapping method. Section 5.5 discusses the methods employed to test the presence of herding behaviour, and differentiate between intentional and unintentional herding. The section also highlights the approaches used to test the presence of herding in different market conditions. Section 5.6 concludes.

5.2 Volatility Variables and Methods

The first objective of this thesis is to model volatility using symmetric and asymmetric models, and find the best model that fits the sample. In order to measure volatility of the eight MENA region countries (Bahrain, Egypt, Jordan, Oman, Kuwait, Turkey, Saudi Arabia, and UAE), the monthly prices of their stock market indices are required. The data is obtained from Bloomberg, which contains several sources for MENA region data. The data covers the sample period from January 2003 to December 2018.

The nominal monthly returns of each of the aforementioned stock market indices are calculated as logarithmic price relatives $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100$, where P_t is the monthly closing price. Given the fact that most of the currencies in the MENA region are subject to huge fluctuations given their highly volatile economic and political conditions and to ensure that one currency is used for all the eight countries to be able to compare between them, the dollar prices are used to estimate the nominal returns. To calculate the dollar returns, first the exchange rate change is calculated as: $ER_t = \log\frac{x_t}{x_{t-1}}$, where x_t is the monthly exchange rate of the local currency to the US dollar. Then, the dollar returns are calculated as: $\$R_t = (1 + R_t/1 + ER_t) - 1$, where R_t is the nominal (local) returns, and ER_t is the change in exchange rate.

Before choosing the most appropriate method to model volatility in the MENA region, the descriptive statistics of the monthly returns whether local or dollar is needed in order to understand the nature and the distributional characteristics of the eight MENA countries. The descriptive statistics include monthly mean, minimum, maximum, standard deviation, skewness, kurtosis, and Jarque-Bera of returns for each of the eight markets. Moreover, a standard assumption is that stock prices are non-stationary while the returns are stationary (Francq and Zakoïan, 2010). However, sometimes this assumption does not hold. Having non-stationary data in financial models may produce unreliable and spurious results and the solution in this case is to transform it to stationary. Therefore, the unit root test is employed to test for stationarity, by using the Augmented Dickey Fuller test, since it handles complex models and is used with serial correlation (Fuller, 1976). The next sections shed the light on the appropriate models used in this thesis and the reasons behind the choice.

5.2.1 Model selection and specification

While several models exist for volatility estimation from historical data, one of the most common approaches in identifying volatility includes the ARCH/GARCH models. However, before implementing these models, it is required to ensure that these models are appropriate. An important argument is that uncorrelated time series can still be serially dependent due to a dynamic conditional variance process. This may bias the estimates of the conditional variance. If a time series exhibits conditional heteroscedasticity or in other words autocorrelation in the squared returns, then there is an autoregressive heteroscedastic (ARCH) effects. The Engle's ARCH test is constructed based on the fact that if residuals are heteroscedastic, the squared residuals are autocorrelated. Using Engle's (1982) proposal of the Lagranger Multiplier test by fitting a linear regression model for the squared residuals and examine whether the fitted model is significant. The test for the presence of ARCH effect in the residuals is calculated by regressing the squared residuals on a constant and p lags, where p is a set by choosing the optimal lag length by the Akaike Information Criterion (AIC) (Akaike, 1973) and/or Schwarz Bayesian Criterion (SBC) (Schwarz, 1978; Brooks, 2015).

Furthermore, given that financial time series exhibit conditional heteroscedasticity data (Akgiray, 1989), most of the existing empirical studies apply the ARCH-GARCH specifications to model stock market volatility. Therefore, the ARCH-GARCH models are utilized in this thesis to estimate the stock market volatility of the eight MENA markets.

5.2.2 ARCH/GARCH Models

The first model proposed by Engle (1982) to estimate the variance of returns, is the Autoregressive conditional heteroscedasticity (ARCH) model. The ARCH model allows the conditional variance to change overtime as a function of past errors. The simplest is the ARCH (1):

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{5.1}$$

where $\alpha_1 > 0$. The conditional variance of the error term depends on the previous value of the squared error. The ARCH (1) means that the conditional variance depends on only one lagged squared error. This model can be extended such that the conditional variance depends on more than one lagged realization. However, there are limitations for the ARCH model, first, the model requires determining the value of the q, the number of lags of squared residuals in the model, where no clear approach is found to best find it. Second, the model requires many parameters to be able to capture volatility which is a problem as it is difficult to decide how many lags to include that may result in a large conditional variance model. Third, the non-negativity constraints may be violated, where the more parameters there are in the conditional variance equation, the more likely it is that one or more of them will have negative estimated values.

Given the limitations of the ARCH model, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was proposed by Bollerslev (1986) as an extension to the ARCH models in order to overcome these limitations. The GARCH model is more parsimonious, and avoids overfitting. Consequently, the model is less likely to breach non-negativity constraints. Overall, the GARCH model allows for longer memory and avoids overfitting.

According to Bollerslev (1986) and Engle (1993) the GARCH (1,1) specification is enough since it is a parsimonious representation of conditional variance that fits many high-frequency time series. The model includes just one lag of conditional variance and one lag of the squared error. Therefore, GARCH (1,1) models are favoured over others by many economists due to their relative simple implementation (Williams, 2011). The GARCH model allows the conditional variance to be dependent upon previous own lags, so that the conditional variance equation is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{5.2}$$

Under the conditions $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, to ensure that the conditional variance is always positive, and $\alpha_1 + \beta_1 < 1$ is required for stationarity condition to hold, in order to be able to obtain meaningful sample statistics to be used as a descriptive of future behaviour. The conditional variance (σ_t^2) at time t is the one period ahead estimate for the variance calculated based on any past information thought relevant, it is interpreted as a weighted function of a long-term average value or the mean of the conditional variance (dependent on α_0), information about volatility during the previous period ($\alpha_1 u_{t-1}^2$), and the fitted variance from the model during the previous period ($\beta_1 \sigma_{t-1}^2$). In other words, the conditional variance depends both on the past values of the shocks captured by the lagged squared error terms (u_{t-1}^2) and past values of itself (σ_{t-1}^2). From Equation 5.2, it is apparent that the main assumption of GARCH (1,1) is that the present volatility depends only on the previous period's volatility, therefore it is easy to calculate and simulate since there are only three parameters in the model to be estimated ($\alpha_0, \alpha_1, and\ \beta_1$) (Dong, 2012).

GARCH models are estimated by maximum likelihood. Log-likelihood function (LLF) to maximize will be:

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}(u_t)^2 / \sigma_t^2 \tag{5.3}$$

A simple regression is often used to provide initial parameter estimates. Choosing good initial guesses is crucial since poor initial guesses may lead to convergence problems (Brooks, 2015).

According to Oskooe and Shamsavari (2011) one of the weaknesses of the GARCH model is its premise of symmetric response to positive and negative shocks, which is due to the conditional variance in the basic model being a function of squared lagged residuals regardless of the signs. In order to capture these asymmetric effects in the volatility of stock returns, the next section provides more details about the two extensions of GARCH that are used to estimate stock market volatility of the MENA region, EGARCH and GJR GARCH.

5.2.3 Asymmetric models

There are several extensions that are proposed as a consequence of the observed problems of GARCH model. The model assumes that positive and negative error terms have the same effect on volatility. This assumption is violated if volatility tends to increase more after bad news than after good news. This asymmetry, or leverage effect, represents the tendency of variation in the prices of stocks to be negatively correlated with changes in the stock volatility. To overcome these constraints, asymmetric models such as the EGARCH and the GJR-GARCH are implemented.

Starting with the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model, Nelson (1991) extends the ARCH framework in order to better describe the behaviour of returns volatilities. The EGARCH model allows the variance of return to be influenced by positive and negative excess returns differently. The model captures the leverage effects of shocks such as events and news (such as the Global Financial Crisis or the Arab Spring) in financial markets. When bad news hit the market, assets tend to enter a state of turbulence and volatility increases. The EGARCH conditional variance equation:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{5.4}$$

The log of the variance (σ_t^2) makes the model free from restrictions on the parameters. This is one of the advantages of this model ensuring that the estimated variance is non-negative. Therefore, there is no need for non-negativity constraints on the model parameters. Asymmetry is found from $\gamma,$ which is the leverage term, where negative shocks at time $t-1$ have a stronger impact in the variance at time t than positive shocks. If $\gamma = 0$ then the model is symmetric and if $\gamma \neq 0$, the model is asymmetric. If < 0 , it indicates that the bad news or negative shocks generate larger volatility than good news or positive shocks, implying the presence of leverage effect (Nelson, 1991).

Similar to the EGARCH model, GJR-GARCH model is a simple extension of GARCH with an additional term (dummy variable) to capture asymmetric effects in the series. Glosten, Jagannathan, and Runkle (1993) proposed the GJR-GARCH model as an extension of the original GARCH model. The GJR-GARCH conditional variance equation is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{5.5}$$

where the dummy variable is $I_{t-1} = 1$ if $u_{t-1} < 0$, OR $I_{t-1} = 0$ if $u_{t-1} > 0$. For a leverage effect we would see $\gamma > 0$. The non-negativity constraint that must be imposed required that $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, and $\alpha_1 + \gamma \geq 0$, and explains why this model is less likely to breach the non-negativity constraint that the GARCH model. The model is still accepted if $\gamma < 0$, provided $\alpha_1 + \gamma \geq 0$ holds.

Although the EGARCH and GJR-GARCH models have the same purpose, the way the models act is different. The EGARCH leverage coefficient is directly connected to the actual innovations while the GJR-GARCH leverage coefficients are connected through an indicator variable I. Therefore, when an asymmetric shock happens, the leverage effect for the GJR-GARCH model should be positive, while the leverage effect should be negative for the EGARCH model. The two models are different although both aim to capture the same effects (Pilbeam and Langeland, 2015).

After implementing each of the mentioned models in order to compare between their outcomes and find the best model that fits the data, the ARCH test is done to see if there are any more ARCH effects found. If there are no ARCH effects present, then the model captures all the ARCH effects. If more than one model shows no signs of ARCH effects, then a model selection is needed to find the best model. In order to determine which model is the best in order to depend on in further analysis. Measures are proposed for selection of a model which can be an optimal model by an information criterion such as the AIC or the BIC criterion (Javed, 2011). Information Criteria assume that the best model is the one that gives the lowest function of weighted squared residuals. After finding the best model that estimates stock market volatility for each of the eight MENA markets, then the next step is to examine if this volatility affects the country or neighbouring countries. The next section provides an explanation of the spillover framework employed to estimate volatility spillover between the eight MENA countries in order to have a better view of the MENA region.

5.3 Spillover Variables and Methods

To satisfy the second objective of this thesis, which is investigating the volatility spillover among the MENA region markets and highlighting the important spillover among the markets, the Diebold and Yilmaz (2009, 2012) approach is used as it is the most commonly used spillover framework in recent research. Using the outcome of the best model of volatility, the GJR-GARCH model, the DY index is implemented to investigate the volatility spillover between the eight MENA markets.

Diebold and Yilmaz (2009) introduces a volatility spillover measure that is based on forecast error variance decompositions from the vector autoregressions (VAR). The main advantage of the VAR model is that it is a multivariate autoregression model that enables testing the bidirectional relation between variables rather than just the unidirectional relationship. The spillover index aggregates spillover effects across countries, distilling a wealth of information into a single spillover measure. Simply put, index sets each market as i then adds the shares of its forecast error variance coming from shocks to market j, for all $j \neq i$, and then add across all $i = 1, \ldots, 8$. In order to minimize notational clutter, consider a covariance stationary first-order two-variable VAR,

$$x_t = \Phi x_{t-1} + \varepsilon_t, \tag{5.6}$$

where $x_t = (x_{t1}, x_{2t})$ and Φ is a 2x2 parameter matrix. So, here x_t will be a vector of stock return volatilities. The moving average representation of the VAR will be:

$$x_t = \Theta(L)\varepsilon_t, \tag{5.7}$$

where $\Theta(L) = (I - \Phi \mathrm{L})^{-1}$. Rewriting the moving average to $x_t = A(L)u_t$, where $A(L) = \Theta(L)Q_t^{-1}$, $u_t = Q_t\varepsilon_t$, $E(u_t u_t') = I$, and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ε_t. If considering 1-step ahead forecasting, $x_{t+1,t} = \Phi x_t$, with corresponding 1-step ahead error vector:

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \tag{5.8}$$

which has covariance matrix

$$E\left(e_{t+1,t} e'_{t+1,t}\right) = A_0 A'_0 \tag{5.9}$$

Therefore, the variance of the 1-step ahead error in forecasting x_{1t} is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the 1-step-ahead error in forecasting x_{2t} is $a_{0,21}^2 + a_{0,22}^2$. Taking a simple two variable example there are two possible spillovers: x_{1t} shocks that affect the forecast error variance of x_{2t} (with contribution $a_{0,21}^2$), and x_{2t} shocks that affect the forecast error variance of x_{1t} (with contribution $a_{0,12}^2$). Then the total spillover is $a_{0,12}^2 + a_{0,21}^2$. Total forecast error will be $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = trace(A_0 A_0)$. The spillover index is:

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A_0)} x\ 100 \tag{5.10}$$

For the general p^th order N-variable VAR, using H-step-ahead forecast the spillover index is:

$$S = \frac{\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{8} a_{h,ij}^2}{\sum_{h=0}^{H-1} trace(A_0 A_0)} \tag{5.11}$$

In this thesis, we use second-order 8-variables VARs with H-step-ahead forecasts. The step ahead horizon is chosen after trying from 1 to 20 step ahead and finding out when the spillover index changes by small amount or is nearly stable. However, this approach depends on the Cholesky-factor identification of the VARs where the results are dependent on the ordering of variables. Another limitation is that the framework measures only total spillover and not directional. Therefore, Diebold and Yilmaz (2012) introduced an extension method of measuring total and directional spillover in a generalized VAR framework in which the results are invariant to the ordering of variables. Hence, the generalized VAR framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1980) (henceforth KPPS) is followed here. This approach produces variance decompositions that are invariant to ordering. This generalized approach allows correlated shocks and accounts for them appropriately using the historically observed distribution of the errors. As the shocks of each variable are not orthogonalized, the sum of contributions to the variance of forecast error is not necessarily equal to one. To define the total spillover index of DY (2012) there are two things to consider. First, the assets' own variance shares, which is the fractions of the H-step-ahead error variance in forecasting the ith variable that are due to assets' own shocks. Second, the cross variance shares, or spillover, which are the fractions of the H-step-ahead error variance in forecasting the ith variable that are due to shocks to the jth variable, for $i, j = 1, \dots, N$, such that $i \neq j$. KPPS H-step-ahead forecast error variance decompositions, denoted by $\theta_{ij}^{g}(H)$, for $H = 1,2, \dots$, are given by

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{5.12}$$

where Σ is the variance matrix for the error vector ε, σ_{ii} is the standard deviation of the error term for the ith equation and e_i is the selection vector with one as the ith element and zeros otherwise. The sum of the elements of each row of the variance decomposition is not equal to 1: $\sum_{j=1}^{8} \theta_{ij}^{g}(H) \neq 1$. In order to use the information available in the variable decomposition matrix in the calculation of the spillover index, we normalize each entry of the variance decomposition matrix by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{8} \theta_{ij}^{g}(H)} \tag{5.13}$$

Note that, by construction, $\sum_{j=1}^{8} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{8} \tilde{\theta}_{ij}^{g}(H) = 8$, thus the contribution of spillover from volatility shocks are normalized by the total forecast error variance.

Constructing total volatility spillover index using the volatility contributions from the KPPS variance decomposition:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{8} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ij}^{g}(H)}{8} \times 100 \tag{5.14}$$

The total spillover index measures the contribution of spillover of volatility shocks across the eight markets to the total forecast error variance. Studying total spillover provides an understanding of how much of shocks to volatility spill over across major markets. The generalized VAR approach enables us to learn about the direction of volatility spillover across major markets. As the generalized impulse responses and variance decompositions are invariant to the ordering of variables, we calculate the directional spillover using the normalized elements of the generalized variance decomposition matrix. Directional volatility spillover received by market i from all other markets j as:

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{8} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{8} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{5.15}$$

Similarly, directional volatility spillover transmitted by market i to all other markets j as:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{8} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{8} \tilde{\theta}_{ji}^{g}(H)} \times 100 \tag{5.16}$$

Net volatility spillover from market i to all other markets j as:

$$S_{i}^{g} = S_{\cdot i}^{g}(H) - S_{i \cdot}^{g}(H) \tag{5.17}$$

The net volatility spillover is simply the difference between gross volatility shocks transmitted to and gross volatility shocks received from all other markets. It provides summary information about how much in net terms each market contributes to volatility in other markets. As for net pairwise volatility spillover between markets i and j is simply the difference between gross volatility shocks transmitted from market i to j and gross volatility shocks transmitted from j to i. The net pairwise volatility spillover as:

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{k=1}^{8} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{k=1}^{8} \tilde{\theta}_{jk}^{g}(H)} \right) \times 100 \tag{5.18}$$

After implementing the DY (2012) framework to investigate the volatility spillover of the eight MENA countries, and as discussed previously in Chapter 4, the DY (2012) approach index is criticized for the inability to carry out statistical inference on the index outcome. Since the index is highly nonlinear, it is difficult, if not impossible, to derive the statistical properties of such an index. We propose a feasible solution by using a bootstrapping approach, which is discussed in the next section.

5.4 Testing for the Significance of the Index

Once total and directional spillovers in the MENA region are estimated, it is important to test for the significance of each of these indices. The generalized forecast error variance decomposition that is used in the Diebold and Yilmaz framework highlights the economic significance of responses, and whether they actually produce any significant movement in other variables. However, it does not specify whether this response is statistically significant which makes the spillover percentages hard to interpret. As discussed in Chapter 3, there are no estimation methods available in previous studies for standard errors of the volatility spillover indexes. Choi and Shin (2018) suggest using bootstrapping in order to get the standard errors and confidence interval estimations, which is discussed in the next section.

5.4.1 Applying Bootstrapping

The standard approaches do not provide a way for testing volatility spillover indexes. In particular, a closed form formula for the standard error is not available. Given this hurdle, a bootstrap procedure is used to develop statistical methods of volatility spillover index. This helps fulfil the fourth and fifth objectives, which are re-evaluating the DY index results, volatility spillover of the MENA region results and assessing whether the conclusions and interpretations can change when the significance of the estimates are considered.

The idea of bootstrapping was developed by Efron (1979), arguing that the observed data set is a random sample of size T drawn from the actual probability distribution generating the data. Accordingly, he argues that the empirical distribution of the data is the best estimate of the actual distribution of the data. Bootstrapping is simply a simulation technique that resamples the actual data or something derived from it for example residuals. Applying bootstrapping of standard error has not been used in previous empirical studies of spillover. Therefore, it is attractive since finite sample performances of bootstrap methods are frequently reported in the literature to be better than the usual methods that are based on central limit theorems.

In this thesis we are considering the stationary block bootstrapping as the most appropriate to measure the significance of the DY volatility spillover index due to the following reasons as discussed previously in Chapter 4. First, taking into consideration that we are using monthly stock market volatility (time series data), then we can't just resample the data since that breaks the time sequencing between the variables and their lags. Second, the block length is random rather than fixed, which samples the data in time blocks, so there are only occasional data points which are subject to sequencing issues. Third, it is used with almost any sort of dynamic models; and fourth it handles heteroscedasticity and serial correlation (Politis and Romano, 1994).

In applying the stationary bootstrapping to test the significance of volatility spillover index estimates, the volatility data set $\{x_1, \ldots, x_T\}$, represents the sample volatilities. Choosing the proper block size is the most important part especially with highly persistent data. In simple Block Bootstrap the block length L is fixed and should equal to $sample\ size^{1/3}$, representing the rate of increase of L as m increases (MacKinnon, 2007). However, in Stationary Bootstrap, the block length is chosen randomly at each replication.

The stationary bootstrap procedure is as follows:

Step 1: Draw L randomly from a geometric distribution. Let m be the minimum integer such that $mL \geq T-1$. Make m random draws $\{i_1, i_2 \dots., i_m\}$ from $\{2,3 \dots., T\}$.

Step 2: Let $B_j = \left\{x_{i_j}, \dots., x_{i_{j+L-1}}\right\}$, be the jth block of size L_j starting from x_{i_j}, $j = 1, \dots, m$. Where the B_j represents the new random draw set from the original volatility data.

Step 3: By combining m blocks, $\{B_1, \dots., B_m\}$ and deleting the last $\sum_{j=1}^{m} L_j - (T-1)$ elements in order to form a sample length of T, attaining $\{x, t = 1, \dots., T\}$.

By repeating steps 1 to 3, the bootstrap samples $\{x_t^*, t = 1, \dots., T\}$ are generated 1000 times with the exception that for each block, the block size L is generated randomly from a geometric distribution with success probability $\tau \in (0,1)$ from the generated block sizes $L_1 + L_2 + \cdots + L_m \geq T-1$. These bootstrap samples that are drawn from the monthly variance, are then estimated by the VAR equation in order to calculate volatility spillover. For each bootstrap, sample $\{x_t^*, t = 1, \dots., T\}$ is estimated through VAR model equation $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$ from which H-step volatility indexes are obtained.

Total volatility spillover index:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{8} \times 100; \tag{5.19}$$

Directional volatility spillover received by market i from all other markets j:

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{8} \tilde{\theta}_{ij}^{g}(H)} \times 100; \tag{5.20}$$

Directional volatility spillover transmitted by market i to all other markets j:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100; \tag{5.21}$$

Net volatility spillover from market i to all other markets j:

$$S_{i}^{g} = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H); \tag{5.22}$$

$i = 1, \dots, N$, interpreting each of the above spillover indexes as a statistic, $\hat{\theta}$. Where N reflects the eight MENA markets in the sample. The standard error of $\hat{\theta}$ representing the volatility index estimator is $se(\hat{\theta})$. Since no method is directly applicable in literature for estimating the standard error, an alternative is replacing $se(\hat{\theta})$ by a bootstrapping approximation $se^{*}(\hat{\theta}^{*})$. Bootstrap confidence interval (pivot with normal quantile):

$$CI_{NorP} = \hat{\theta} \pm 1.96\, se^{*}(\hat{\theta}^{*}) \tag{5.23}$$

where $se^{*}(\hat{\theta}^{*})$ is the standard deviation of, B say, bootstrapped volatility indexes $\{\hat{\theta}^{*(b)}, b = 1, \dots, B\}$. The interval is constructed from the asymptotic normality of the pivot $z = \frac{\hat{\theta}-\theta}{se^{*}(\hat{\theta}^{*})}$, giving the normal quantile 1.96 for 95% confidence interval in Equation 5.23.

Resampling the data and re-estimating the VAR model several times using these bootstrapped samples reflect a method for estimating the distribution of an estimator or test statistic. Bootstrapping provides approximations to distributions of statistics, coverage probabilities of confidence intervals, and rejection probabilities of hypothesis tests that are more accurate than the approximations of first-order asymptotic distribution theory (Horowitz, 2003). According to Nisbet *et al.* (2018), bootstrapping technique has shown to provide a more accurate estimate of a parameter than the analysis of any one of the n samples.

Specifically, bootstrapping the volatility spillover is important since the conclusions drawn from the outcome are used in a wide variety of decisions such as for academics and practitioners understanding whether financial markets become more independent during financial crises (Kenourgios and Padhi, 2012). Along with helping policymakers understand the transmission process of volatility across domestic and international financial markets (Becketti and Sellon, 1989). Moreover, the integration and link among stock markets is of interest to investors due to their potential international portfolio diversification benefits (Dovhunova, 2014). The following section highlights the significance of the sample period.

5.4.2 Significance of the Sample period

As previously highlighted in Chapter 2 and 3, the MENA region is an interesting region to investigate as relatively few studies have focused on it. Moreover, in the recent years the region has been affected by a wide array of adverse economic and political events. This enables investigating the volatility spillover since the region's markets are likely to have been in turmoil at least during part of the sample. Given that our sample coincides with the credit crunch, we will divide the sample into three subsamples, pre-crisis, during crisis, and post-crisis. The first sample represents the pre-crisis period from January 2003 to December 2007, where the sample ends right before the Global Financial Crisis (GFC). The second sample represents the crisis period from January 2008 to December 2013. This covers more than one event, including the Arab Spring. Finally, the third sample represents the post-crisis period from January 2014 to December 2018. This fulfils the third objective of this thesis, which is to test if the spillover evolves over time with different market conditions.

After measuring the volatility of the MENA region, examining the volatility spillover within it, and assessing the significance of the estimates of the spillover outcome, the last part of this thesis aims to test the presence of herding behaviour in the Egyptian market. The selection of the Egyptian market is due to several reasons. First, the Egyptian market is one of the largest developing markets in the region. Second, it is the only market that experienced several events during the sample period. Third, after investigating the volatility spillover of the MENA region, which includes the Egyptian market, the results would provide an overview of the market behaviour but does not reflect the investor behaviour. Therefore, it is interesting to see if this market is experiencing any herding behaviour. The next section discusses the data, variables and methods that are used in order to test the presence of herding behaviour in the Egyptian stock market.

5.5 Herding Behaviour

This section focuses on fulfilling the last objectives of testing the presence of herding behaviour in the Egyptian stock market. We distinguish between intentional herding that results from exposures to common fundamental factors and unintentional herding that ignores these factor variations. Furthermore, we examine herding behaviour under different market conditions by dividing the sample into subsamples which reflect different market conditions such as stable periods and crisis periods. The data set employed in this part of the thesis is different from the previous part. As discussed in Chapter 4, herding is best captured using daily data of the listed companies in the Egyptian stock market. We collect data that includes all listed companies in the Egyptian stock market from 1st of July, 2005 to the 27th of July 2019, where all daily individual stocks prices are converted to US dollars. The number of listed companies by the end of the sample is 173 companies. The data include all active, dead, and suspended companies to eliminate any potential survivorship bias. The data are obtained from Bloomberg, all the weekends and vacations are removed from the data and treated as missing. In light with the discussion in Chapter 4 about the significance of the Egyptian market, the sample period chosen covers a wide array of events such as the Global Financial Crisis, the Arab Spring, and the floatation of the currency.

In this thesis, daily market returns are calculated in two different ways. First, they are calculated as the value weighted average returns of all the listed stocks used:

$$R_{w,t} = \sum_{i=1}^{N} (MC_i/TMC_t) \times R_{i,t} \tag{5.24}$$

where $R_{w,t}$ is the average weighted return at each day t. $MC_{i,t}$ is the market capitalization of each company i on that day. TMC_t is the total market capitalization of all companies on that day. R_i is the nominal returns of each company i at that day. Nominal returns are used since the daily consumer price index (CPI) is not seen to be reliable for this sample period. The official figures suggest that there is deflation, which is clearly not true in the case of Egypt.

Second, market returns are calculated from the EGX30 index, since it is considered to be the oldest and most reliable index representing the Egyptian stock market. Market returns are estimated from the price index as follows:

$$R_{index,t} = (P_t - P_{t-1})/P_{t-1} \tag{5.25}$$

where P_t is the stock market index price of the day, and P_{t-1} is the stock market index price of the previous day. The next section discusses the method used to test herding using the calculated returns.

5.5.1 Cross-Sectional Absolute Deviation

The dispersion is measured using the cross sectional absolute deviation, which is the most commonly used method of measuring herding behaviour as discussed in Chapter 4. Following Chang *et al*. (2000) who propose the use of the cross-sectional absolute deviation (CSAD) as a measure of dispersion:

$$CSAD_t = \frac{1}{173}\sum_{i=1}^{173}\left|R_{i,t} - R_{m,t}\right| \tag{5.26}$$

where $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is defined in two different ways. First, it is defined as the value weighted average return of the 173 stocks in the portfolio at time t ($R_{w,t}$ in Equation 5.24) Second, it is defined as the market index return ($R_{m,t} = R_{index,t}$, see Equation 5.25). Since CSAD is a quantity that describes how asset returns tend to rise and fall with market returns, therefore its relationship with the market returns can detect herding behaviour.

Moreover, Chang *et al*. (2000) argue that when markets are herding, the linearity of the measure is violated and herding is indicated if the dispersion measure increases with market returns in a non-linear way at a decreasing rate. Consequently, an appropriate specification that may be used to detect the herding behaviour in financial markets is:

$$CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t \tag{5.27}$$

Where the relationship between $CSAD_t$ and $R_{m,t}$ is used to detect herding behaviour. If herding behaviour exists then the relationship between $CSAD_t$ and the market return is non-linear, since the dispersions are predicted to be low despite a big possible change in the market and this is reflected by the negative association between dispersion and the squared returns. Hence, if the coefficient β_2, representing the nonlinear parameter, is negative and significant, it is an indication of herding behaviour in the market (Chang *et al*., 2000). In normal conditions the individual stock returns are expected to move with the market according to their betas and the value of the CSAD should increase linearly with market returns. Using both the weighted and index market returns and comparing between the outcomes, gives a clearer more reliable outcome of the Egyptian stock market.

Furthermore, after testing the presence of herding in the Egyptian stock market, it is worth assessing whether herding is intentional or unintentional. A distinguishing feature of this study compared to previous studies on Egypt is differentiating between intentional herding that results from exposures to the common fundamental risk factors and unintentional herding that ignores these factors. Gabbori *et al.* (2020) argue that investors may make similar investment decisions whether individually or independently, as a response to fundamental market information. As previous research has not accounted for market co-movement of similar style investors may be incorrectly interpreted as herding, which possibly leads to over reporting of herding tendency in financial markets by the reported inferences on herding.

Therefore, they suggest partialing out the Fama-French-Carhart investment styles/risk factors from the CSAD. It is worth mentioning that the literature shows that these factors capture fundamental information (Liew and Vassalou, 2000; Kessler and Scherer, 2010). To filter the part of the CSAD that is related to the risk factors, by regressing it on four risk/style factors as follows:

$$CSAD_t = \beta_0 + \beta_1\left(R_{m,t} - R_f\right) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + e_t \tag{5.28}$$

where $R_{m,t}$ is the return on the market portfolio, while the R_f is the return on the risk-free asset. $R_{m,t} - R_f$ is a market-oriented investment style which establishes exposure to the general market. The HML_t factor is the return on the portfolio that longs the high book to market value stocks and shorts the low book to market companies. The SMB_t factor is the return on the portfolio that invests in small companies and sells large ones, which is expected to capture small-cap investment style. The MOM_t (momentum) factor of Carhart

(1997) represents the return on a portfolio that buys previous winners and sells previous losers.

5.5.2 Constructing Fama-French-Carhart Variables

This thesis uses the Egyptian version of the Fama-French-Carhart factors as the main risk factors. Since the Fama and French portfolios are not readily available for the Egyptian stock market, and following the lead of Abdou (2018) in constructing them, these portfolios are constructed by the author using the Fama and French (1993) approach.

The market factor is the difference between value weighted average return of all the stocks listed and used (173 companies) in this thesis and the risk free rate in this case the three-month Treasury bill rate. The market factor is considered to be the excess return on the market portfolio, which reflects exposure to the general market. As for the SMB (small minus big), HML (high minus low) and MOM (momentum) are constructed from the filtered data of 173 companies. The SMB and the HML are constructed from portfolios formed based on 2x2 sorts on size and the B/M ratio. For a stock to be included in the portfolio, then it has a stock price for December of year $t-1$ and June of year t, and book equity for year $t-1$.

There are two steps required for the SMB and HML factors to be constructed. First, the stocks are sorted based on market capitalization at the end of June of year t, then the stocks whose market capitalization constitutes 90% of the total market capitalization of all stocks used (173 stocks) are classified as big stocks “B” while the remaining stocks are classified as small stocks “S” (Cakici *et al.* 2013). The second step is to sort stocks into two portfolios Value “H” and Growth “L” based on the book to market ratio. The B/M ratio is used to determine the value of a company by comparing its book value to its market value. Which is calculated as the ratio of the book value of stockholders' equity for the fiscal year ending in calendar year $t-1$, to the market equity at the end of December $t-1$. The end of December market capitalization is used to calculate the firm B/M ratios regardless the firms' fiscal year end to neutralize the impact of market conditions on the ratio.

To determine the B/M ratio breakpoint, stocks in the big portfolio are classified based on their B/M ratio to determine the median that is used to sort the bottom (growth) and the top (value) breakpoints. Determining the breakpoints using stocks in the big portfolios is intended to ensure that the factors are not dominated by less important illiquid small and tiny stocks which may jeopardize the results of testing asset pricing models (Gregory *et al.*, 2013; Fama and French, 2012). By the end of this step, two portfolios are formed which are the value "H" portfolio, and the growth "L" portfolio. Then, from the intersection of the two market capitalization and the two B/M groups, four portfolios are formed which are (SH, SL, BH, BL), such as SH portfolio include stocks that are in the small market capitalization portfolio and that are in the high B/M ratio portfolio.

The daily value weighted return for each of these portfolios from July of year t to June of year $t+1$ is calculated. Returns are calculated starting from 1st of July to ensure that the book equity for year $t-1$ has been announced to the public and this representing a full fiscal year. Using value weighting ensures that the variance of firm specific factors is minimized as return variance is negatively correlated with firm size, as well as to ensure constructing mimicking portfolios that capture the different return behaviours of small and big stocks, or value and growth stocks, in a manner that corresponds to real investment strategies followed by investors.

Finally, the SMB return is calculated for each day as:

$$SMB = \left(\frac{SH + SL}{2}\right) - \left(\frac{BH + BL}{2}\right) \tag{5.29}$$

which represents the difference between the small and big portfolios with the same weighted average book-to-market equity intending to disentangle between the size and B/M effects (Fama and French, 1993).

Similar to the SMB construction, the HML factor is calculated daily as:

$$HML = \left(\frac{SH + BH}{2}\right) - \left(\frac{SL + BL}{2}\right) \tag{5.30}$$

Which again ensures that the size and the B/M effects are disentangled.

The last factor is the Carhart (1997) momentum (MOM) return, which represents the return on a portfolio that buys previous winners and sells previous losers. To construct the momentum style factor, to be included in the portfolio for day t (formed at the end of day $t-1$), a stock must have a price for the end of day $t-250$ and a return for $t-20$, then the average return is calculated. Next, dividing the portfolios into Big and Small based on market capitalization at the end of June of year t. Then they are classified into two momentum portfolios which are momentum winner (high returns, W) and loser (low or negative returns, L) portfolios forming four portfolios (BW, BL, SW, SL) by using the median of the portfolios. These portfolios are rebalanced monthly on the basis of the previous year’s performance of companies. The MOM factor is then calculated as the difference between the averages of the two winner portfolios (SW and BW) and the two loser portfolios (SL and BL).

$$MOM = \left(\frac{BW + SW}{2}\right) - \left(\frac{BL + SL}{2}\right) \tag{5.31}$$

Returns on the factors are computed as averages of value weighted returns of the relevant company portfolios. After constructing the Fama-French-Carhart factors, the next section explains how to eliminate these fundamental factors from the CSAD in order to differentiate between intentional and unintentional herding.

5.5.3 Intentional and Unintentional Herding

In light of the discussion in Chapter 4 on differentiating between intentional herding which is the outcome of the fundamental factors, from unintentional herding, which is the outcome of the non-fundamental factors, this section provides the applied method to examine them. This will help fulfil the seventh objective of this thesis, which is analysing whether herding in Egypt is due to fundamental risk factors or due to non-fundamental factors.

By regressing the CSAD on the Fama-French-Carhart factors, this conditional CSAD on the factors represents the part of the deviation that emanates from identical decisions or investor similar responses to the same information. Hence, the rest of the CSAD can be attributed to pure market sentiment and unintentional herding. Starting with regressing the CSAD on the factors and then subtracting the actual CSAD from the fitted CSAD this reflects the part of the CSAD that is considered unintentional herding behaviour, where the non-fundamental is the estimate of the error term of equation (5.28).

$$CSAD_{NONFUND,t} = e_t \tag{5.32}$$

The remaining part of CSAD represents the intentional herding which is linked to the fundamental factors and estimated as:

$$CSAD_{FUND,t} = CSAD_t - CSAD_{NONFUND,t} \tag{5.33}$$

Therefore, examining the significant of intentional herding ($CSAD_{FUND,t}$) and unintentional herding ($CSAD_{NONFUND,t}$) using:

$$CSAD_{FUND,t} = \beta_0 + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + e_t \tag{5.34}$$

$$CSAD_{NONFUND,t} = \beta_0 + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + e_t \tag{5.35}$$

Furthermore, after differentiating between intentional and unintentional herding, the next section applies this on different market conditions and examine whether investors reactions are different.

5.5.4 Herding in Different Market Conditions

Differentiating between the intentional and unintentional herding, it is interesting to analyse the effect of the major events that took place in Egypt in the sample period. As mentioned before, the sample period is rich with numerous events such as the Global Financial Crisis, the Arab Spring and the floatation of the currency. In order to fulfil the eighth objective of this thesis, which is to analyse the presence of herding behaviour in different market conditions, the sample period is divided into six subsamples.

The first subsample is the pre-crisis period, which covers the period from the beginning of 2005 to the end of 2007 which is considered a stable period, where no major events took place. The second subsample is the Global Financial Crisis (GFC) period, which covers the period from the beginning of 2008 to the end of 2009. The third subsample is the Arab Spring period, which represents the period from the beginning of 2010 to 30 June 2013. This crisis affected many MENA economies not just Egypt. It is possible to specify the end of this subsample because the specific date of 30 June 2013 is a turning point for Egypt where the start of the second crisis begins. The fourth subsample is the second Egyptian revolution which covers the period from 1 July 2013 to the end of 2014. The fifth subsample is the economic reform, which represents the period from beginning of 2015 to the end of 2016 where the government carried out a number of reform policies in an attempt to boost the economy such as the floating of the Egyptian Pound. Finally, the sixth subsample is the post-crisis period, which represents the period from the early of 2017 to the mid of 2019, where no major events is taking place. Testing the presence of herding behaviour for these six subsample will indicate which period were the investors herding the most and help interpret the behaviour of the investors in different market conditions.

5.6 Conclusion

This chapter described the methodologies employed in estimating and testing volatility spillover of the selected markets representing the MENA region. Testing the significance of the various spillover indexes needs estimating the standard errors of these indexes. A bootstrap procedure is employed to develop statistical methods of volatility spillover index.

Finally, the chapter narrows the scope to testing the presence of herding behaviour in the Egyptian stock market by employing the cross sectional absolute deviation (CSAD) and regressing it on the absolute and squared returns. Differentiating between intentional and unintentional herding requires regressing the Fama-French-Carhart factors representing the fundamental risk factors and eliminating them from CSAD. Finally, we analyse the presence of herding behaviour whether intentional or unintentional in different market conditions by dividing the sample period into six subsamples each representing a different phase of the Egyptian market.

Chapter 6

Descriptive Statistics, Volatility, and Spillover

6.1 Introduction

Over the past decades, several researches are being devoted to modelling and forecasting volatility of financial returns aiming to understand its meaning and to support the investing decisions in general (Chen *et al*., 2001). Moreover, volatility spillover became recently one of the most important aspects to be studied for emerging markets. Many researchers decide to examine the volatility spillover effect trying to explore the link between variables or markets taking into consideration economic and political activities that affects this link. Understanding how a given market contributes to the volatility of other markets is important for academics as well as investors (Alshbiel and Al-Zeaud, 2012).

Understanding the spillover scale and mechanism contributes to our understanding of global diversification. Investments within the MENA region remain minimal and are subject to year to year fluctuations which makes it interesting to examine. The World Bank (2011) states that investments nowa-days in the MENA region are less attractive even for global markets than it was in 1996, and little progress is achieved in the region's integration. However, Hassan and Bashir (2005) mention that only Morocco and Egypt allow unrestricted access to foreign investors and Jordan allows foreigners to hold up to 50% of a company's capital. Moreover, regulations in the Gulf Cooperation Council like Bahrain, Oman, Saudi Arabia, Kuwait, and UAE equity markets restrict investments by non-GCC citizens. Therefore, since the MENA region markets exhibit different degrees of financial liberalization and movements over time, it is important to examine the linkages and spillover effects among these markets (Neaime, 2002).

Furthermore, the MENA region is interesting due to the large number of adverse political events that took place. Since several events took place in this region, the importance of spillover is to measure the effects these events had on markets; whether they recovered or not, and most importantly seeing the investing opportunities available in these markets. Lehkonen (2015) argues that the link between spillover and financial crisis is not examined enough in previous studies. Therefore, examining volatility spillover for the MENA region is significant especially after the Global Financial Crisis, the Arab spring and other events that took place.

Initially, this chapter aims to describe the data employed in this study. The chapter begins by presenting descriptive statistics for Bahrain, Egypt, Jordan, Kuwait, Oman, Saudi Arabia, Turkey, and UAE nominal stock markets returns along with estimating volatility. Furthermore, the chapter highlights the importance of real returns and estimates their volatility using different models and provides a comparison between the models. Additionally, the chapter investigates the MENA region stock market volatility spillover using the Diebold and Yilmaz framework in order to see the transmission of information between the markets. Finally, dividing the sample in order to reflect the three major events that took place in the MENA region. We set a pre-crisis period (2003 to 2007); the Global Financial Crisis and Arab Spring period (2008 to 2013); and a post-event period (2014 to 2018) in order to capture the transmission of these events and see their effect on each market.

This chapter is outlined as follows. First, section 6.2 presents the nominal returns descriptive statistics along with testing for ARCH effects and modelling volatility using symmetric model. Secondly, section 6.3 introduce the real returns descriptive statistics and analyse volatility using different symmetric and asymmetric models. Section 6.4 examines the volatility spillover using the DY framework. Section 6.5 explores the spillover of the three categories of the sample pre-crisis, during the events, and post-events that happened. Lastly, section 6.6 concludes.

6.2 Nominal Returns

This section presents the descriptive statistics of the returns for the eight countries considered in this thesis. Looking at the monthly data from January 2003 till December 2018, there are 192 observations for each of the eight countries as a representative sample of the MENA region. The descriptive statistics are needed to capture and ensure that using the ARCH/GARCH models are the right choice (Engle, 2001) (Lee *et al*., 2001). The nominal returns are calculated as logarithmic price relatives $R_t = \ln(P_t/P_{t-1})$, where P_t is the monthly nominal local-currency stock market index. The next section provides the descriptive statistics for the nominal returns.

6.2.1 Nominal Returns Descriptive Statistics

The importance of descriptive statistics emerges from examining the validity and the accuracy of applying the design and methods intended to be used on the sample by using measures of central tendency, such as the mean, the median and measures of spread like standard deviation. Furthermore, descriptive statistics presents the skewness and kurtosis of the sample which are helpful tools to identify the location and the variability of the data

(Thessaloniki, 2014). The summary of the descriptive statistics for the returns of each market is reported in Table 6.1.

Egypt and Turkey have the two largest means among the eight countries due to the depreciation of their currency and inflation, whereas, Bahrain has the lowest mean. The gap between the maximum and minimum reflects the level of dispersion from the average return in a market. As for the standard deviation, Egypt and Turkey are the most dispersed while Bahrain is the least, implying that there is more uncertainty in the returns on Egypt and Turkey and less uncertainty on Bahrain market. This seems to be consistent with the positive correlation between return and risk, but the picture is clear since these two countries also suffered currency devaluation during the period of study, so the abnormally high average return could simply be a reflection of currency devaluation rather than real return to investors.

All countries except for UAE have negative skewness, which means that there is a long tail in the negative direction of the distribution. Heuristically, it seems that all but one markets have been hit by more bad news than good news. However, this implies a large number of extreme (positive and/or negative) returns. Given the skewness and excess kurtosis, the distribution of returns departs significantly from normality. The Jarque-Bera test confirms departure of return distributions from normality for all eight markets as the p-values are significant. Turkey seem to be the most stable (or least unstable) country, having the lowest negative skewness and the lowest excess kurtosis. However, The Jarque-Bera statistic is 7.564, which is greater than 5% critical value of 5.99 for a Chi-square with 2 degrees of freedom, though less than the 1% critical value of 9.21. Thus, it seems fair to conclude that the Turkish returns are close to normal.

Table 6.1: Nominal Returns Descriptive Statistics

	Mean	Min.	Max.	SD	Skewness	Kurtosis	Jarque-Bera	p-value
Bahrain	0.001	-0.130	0.092	0.034	-0.350	1.759	28.543	0.000
Egypt	0.016	-0.403	0.312	0.095	-0.316	2.150	39.996	0.000
Jordan	0.003	-0.248	0.150	0.047	-0.647	4.932	206.978	0.000
Kuwait	0.005	-0.271	0.184	0.053	-0.562	4.619	179.939	0.000
Oman	0.004	-0.313	0.162	0.051	-1.225	7.979	554.548	0.000
Saudi Arabia	0.005	-0.297	0.178	0.075	-0.803	1.911	49.617	0.000
Turkey	0.011	-0.269	0.242	0.079	-0.254	0.812	7.564	0.020
UAE	0.006	-0.191	0.359	0.065	0.517	5.145	219.229	0.000

Note: Nominal returns for all eight markets are calculated as $R_t = ln(P_t/P_{t-1})$. The mean, min - minimum, max - maximum, SD- standard deviation, skewness, kurtosis, and Jarque-Bera tests the null hypothesis of normality of returns along with its p-value are shown in columns for the eight markets.

The second step is unit root test using the Augmented Dickey Fuller (ADF) test, to ascertain return stationarity. Stationarity is necessary to avoid spurious statistical results. Table 6.2 presents the results of the Ljung-Box Q-statistics where evidence of autocorrelation significantly at 1% level (p-value=0.000) is found for all eight markets. Furthermore, Table 6.2 displays the Ramsey's RESET test results which provides evidence of non-linearity for the eight markets.

Figures 6.1 to 6.8 show the stock indexes and returns for each of the eight countries. Looking at the Price index of the eight countries, it is very interesting to see that Saudi Arabia, Kuwait, Oman, Bahrain and Jordan did not recover after the crisis in 2008. While UAE seems half-recovered from the crisis, and apparently Egypt and Turkey recovered. These results shed light on an important aspect which is the currency fluctuations of each country. Realistically, Egypt and Turkey did not recover after the crisis while the other countries did not, taking into consideration that both markets faced depreciation as well as inflation. This points out that exchange rate may be a major factor behind these price index illusionary recovery.

Table 6.2: Autocorrelation and Linearity tests output

	Ljung Box Q-statistics		Ramsey’s RESET test	
	Statistics	p-value	F-test	p-value
Bahrain	91.833	0.000	21.664	0.019
Egypt	25.828	0.000	18.402	0.006
Jordan	51.547	0.000	23.145	0.004
Kuwait	60.822	0.000	52.472	0.006
Oman	75.209	0.000	14.963	0.021
Saudi Arabia	37.054	0.000	11.241	0.017
Turkey	22.169	0.000	22.154	0.029
UAE	50.535	0.000	41.241	0.008

Note: Ljung Box Q-statistics measures the serial autocorrelation in the returns up to 10 lags, statistics and its significance level for each market. Non-linearity results are shown by Ramsey’s RESET test, F-test and its significance level for each market.

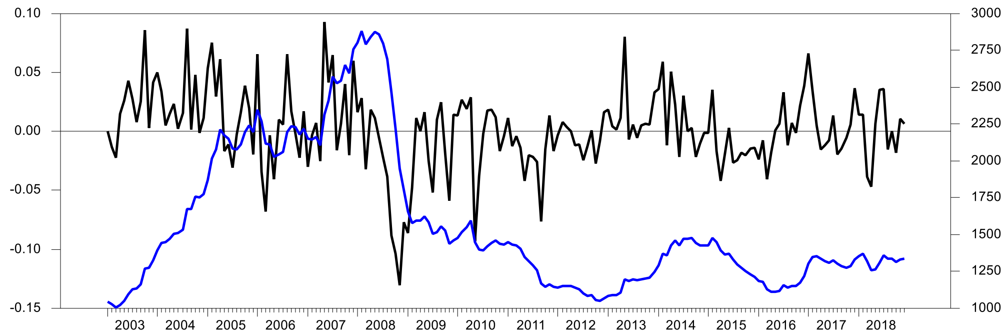

Figure 6.1 Bahrain Stock Index Prices and Returns

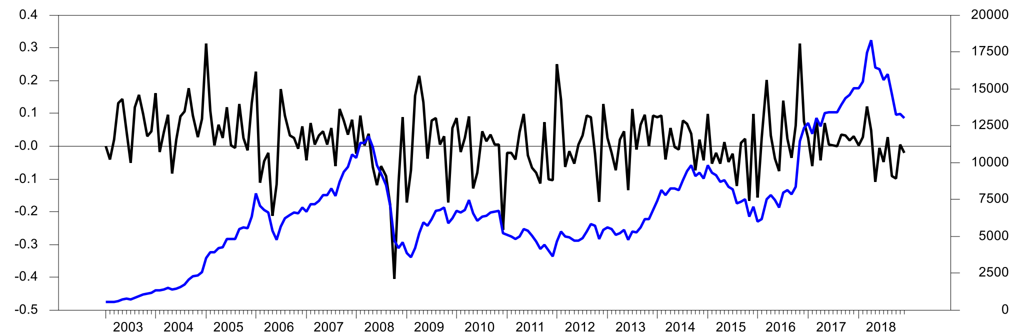

Figure 6.2 Egypt Stock Index Prices and Returns

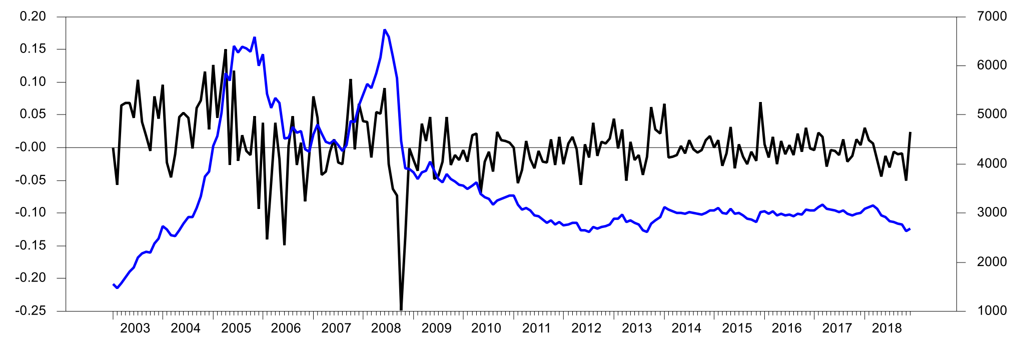

Figure 6.3 Jordan Stock Index Prices and Returns

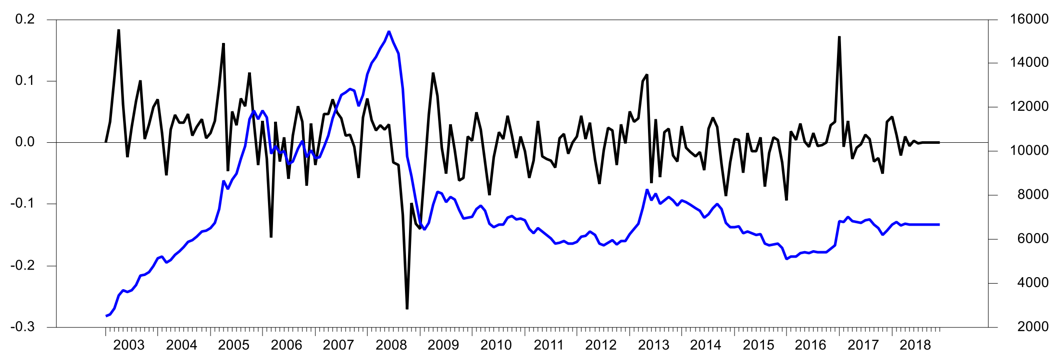

Figure 6.4 Kuwait Stock Index Prices and Returns

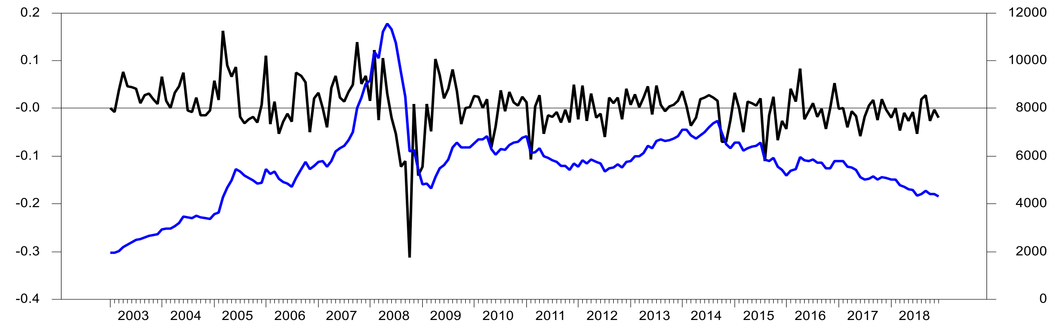

Figure 6.5 Oman Stock Index Prices and Returns

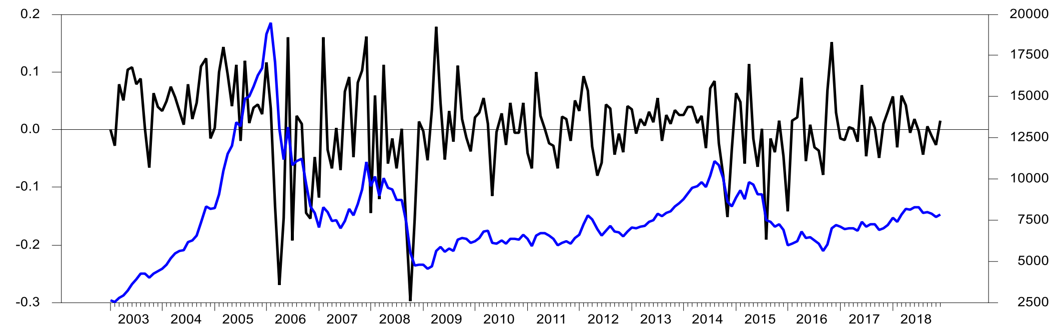

Figure 6.6 Saudi Arabia Stock Index Prices and Returns

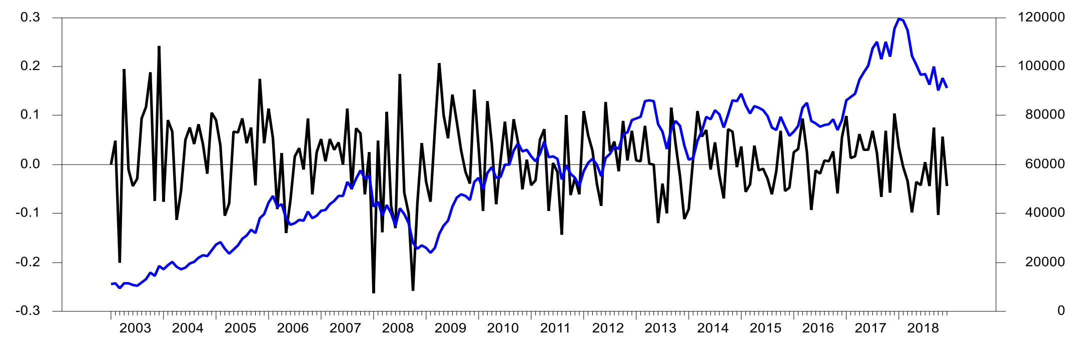

Figure 6.7 Turkey Stock Index Prices and Returns

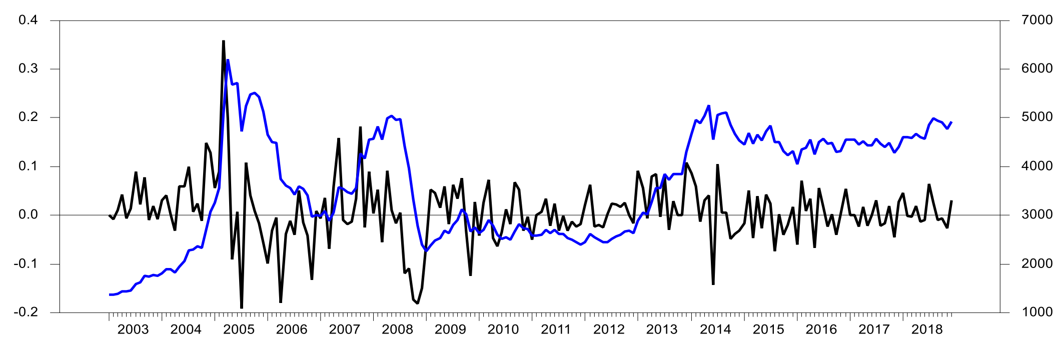

Figure 6.8 UAE Stock Index Prices and Returns

Note: The x-axis of the graphs reflects the sample dates by months from year 2003 to year 2018. The left y-axis reflects the returns and shown on the graph by the black, while the right y-axis reflects the stock market prices and reflected on the graph by blue.

Another important feature that can be noticed in the figures is that the amplitude of the returns varies over time, suggesting "volatility clustering" (Mandelbrot, 1963). In turn, heteroscedasticity or volatility clustering suggests the presence of non-linear dependence in returns. In other words, large returns tend to be followed by large returns, while small returns are followed by small returns. The standard models that are appropriate for heteroskedastic returns are the ARCH/GARCH models. Before estimating GARCH models, one must compute the Lagranger Multiplier test proposed by Engle (1982) for ARCH effects to make sure that this class of models is appropriate for the data. A test for the presence of ARCH effect in the residuals is calculated by regressing the squared residuals on a constant and p lags, where p is a set by choosing the optimal lag length by the Akaike Information Criterion (AIC) (Akaike, 1973) and Schwarz Bayesian Criterion (SBC) (Schwarz, 1978) (Brooks, 2015).

Table 6.3 presents the results of the "ARCH test" where the Chi-squared is highly significant suggesting the presence of ARCH in returns. The next section estimates volatility using the ARCH/GARCH model.

Table 6.3: Test for ARCH

	Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE
Chi-squared	28.8	8.2	9.15	11.44	2.17	21.95	8.17	15.28
Signif. level	0.000	0.0001	0.002	0.0007	0.001	0.000	0.000	0.000

Note: ARCH effects in returns are shown by the ARCH test, where Chi-squared and significance level are below each market.

6.2.2 Modelling Volatility for Nominal Returns

Policy makers rely on volatility as a measure of risk to assess financial markets and the economy. An appropriate selection of volatility models is therefore needed to capture an accurate measure of volatility (Poon and Granger, 2003). This section aims to model volatility using the ARCH/GARCH model. When volatility evolves over time, simple standard deviation becomes inadequate, while ARCH/GARCH models are better able to capture the time variation in volatility.

Implementing the GARCH model allows for symmetric impact of news on volatility. The GARCH mean equation is given by

$$r_t = \mu + \lambda r_{t-1} + \varepsilon_t \tag{6.1}$$

and the variance equation by

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{6.2}$$

$\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, $\alpha_1 + \beta_1 < 1$. Where the mean is given by $\mu/(1-\lambda)$, α_1 is the influence of random deviations in the previous period on σ_t, β_1 is the part of the realized variance in the previous period that is carried over into the current period. The size of α_1 and β_1 determine the short run dynamics of the resulting time series. In other words, the news about volatility from the previous periods has an explanatory power on current volatility (Engle and Bollerslev, 1986). Table 6.4 presents the estimation results for the GARCH model. We first note the marked difference in the behaviour of volatility and the impact of past volatilities and shocks (news) across the eight markets. The persistence (β_1) is generally high varying between 0.71 and 0.88 for Egypt, Jordan, Saudi Arabia, Turkey and UAE. Bahrain's persistence is very low (0.26), but Kuwait is almost inexistent (0.02). This suggests that volatility in these two markets is mostly driven by news and shocks.

Thus, seven models are acceptable, satisfying the condition $\alpha_1 + \beta_1 < 1$. However, for Egypt the model is rejected as the sum of the two slopes is greater than 1. This is perhaps due to the extreme and repeated shocks that the Egyptian market has undergone during the last decade. We have therefore run an IGARCH in order to impose the equality $\alpha_1 + \beta_1 = 1$ as the volatility seems to be integrated for Egypt. The model is significant with the slope equalling 1.000, with a p-value of 0.000. This model is used to estimate volatility for Egypt.

Table 6.4: GARCH Model Output for nominal returns

	Intercept	p-value	α_1	p-value	β_1	p-value	$\alpha_1 + \beta_1$
Bahrain	0.334	0.000	0.372	0.036	0.260	0.001	0.632
Egypt	1.551	0.002	0.310	0.013	0.712	0.031	1.022
IGARCH (EGYPT)	0.017	0.000	0.001	0.000	1.000	0.000	1.000
Jordan	0.064	0.010	0.172	0.008	0.811	0.000	0.983
Kuwait	0.301	0.000	0.833	0.000	0.021	0.007	0.854
Oman	0.453	0.036	0.191	0.004	0.592	0.000	0.783
Saudi Arabia	1.130	0.011	0.241	0.004	0.750	0.000	0.991
Turkey	0.861	0.005	0.070	0.020	0.880	0.003	0.950
UAE	0.473	0.009	0.181	0.000	0.804	0.000	0.985

Note: GARCH output for nominal returns. The intercept, α_1, and β_1 are shown beside each market along with each significance. $\alpha_1 + \beta_1 < 1$ for all markets, except for Egypt, therefore IGARCH is done.

Figures 6.9 to 6.16 show estimated volatilities for the eight markets. Except for Egypt (IGARCH) the volatilities were produced using the GARCH models shown in Table 6.4. There are several remarks that can be drawn from the eight graphs. The y-axis in all graphs represent the volatilities percentage, and the x-axis reflect the monthly time frame from 1/2003 to 12/2018. Noticing that around 2008 all markets volatility increased to their peak, except for the UAE. It is clear that this period increase is a reaction to the Global Financial Crisis, where Kuwait's volatility increased by almost 7% the highest among all markets, while Bahrain the lowest volatility increase by 0.8%. Markets like Jordan, Oman, and UAE seem almost stable with minimal turmoil in the preceding years. As for Bahrain, the market's highest turmoil is around 2008 but throughout the year's minimal instabilities took place. Similarly, Kuwait's market is like the Bahrain market but had another high turmoil around the end of 2016 and beginning of 2017. Unlike the other markets, UAE highest turmoil took place around 2005, and began to stabilize by 2010. With regards to Turkey the market experienced fluctuations until 2011 it became less instable. Finally, Egypt's volatility measured by IGARCH shows ups and downs throughout the years and no stability in any of the years.

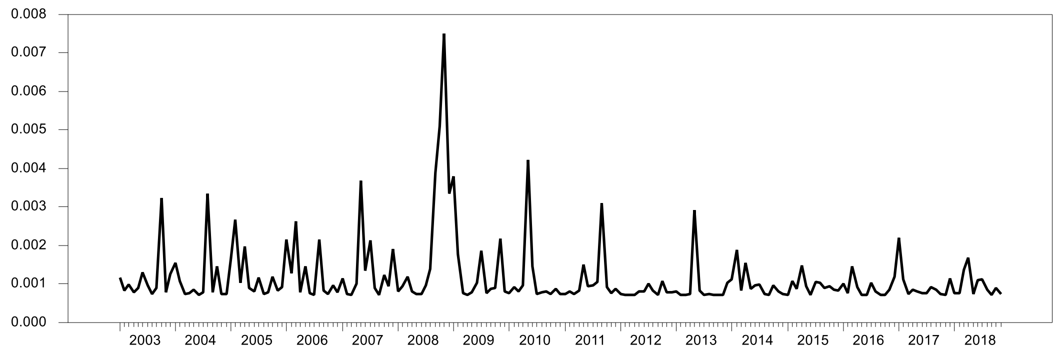

Figure 6.9 Bahrain GARCH output (Nominal returns)

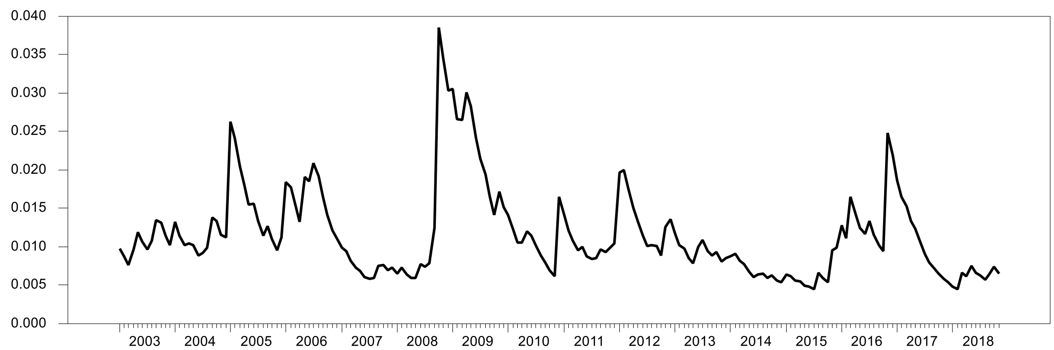

Figure 6.10 Egypt IGARCH output (Nominal returns)

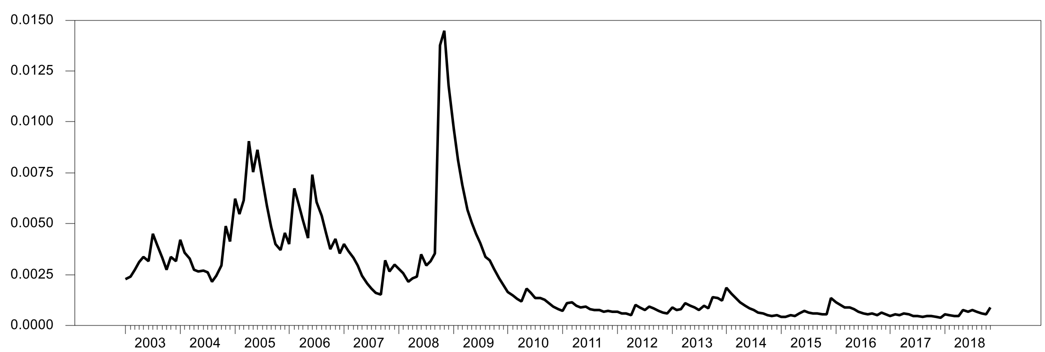

Figure 6.11 Jordan GARCH output (Nominal returns)

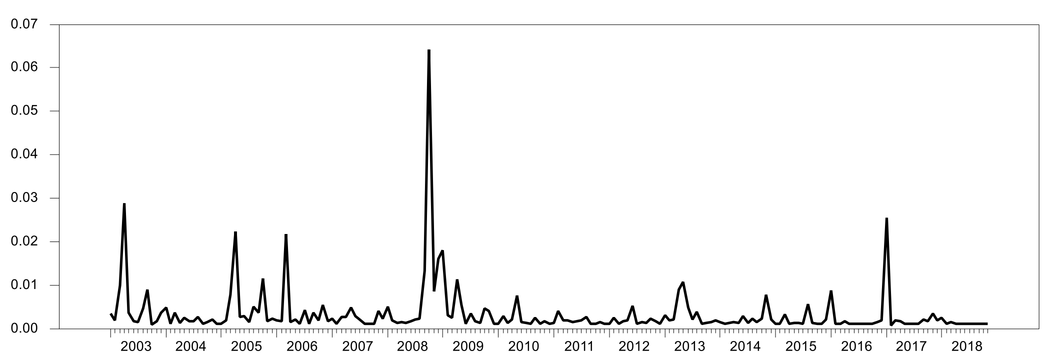

Figure 6.12 Kuwait GARCH output (Nominal returns)

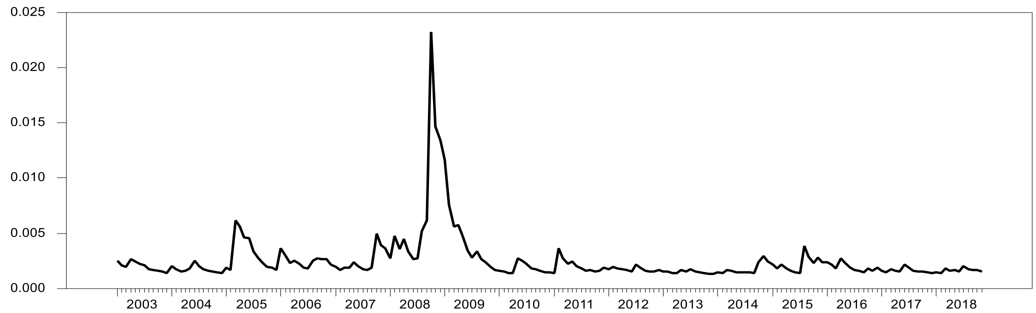

Figure 6.13 Oman GARCH output (Nominal returns)

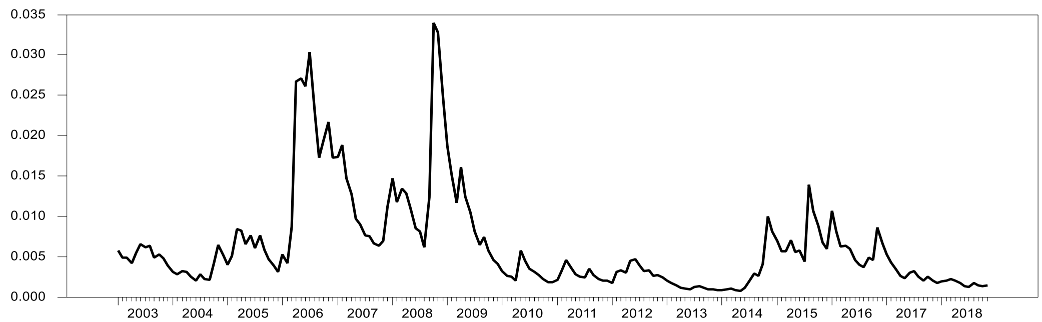

Figure 6.14 Saudi Arabia GARCH output (Nominal returns)

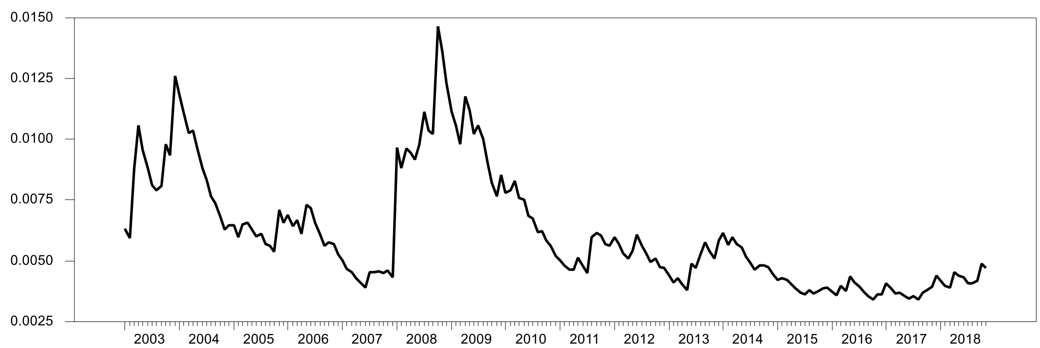

Figure 6.15 Turkey GARCH output (Nominal returns)

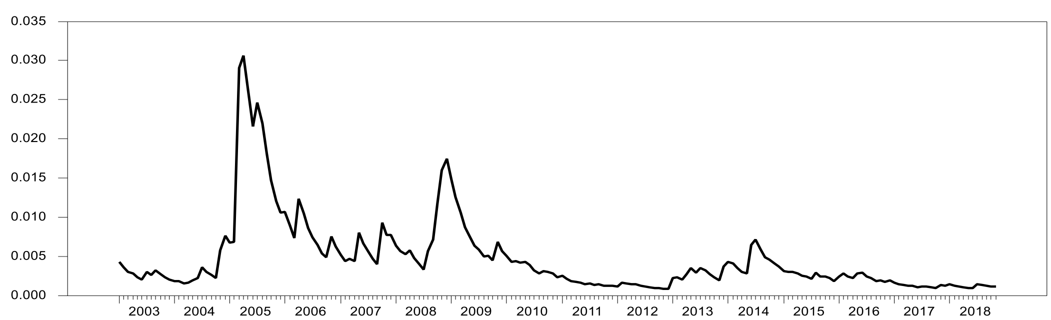

Figure 6.16 UAE GARCH output (Nominal returns)

Note: The x-axis of the graphs reflects the sample dates by months from 1/2003 to 12/2018. The y-axis reflects the volatility measured by GARCH model for all figures except for figure 5.10 Egypt's volatility is measured using IGARCH.

After looking at the eight MENA region market's prices, returns, and volatility graphs along with the statistics and output of the applied tests; the results may not be realistic nor compatible with the real life market. This can be due to other factors affecting the output making it vary from what it should be. One of the main factors that can have a huge effect on the MENA region markets is the currency. Since, the local currency nominal returns might be the reason of some of the anomalies and discrepancies found. Therefore, currency returns are calculated in order to see the effect of depreciation and compare across countries. Hence, from this point on currency returns is employed rather than nominal returns. The next section discusses the currency returns in details along with providing its calculation method, its importance, its descriptive statistics, and analysing volatility using it.

6.3 Currency Returns

Taking into consideration depreciation of the currency signifies the importance of calculating the currency returns. As seen from the previous descriptive statistics some of the MENA region countries face currency fluctuations. Especially in the period of study we are examining, there were depreciation of currency for some of the countries. This shreds the light on the importance of calculating the currency returns. The currency returns are simply calculating nominal returns which was dealt with in the above section but now taking into account the percentage exchange rate change. First, to be consistent, we calculate exchange rate change as we calculated the returns: $ER_t = \log \frac{x_t}{x_{t-1}}$, where x_t is the monthly exchange rate of the local currency to the US dollar. Then, calculating the currency returns as: $\$R_t = (1 + R_t/1 + ER_t) - 1$, where R_t is the nominal returns, and

ER_t is the change in exchange rate. Examining the nominal returns for the eight countries in terms in US dollars makes it behave like real returns also it allows for an easier comparison across countries. Moreover, since our sample contains developing countries, we can assume that the dollar exchange rate is close to the inflation rate, which confirms our assumption that the currency returns can be considered real returns. The expression "real returns" is used throughout the rest of the chapter. The next section provides the descriptive statistics of the real returns.

6.3.1 Real Returns Descriptive Statistics

Descriptive statistics for the real returns of each market are presented in Table 6.5 to aid our understanding of the nature, distributional characteristics of the markets, and compare with the nominal returns. Egypt and Turkey still have the largest mean but Egypt's mean increased compared to the nominal returns statistics while Turkey's mean declined. This explains that currency depreciation has played a major role in Egypt and was one of the main factors that affected the Egyptian stock index. Other countries where the currency did not affect the index, are found with almost the same mean as the nominal returns statistics reported. In addition to the similar results of the nominal returns, Egypt and Turkey are still the most volatile and Bahrain the least volatile.

However, the real returns report higher volatile markets than the nominal returns, which again confirms that the high average returns are due to the devaluation of the currency. The skewness and kurtosis is not different than what the nominal returns statistics have reported, all countries are negatively skewed except for UAE and excess kurtosis is high for all counties except for Turkey. Unlike the nominal returns Jarque-Bera for Turkey that presented almost normal returns, the real returns Jarque-Bera for Turkey are high and significant confirming non-normal returns. These results suggest using real returns over nominal returns since the currency devaluation clearly affected the MENA region markets. The next section models volatility using symmetric and asymmetric ARCH/GARCH models using real returns.

Table 6.5: Real Returns Descriptive Statistics

	Mean	Min.	Max.	SD	Skewness	Kurtosis	Jarque-Bera	p-value
Bahrain	0.001	-0.129	0.092	0.033	-0.345	1.780	29.190	0.000
Egypt	0.011	-0.411	0.341	0.104	-0.342	2.159	41.048	0.000
Jordan	0.003	-0.250	0.150	0.047	-0.666	5.039	217.400	0.000
Kuwait	0.005	-0.270	0.177	0.054	-0.621	4.227	155.331	0.000
Oman	0.004	-0.313	0.162	0.050	-1.223	8.029	563.727	0.000
Saudi Arabia	0.005	-0.299	0.178	0.075	-0.798	1.955	51.005	0.000
Turkey	0.007	-0.306	0.260	0.091	-0.349	0.496	25.873	0.043
UAE	0.006	-0.191	0.358	0.065	0.520	5.177	223.11	0.000

Note: Real returns for all eight markets are calculated as \$$R_t = (1 + R_t/1 + ER_t) - 1$. *The mean, min - minimum, max - maximum, SD - standard deviation, skewness, kurtosis, Jarque-Bera and its p-value are shown in columns for all markets.*

6.3.2 Symmetric Models with Real returns

This section estimates volatility of real returns using the GARCH model as the previous section. It is expected that there is a difference between the GARCH's output of nominal returns and GARCH output of real returns if the currency devaluation had a role in that stock market. Table 6.6 presents the GARCH output of real returns volatility. In agreement with the previous section, it is noted that the marked difference in the behaviour of volatility and the impact of past volatilities and shocks (news) across the eight markets.

The markets with persistence (β_1) that is generally high varying between 0.63 and 0.87 Oman, Jordan, Saudi Arabia, Turkey and UAE which is different than the previous results. Egypt's persistence decreased to 0.439 than the output of the nominal returns, which explains the currency's effect on the market. While Oman became more persistence (0.634) than nominal returns results. On the other hand, Bahrain's persistence is still very low (0.27), and Kuwait is almost inexistent (0.014). This again suggests that volatility in these two markets is mostly driven by news and shocks.

Bahrain, Jordan, Kuwait, Oman, and UAE did not differ much from the volatility output of the nominal returns using GARCH model. Meanwhile, Egypt's volatility here is measured by GARCH and is satisfying the condition $\alpha_1 + \beta_1 < 1$. Saudi Arabia did not meet the conditioned benchmark; the model is rejected as the sum of the two slopes is greater than 1. We have therefore run an IGARCH in order to impose the equality $\alpha_1 + \beta_1 = 1$ as the volatility seems to be integrated for Saudi Arabia. The model is significant with the slope equalling 1.012, with a p-value of 0.000. This model is used to estimate volatility for Saudi Arabia. Confirming these interpretations graphically, Figures 6.17 to 6.24 show the volatility of nominal returns using GARCH for all countries except for Egypt using IGARCH, and the volatility of real returns using GARCH for all countries except for Saudi Arabia using IGARCH. Graphing the two output shows the difference between the two volatilities. As mentioned, there is no difference between the two outputs for Bahrain, Jordan, Kuwait, Oman, and UAE. Meanwhile, Egypt, Saudi Arabia, and Turkey the difference between the real and nominal outputs can be seen clearly. This means that the currency devaluation has a great effect on their markets. Egypt and Turkey's volatility became less unstable, and one of the main reasons of their high turmoil is their currency fluctuations. The next section estimates volatility using asymmetric models of the real returns in order to capture the asymmetric effects in the markets.

Table 6.6: GARCH output using Real Returns

	Intercept	p-value	α_1	p-value	β_1	p-value	$\alpha_1 + \beta_1$
Bahrain	0.342	0.000	0.381	0.020	0.276	0.001	0.657
Egypt	0.794	0.000	0.299	0.020	0.439	0.019	0.738
Jordan	0.152	0.04	0.128	0.008	0.738	0.000	0.866
Kuwait	0.251	0.004	0.685	0.022	0.014	0.008	0.699
Oman	0.424	0.024	0.188	0.011	0.638	0.023	0.826
Saudi Arabia	1.130	0.011	0.257	0.001	0.755	0.000	1.012
IGARCH Saudi Arabia	0.085	0.004	0.216	0.000	0.784	0.000	1.000
Turkey	0.379	0.014	0.075	0.015	0.872	0.000	0.947
UAE	0.459	0.005	0.186	0.000	0.810	0.000	0.996

Note: GARCH output for real returns. The intercept, α_1, and β_1 are shown beside each market along with each significance. $\alpha_1 + \beta_1 < 1$ for all markets, except for Saudi Arabia, therefore IGARCH is done.

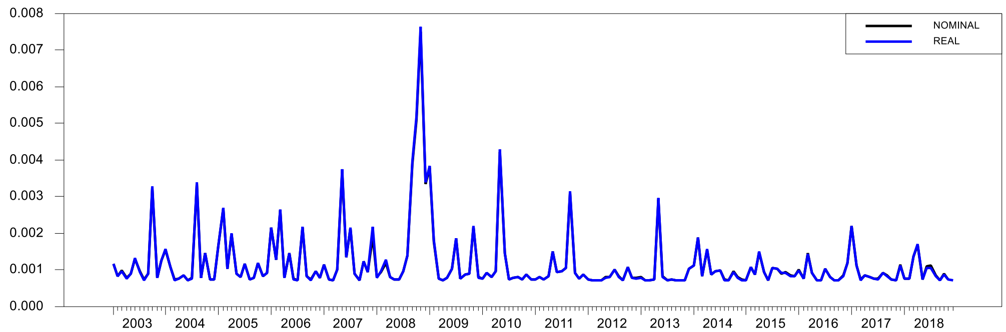

Figure 6.17: Bahrain Real and Nominal Returns GARCH

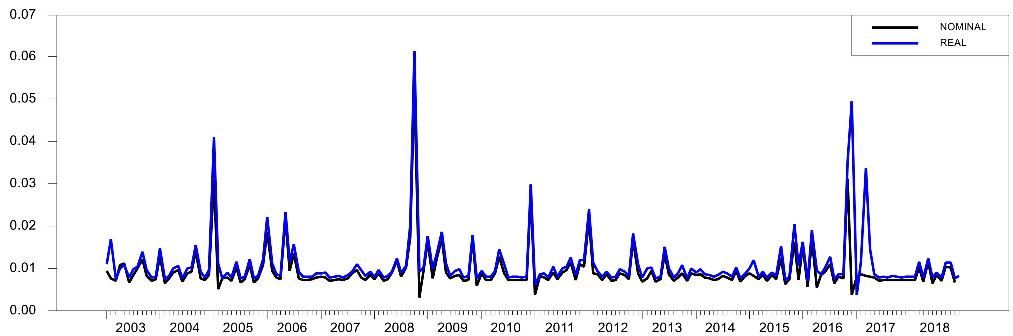

Figure 6.18: Egypt Real and Nominal Returns GARCH

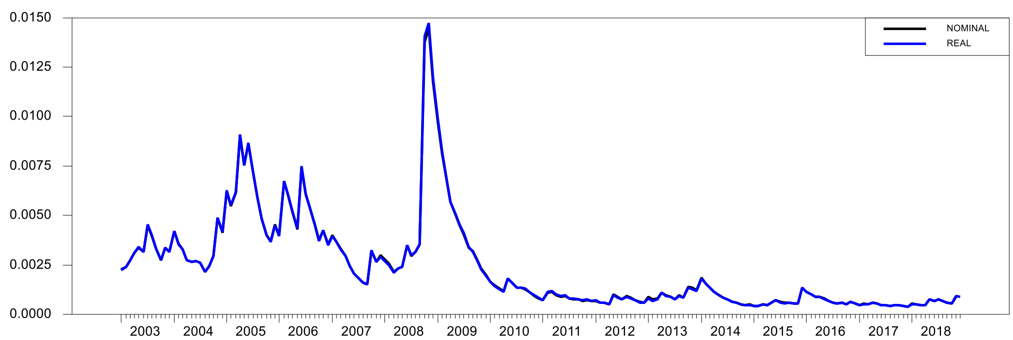

Figure 6.19: Jordan Real and Nominal Returns GARCH

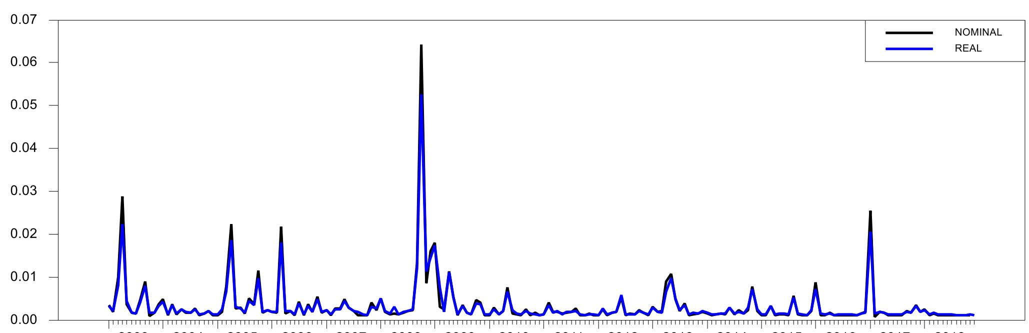

Figure 6.20: Kuwait Real and Nominal Returns GARCH

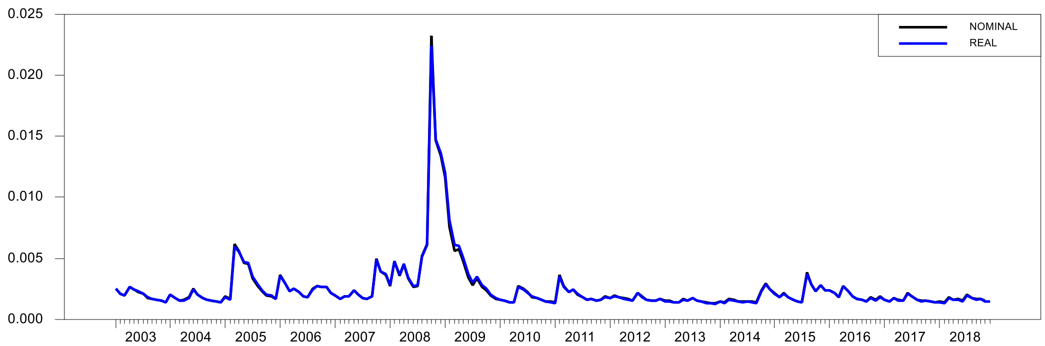

Figure 6.21: Oman Real and Nominal Returns GARCH

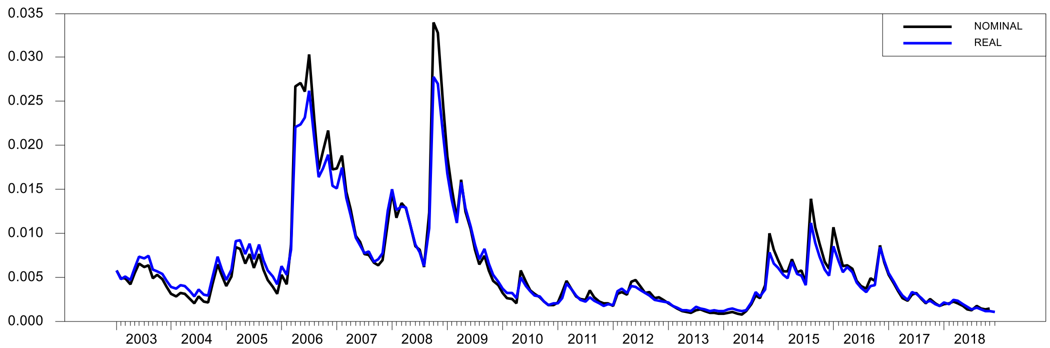

Figure 6.22: Saudi Arabia Nominal Returns GARCH and Real Returns IGARCH

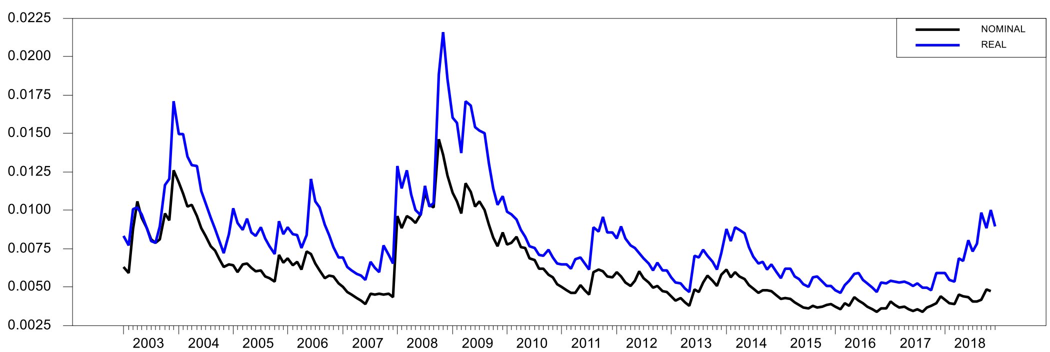

Figure 6.23: Turkey Real and Nominal Returns GARCH

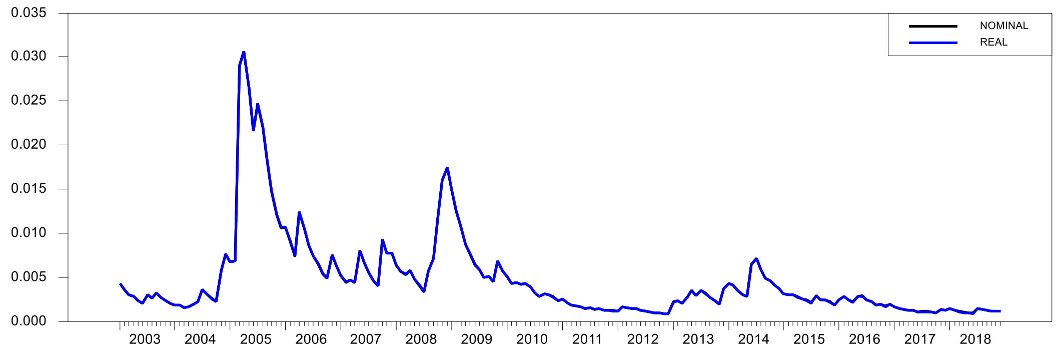

Figure 6.24: UAE Real and Nominal Returns GARCH

Note: The x-axis of the graphs reflects the sample dates by months from 1/2003 to 12/2018. The y-axis reflects the volatility measured by GARCH model for all figure except for figure 6.10 Egypt's volatility is measured using IGARCH.

6.3.3 Asymmetric Models with Real returns

This section models volatility by two popular asymmetric models EGARCH and GJR GARCH which are used to investigate the existence of leverage effects in the returns of each market. The main difference between EGARCH and GJR GARCH is that EGARCH model does not need the nonnegative restriction of the parameters (Irfan *et al.*, 2010).

The EGARCH conditional variance equation (Nelson, 1991):

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{6.3}$$

Since $\log(\sigma_t^2)$is modelled, then even if the parameters are negative σ_t^2 is positive, therefore no need for non-negativity constraints on the model parameters. Asymmetry is found from γ, which is the leverage term. If $\gamma = 0$ then the model is symmetric. If γ is negative statistically different from zero, it indicates the existence of the leverage effect.

The GJR GARCH conditional variance equation (Glosten *et al*., 1993):

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{6.4}$$

where I_{t-1}= 1if $u_{t-1} < 0$, or I_{t-1}= 0 if $u_{t-1} > 0$. The condition for non-negativity is $\alpha_0 > 0$, $\alpha_1 > 0, \beta \geq 0$, and $\alpha_1 + \gamma \geq 0$. For a leverage effect we would see $\gamma > 0$. Even if $\gamma < 0$, provided $\alpha_1 + \gamma \geq 0$ the model is still acceptable.

Table 6.7 presents the output of EGARCH model of the real returns. First, looking at the asymmetric term, Egypt, Oman, Saudi Arabia, Turkey and UAE have a negative significant γ, where the effect of the previous period's bad news is greater than the effect of good news of the same magnitude. On the other hand, Bahrain, Kuwait, and Jordan have significant asymmetric term as well but with a positive sign, suggesting the effect of the previous period's positive news to be greater than the effect of bad news of the same magnitude.

Table 6.8 shows the GJR-GARCH of the real returns. Bahrain, Jordan, Kuwait, Oman and UAE have a positive significant asymmetric term γ indicating a negative shock producing higher volatility in the future than positive shocks of the same magnitude. Meanwhile, Egypt, Saudi Arabia and Turkey have a negative significant γ coefficient indicating a positive shock producing higher volatility in the future than negative shocks of the same magnitude. Four markets satisfy the condition of $\alpha_1 + \beta_1 + \frac{\gamma}{2} < 1$, Bahrain, Kuwait, Oman, UAE, which indicates that the shock does not last for a long time. On the other hand, Egypt, Jordan, Saudi Arabia, and Turkey do not satisfy the condition, $\alpha_1 + \beta_1 + \gamma/2$ is greater than one, indicating the persistence of volatility over time.

Taking into considerations the output of both asymmetric models, acknowledge that Egypt, Saudi Arabia, and Turkey's output for both models confirm that the news is stronger and persistent over time. As for Bahrain, Jordan, Kuwait for both models report positive signs indicating that good news produces higher positive shocks in the future, with Jordan reporting persistency and the others didn't. UAE has negative signs for both models, and not persistent. However, Oman shows negative sign for EGARCH and positive sign for GJR-GARCH with no persistency. The next section compares between the symmetric and asymmetric models used to estimate volatility.

Table 6.7: EGARCH Model output (Real Returns)

	Mean	p-value	α_1	p-value	β_1	p-value	γ	p-value
Bahrain	5.185	0.003	0.574	0.002	0.308	0.022	0.069	0.046
Egypt	6.08	0.000	0.603	0.000	0.220	0.015	-0.085	0.040
Jordan	4.65	0.000	0.143	0.000	0.265	0.000	0.012	0.010
Kuwait	3.945	0.000	0.940	0.000	0.469	0.004	0.057	0.015
Oman	1.200	0.046	0.145	0.004	0.986	0.000	-0.070	0.011
Saudi Arabia	1.339	0.012	0.352	0.002	0.990	0.000	-0.016	0.002
Turkey	3.695	0.000	0.245	0.000	0.269	0.000	-0.196	0.005
UAE	4.23	0.000	0.249	0.000	0.270	0.000	-0.029	0.000

Note: EGARCH output for Real returns. The mean, α_1, and β_1 are shown beside each market along with each significance. γ represents the asymmetric term.

Table 6.8: GJR GARCH Model Output (Real Returns)

	intercept	α_1	β_1	γ	$\alpha_1 + \beta_1 + \gamma/2$
Bahrain	0.59***	0.01**	0.20**	0.49**	0.455
Egypt	1.97***	0.611**	0.57**	-0.22***	1.071
Jordan	0.04**	0.25**	1.01**	0.05***	1.285
Kuwait	0.11***	0.80**	0.02**	0.21*	0.925
Oman	0.54**	0.17***	0.56**	0.07***	0.765
Saudi Arabia	0.05***	0.24**	0.79**	-0.02**	1.02
Turkey	0.44*	0.19**	0.85**	-0.01***	1.035
UAE	0.22*	0.040**	1.01**	-0.15**	0.975

*Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% respectively. GJR-GARCH output for Real returns. The mean, α_1, and β_1 are shown beside each market along with each significance. γ represents the asymmetric term. $\alpha_1 + \beta_1 + \gamma/2$ represents the persistence of the volatility over time.*

6.3.4 Comparing Models

Finding the best model is any economists or analysis goal in order to get good results and less prediction error. Sometimes priority is given to the model with the minimum possible lags. Measures are proposed for selection of a model which can be an optimal model by information criteria for example AIC (Javed, 2011). After modelling volatility using symmetric model GARCH and Asymmetric models EGARCH and GJR GARCH, it is important to determine which model is the best in order to depend on in further analysis or decisions.

Information Criterion tests highlight that the best model is the one that gives the lowest values. Table 6.9 presents the output of three information criterion for each of the three models (GARCH, EGARCH, GJR-GARCH) and each of the eight markets. Except for

Saudi Arabia the three models are IGARCH, EGARCH and GJR-GARCH as explained previously. AIC, SBC, and the Hannan-Quinn (HQ) (Hannan-Quinn, 1979) are the three information criterion tests used here. GJR GARCH model is the best model for all of the eight markets according to the three information criterion tests.

Table 6.9: Testing for the Best Model

	GARCH			EGARCH			GJR GARCH		
	AIC	SBC	HQ	AIC	SBC	HQ	AIC	SBC	HQ
Bahrain	4.012	3.944	3.985	4.010	3.933	3.973	4.001	3.923	3.962
Egypt	1.720	1.652	1.692	1.725	1.657	1.698	1.713	1.645	1.685
Jordan	3.595	3.528	3.568	3.293	3.325	3.466	3.113	3.255	3.285
Kuwait	3.185	3.117	3.157	3.201	3.133	3.173	3.182	3.114	3.155
Oman	3.274	3.206	3.246	3.302	3.235	3.275	3.267	3.199	3.239
Turkey	1.961	1.863	1.933	1.934	1.866	1.907	1.929	1.858	1.901
UAE	2.848	2.780	2.848	2.667	2.899	2.740	2.665	2.598	2.638
	IGARCH			EGARCH			GJR-GARCH		
Saudi Arabia	2.520	2.469	2.499	2.516	2.448	2.489	2.510	2.442	2.482

Note: AIC - Akaike information criterion, SBC- Schwarz information criterion, BIC-Bayesian information Criterion, and HQC- Hannan-Quinn criterion are tests for choosing the optimal model from GARCH, EGARCH, GJR-GARCH that best fits the data.

Furthermore, testing for ARCH effects is needed in order to detect any remaining ARCH effects after the estimation of the GARCH models (Effendi, 2015). The ARCH test results show no evidence of remaining ARCH effects, which indicates that there is no need to use higher order GARCH models since all the ARCH effects are captured. Generally, it can be concluded that the GJR GARCH is the best model that can be used, since it is chosen by the information criterion and has captured all ARCH effects.

After estimating volatility using symmetric and asymmetric models, and finding the best model that best fits our sample, the next section analyses spillover between these markets using the volatility previously estimated.

6.4 Volatility Spillover

This section aims to analyse volatility spillover by the volatility estimated by GJR-GARCH chosen to be the best model. The transmitted information of returns and volatilities is measured by spillover indices that is proposed by Diebold and Yilmaz (2009, 2012) which is based on invariant forecast error variance decomposition of vector auto regressive models. They constructed the total volatility spillover index as:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{6.5}$$

where $\theta_{ij}^{g}(H)$ is the H-step-ahead forecast error variance decomposition. The directional volatility spillover received by market *i* from all other markets *j* as:

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{6.6}$$

The directional volatility spillover transmitted by market *i* from all other markets *j* as:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 \tag{6.7}$$

The spillover indices here are useful in order to see the transmission of shocks either positive or negative from one market to another within the MENA region, along with identifying which market is a receiver, borrower or neither. Before running the model, some descriptive statistics are needed in order to learn about the data we are working with. The next section provides an analysis of volatility spillover for each model and compare between them.

6.4.1 Volatility Descriptive Statistics

Volatility is measured using GJR GARCH for each of the eight stock markets. The summary of the descriptive statistics for each volatility model of each market is calculated and reported in Table 6.10. The table shows all eight markets have a positive mean. The gap between the maximum and minimum reflects the level of dispersion from the average volatility in a market. As for the standard deviation, Egypt, Turkey, and Saudi Arabia are the most dispersed while Bahrain is the least, implying that there is more uncertainty in the volatility of Egypt, Turkey, and Saudi Arabia and less uncertainty on Bahrain market. Egypt, Jordan, Saudi Arabia, and Turkey are negatively skewed, confirming that bad news have higher effect than good news as their returns reported. All eight markets show high kurtosis, and Jarque-Bera is significant confirming that they are non-normal.

Figures 6.25 to 6.32 show the GJR-GARCH volatility for the eight markets. It is seen that throughout the sample period for all the eight MENA region markets, there is a peak during 2008. Jordan, Oman, and UAE seem to have high volatility then becomes relatively stable in the later years. Bahrain and Kuwait have several shocks at the beginning of our sample but later on become less unstable with fewer less volatile shocks taking place.

Meanwhile, Egypt, Saudi Arabia, and Turkey do not show any kind of stability, shocks are found throughout the sample. Even though Saudi Arabia seemed to be stable around 2013, but did not last for long. Egypt is seen to have experienced several shocks around 2015 to 2017 which can be the post-revolution effect.

Table 6.10: Volatility Descriptive Statistics (GJR-GARCH)

	Mean	Minimum	Maximum	St. Dev	Skewness	Kurtosis	Jarque-Bera	P-value
Bahrain	0.0011	0.0004	0.0086	0.0009	5.2083	32.3738	9252.56	0.000
Egypt	0.0109	0.0023	0.0568	0.0066	-4.2726	22.2873	4557.96	0.000
Jordan	0.0019	0.0003	0.0058	0.0017	-0.8961	15.8070	30.91	0.000
Kuwait	0.0033	0.0012	0.0483	0.0048	5.6552	42.4476	15437.85	0.000
Oman	0.0024	0.0014	0.0293	0.0026	7.1660	62.7481	33141.97	0.000
Saudi Arabia	0.0062	0.0007	0.0286	0.0056	-1.8408	3.5134	207.19	0.000
Turkey	0.0082	0.0045	0.0212	0.0061	-1.5377	12.5565	127.95	0.000
UAE	0.0048	0.0005	0.0174	0.0046	1.0917	15.1576	38.32	0.000

Note: The mean, minimum, maximum, standard deviation, skewness, kurtosis, Jarque-Bera and its p-value are shown in columns for the volatility of the eight markets. Volatility measured using the GJR-GARCH model.

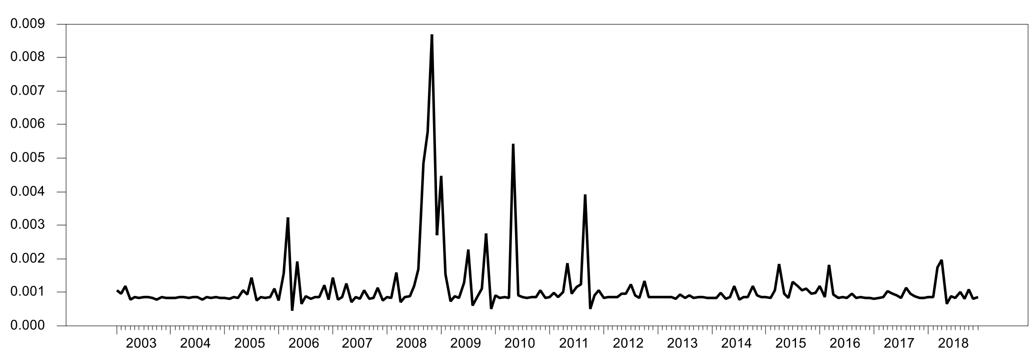

Figure 6.25: Bahrain GJR-GARCH volatility

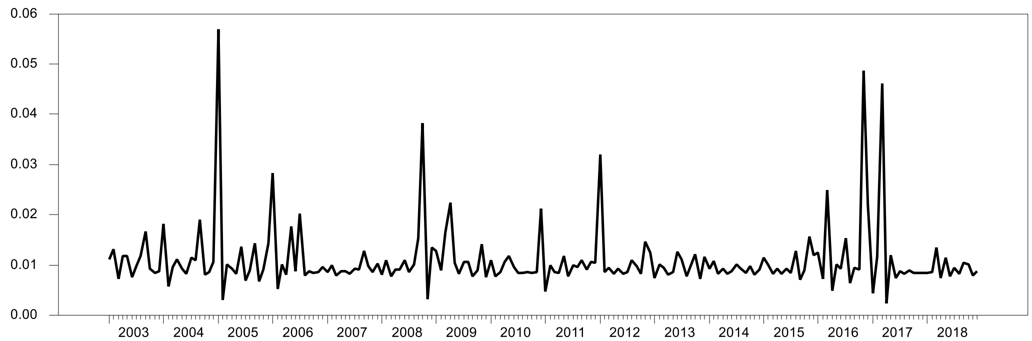

Figure 6.26: Egypt GJR-GARCH volatility

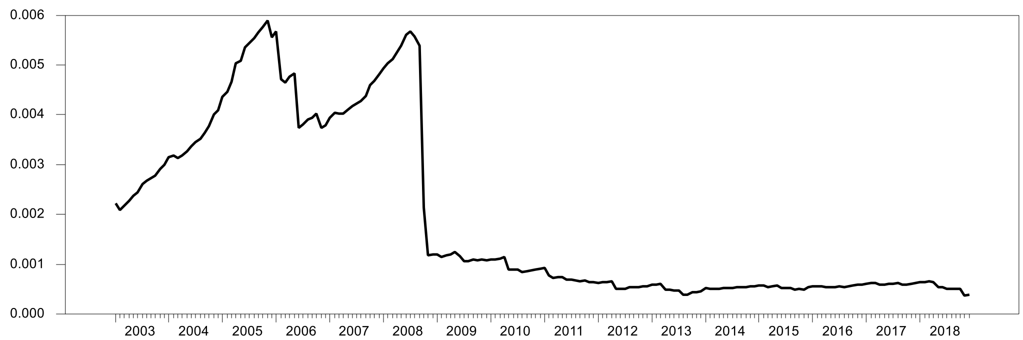

Figure 6.27: Jordan GJR-GARCH volatility

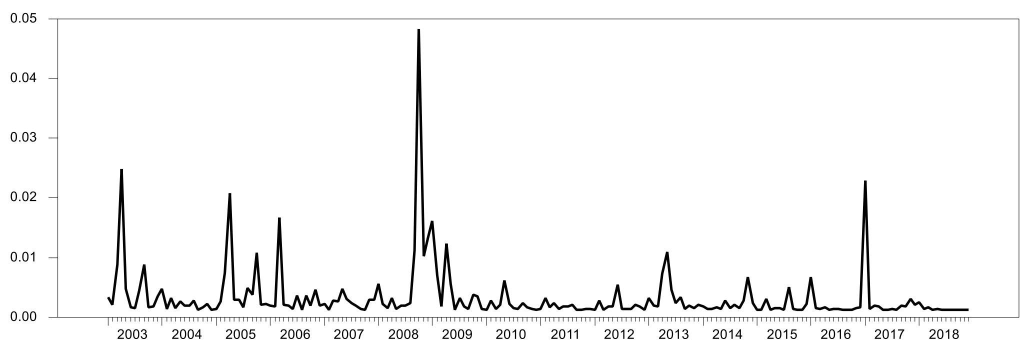

Figure 6.28: Kuwait GJR-GARCH volatility

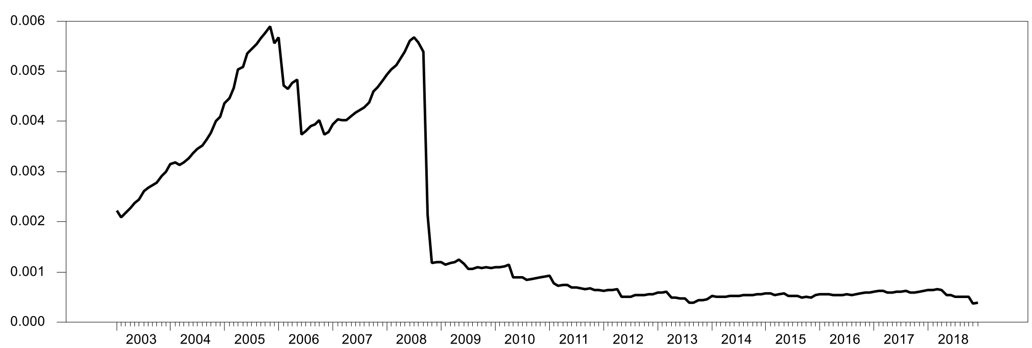

Figure 6.29: Oman GJR-GARCH volatility

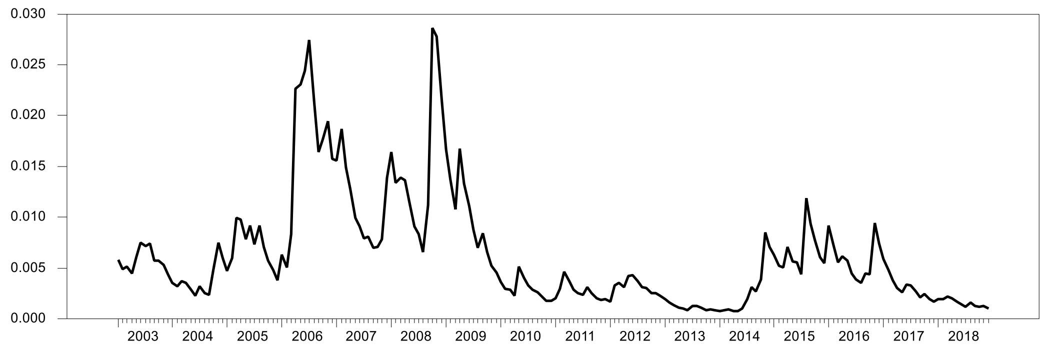

Figure 6.30: Saudi Arabia GJR-GARCH volatility

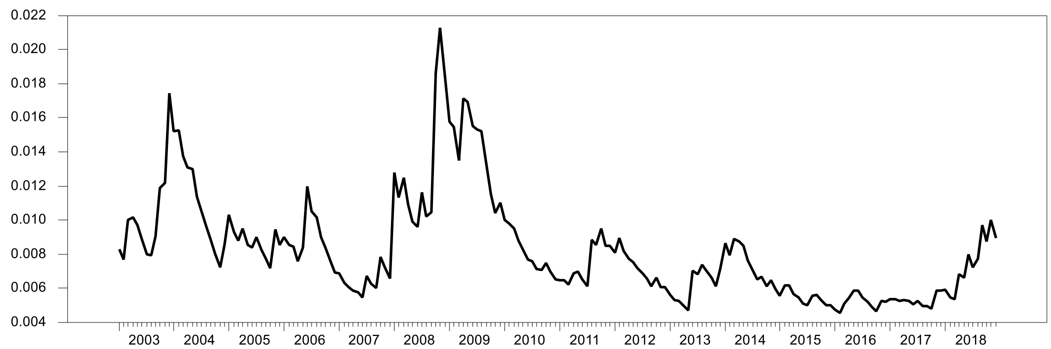

Figure 6.31: Turkey GJR-GARCH volatility

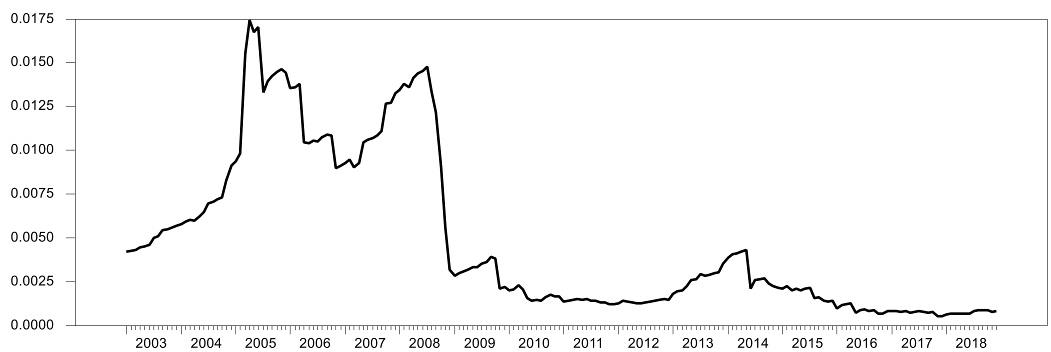

Figure 6.32: UAE GJR-GARCH volatility

Note: The x-axis of the graphs reflects the sample dates by months from 1/2003 to 12/2018. The y-axis reflects the volatility measured by GJR-GARCH model for all figures.

Before implementing the DY framework in order to find the spillover between the countries, it is significant to see the correlation between them, which provides a hint about the relationship between the countries. Table 6.11 provides the correlation matrix between the eight countries, indicating that the highest correlation is between Jordan and UAE by 96.2%, while the lowest correlation is between Bahrain and Jordan by 0.1%. Some of these correlations can be supported by trading agreements between the two countries, or can be supported by certain events that took place within one of the countries that impacted the other country. However, in order to build reliable interpretations about these relations, examining the spillover between the countries is needed. Seeing strong correlations between the countries gives a motive to explore the relationships between the eight countries. Furthermore, understanding the direction of the spillover, which country had the impact on the other, the next section provides the outcome of investigating the volatility spillover within the MENA region selected countries using the DY framework.

Table: 6.11: Eight Selected MENA Countries Correlation Matrix

	Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE
Bahrain	1							
Egypt	0.08652	1						
Jordan	0.00192	0.03692	1					
Kuwait	0.46533	0.18324	0.113702	1				
Oman	0.68912	0.22064	0.07933	0.713449	1			
Saudi Arabia	0.37085	0.11764	0.476943	0.375279	0.546811	1		
Turkey	0.38573	0.07416	0.278091	0.348747	0.507408	0.427834	1	
UAE	0.04315	0.01619	0.962688	0.176404	0.153327	0.505091	0.279915	1

Note: This table shows the correlation matrix between the eight selected countries of the MENA region.

6.4.2 Analysing Spillover

In order to analyse and compare the information transmission between the MENA region selected markets, an aggregate of variance decompositions is necessary. The variance decomposition is based upon a monthly VAR of unknown order, which can be identified using the VAR lag test. The lag selection methods are needed to minimize the error. Generally, the dynamic properties of impulse responses may depend critically on the lag order of the VAR model fitted to the data, which may affect the substantive interpretation of VAR impulse responses estimates (Hamilton and Herrera, 2004). Hence, a prime important step in empirical studies is to select the order of the auto-regression and the most common strategy for selection is by some information criterion.

The VAR lag selection tests implemented here are the information criterion AIC, SIC, and HQC (Grasa, 1989). A criterion underestimates the lag length when it chooses a lower lag length than the true one, while selecting a greater lag length than the true one may overestimate the lag length. Therefore, it is important to choose the true lag length, by estimating lag length using more than one information criterion. Akaike information criterion $AIC_p = -2T\left[\ln(\hat{\sigma}_p^2)\right] + 2p$. Schwarz information criterion $SIC_p = \ln\left(\hat{\sigma}_p^2\right) + [p\ln(T)]/T$. Hannan-Quinn criterion $HQC_p = \ln\left(\hat{\sigma}_p^2\right) + 2T^{-1}p\ ln[\ln(T)]$. Where T is the sample size and p is the true lag length that is being identified. The three criteria have different asymptotic properties. Ivanov and Kilian (2005) argue that HQC is the best test for quarterly and monthly data and AIC is inconsistent while HQC and SIC are consistent. Table 6.12 presents the information criteria results selecting one lag by SIC and HQC while AIC selected 2 lags. According to Liew and Khim (2004) HQC is the most efficient with large samples (more than 120 observations), while AIC is found to produces the least probability of underestimation among all criteria. Since two of out the three optimal lag length selection choose 1 lag, and having more than 120 observations which makes HQC more efficient, we employ 1 lag for our sample.

The step ahead is chosen after trying from 1 to 20 step ahead and finding out when the spillover index changes by small amount or is nearly stable. Figure 6.33 shows the spillover index at every step ahead and it can be seen that it becomes nearly stable at 10-step ahead.

Applying the Diebold and Yilmaz spillover framework, we measure volatility spillover. Primarily, volatility spillover are analysed using the volatility measured by the best selected model GJR GARCH. Secondly, since the spillover table gives only a summary about the transmission between countries, spillover plots are presented and linked to the events that happened at that time.

Table 6.12 VAR lag selection

Lags	AIC	SBC/BIC	HQC
1	-84.52	-83.31*	-69.44*
2	-84.74*	-82.54	-69.36
3	-84.51	-81.39	-68.81
4	-84.07	-80.11	-68.33
5	-83.66	-78.99	-67.77

Note: AIC - Akaike information criterion, SBC- Schwarz information criterion, BIC-Bayesian information Criterion, and HQC- Hannan-Quinn criterion are tests for choosing the optimal lag length.

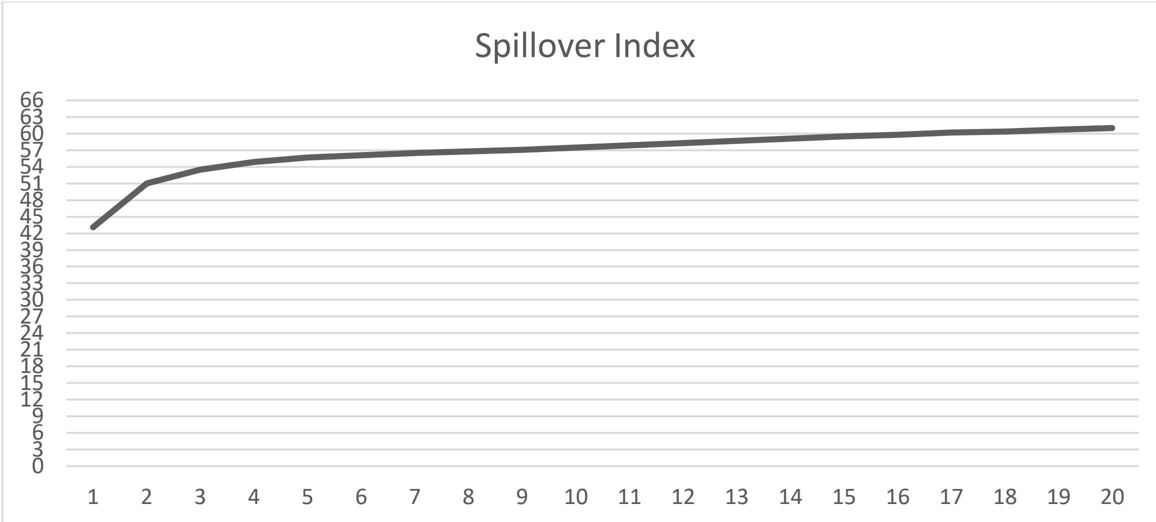

Figure 6.33 Spillover index at h-step ahead
Note: the x-axis represents the h-step ahead starting from 1 to 20. The y-axis represents the total spillover index. It can be seen from the graph that the spillover index begins to change slightly or in other word stable at 10-step ahead.

The spillover Table, provides an "input-output" decomposition of the spillover Index. The (i, j) entry in each panel is the estimation contribution to the forecast error variance of market i coming from innovations to market j. In the results output there is contribution to others and contribution from other. Contribution to others is the directional spillover from a market to all other markets. In other words, it is the sum of the percentage of contribution of each variable except the given variable. Contribution from others is the directional spillover from all markets to a particular market. In other words, it is the sum of the percentage of contribution of each variable except the given variable. Also a spillover index is calculated as the sum of all the contributions in the contributions to others row divided by the number of variables included. The next section provides the output results of the volatility estimated by GJR-GARCH model using real returns.

6.4.3 Spillover output using GJR GARCH model

Table 6.13 reports the output results of volatility spillover while measuring volatility by GJR GARCH model. The Table gives the spillover estimates from/ to the eight markets along with total spillover index, the 'contribution from others', and the 'contribution to others'. The total spillover index is reported at the lower right corner. Let i represent the rows and j represent the columns. In Table 6.12 the contribution to the forecast error variance of the volatility i coming from innovations to volatility j is represented by the $ijth$ entry. The diagonal elements $(i = j)$ measure own market volatility spillover, and the off diagonal elements $(i \neq j)$ provides the cross market volatility spillover within two markets.

Given that these countries are a sample representing the MENA region, the total spillover index is 57.5%, which represents the amount of information transmitted between markets. Turkey reports the lowest 'contribution to others' by 21.8%, while Oman has the highest 'contribution to others' by 125.7%; which means that Oman is a much stronger transmitter than Turkey is. On the other hand, lowest 'contribution from others' is Egypt by 22.6%, while the highest 'contribution from others' is the UAE by 76.6%; which means the UAE is a stronger receiver than Egypt.

Egypt reports the highest spillover to own market 77.44%, moreover, this can be due to the effect of the Arab Spring transmitting risk to its own market. Bahrain transmits the most to the UAE 19.26% which can be attributed to both being members of the GCC and the UAE being one of the main export partners of Bahrain. Likewise, Jordan highest spillover is to the UAE 20.91%. Jordan's second highest spillover is to Oman 19.28%, along with Oman highest spillover to Jordan 25.08%. Indicating that there is a strong bidirectional spillover between Jordan and Oman. This can be attributed to Jordan being one of the major destinations of massive investments by the Gulf countries planning to become a regional logistics hub (Creane *et al*., 2003), while Oman being one of the largest oil and natural gas producers in the MENA region (EIA, 2017). Even though most of the other spillover seems to be low, however judging by the scale of individual spillover index in DY study, the highest index is 10.21%, hence spillover 7.4% is not considered low. Spillover Plot is discussed in the next section and linked to events that took place at each period.

Table 6.13 Volatility Spillover (GJR GARCH)

	Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	36.76	1.85	15.59	9.71	23.81	5.51	2.09	4.68	63.2
Egypt	1.28	77.44	2.65	3.04	7.40	3.96	2.67	1.57	22.6
Jordan	17.98	2.36	58.17	9.45	25.08	4.94	2.35	9.67	71.8
Kuwait	8.06	1.62	11.95	43.75	22.24	7.02	4.79	0.57	56.2
Oman	14.30	2.78	19.28	14.42	34.73	8.34	3.66	2.49	64.3
Saudi Arabia	9.47	2.60	10.48	9.45	14.60	45.90	4.51	2.99	54.1
Turkey	5.98	4.15	10.26	10.04	12.36	4.83	49.84	2.54	50.2
UAE	19.26	2.60	20.91	7.43	20.18	4.49	1.77	23.36	76.6
Contribution to others	79.3	18.0	91.1	63.6	125.7	39.1	21.8	24.5	460.0
Contribution including own	113.1	95.4	119.3	107.3	160.4	85.0	71.7	47.9	57.5%

Note: Monthly real returns from Jan 2003 to Dec 2018, volatility measured by GJR-GARCH. Volatility Spillover Index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. The ith row and the jth column figures are the contribution of country j to country i.

6.4.4 Spillover Plots

From previous tests the spillover tables showed a clear relation between the countries affecting and getting affected by each other. Due to financial market evolution and turbulence, Diebold and Yilmaz (2009) argue that it is unlikely that any single fixed parameter model would apply over an entire sample. The Spillover tables and indexes provide a summary or description of the average behaviour but does not show the secular and cyclical movements of spillover. To solve this, we estimate the model using 24-rolling samples and we assess the extent and nature of spillover variation over time via the corresponding time series of Spillover indexes graphically by Spillover Plots.

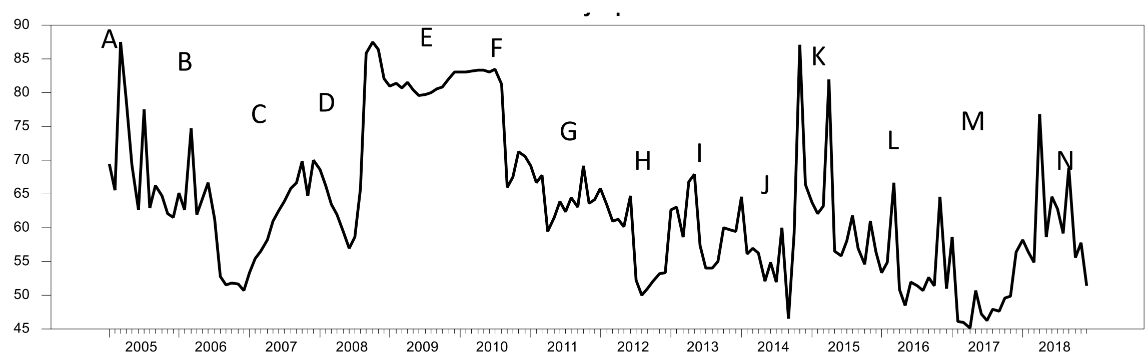

Figure 6.34: Total Volatility Spillover

Note: The x-axis of the graphs reflects the sample dates by months from year 2004 to year 2018. The left y-axis reflects the total volatility spillover measures.

Spillover Plot for the total volatility spillover in figure 6.34, fluctuations and movements are shown responding to economic and political events. Some of the major events that took place during each year are all taken from BBC news profile timeline of each country. Overall, the sample includes Saudi Arabia, the UAE, Bahrain, Kuwait, and Oman are members of the Gulf Cooperation Council (GCC) which explains part of the spillover, since this constitutes financial links and dependency between the members. In addition, Bahrain, Egypt, Jordan, Kuwait, Oman, Saudi Arabia, and the UAE are members of the Greater Arab Free Trade Area (GAFTA) leading to easier and less costly trade. Furthermore, Kuwait, Saudi Arabia and the UAE members of the Organization of the Petroleum Exporting Countries (OPEC).

A) A burst took place at the beginning of 2005 due to several events.

i. **Bahrain:** Protests demanding fully elected parliament.

ii. **Egypt:** In May allowing multiple candidates at presidential elections after months of opposition protests. Bomb attack by islamists in Red Sea resort in Sham el Sheikh killed several people. Clashes between police and supporters of Muslim brotherhood in the Parliament.

iii. **Jordan**: In November - Sixty people are killed in suicide bombings at three international hotels in Amman. Al-Qaeda in Iraq claims responsibility.

iv. **Kuwait**: Deadly gun battles erupt between suspected islamists militant and police. The Law allowing women to vote and run for parliament.

v. **Oman**: Nearly 100 suspected Islamists are arrested; 31 Omanis are subsequently convicted of trying to overthrow the government.

vi. **Saudi Arabia**: King Fahd dies, and the crown goes to Prince Abdallah. World Trade Organization gives the green light to Saudi Arabia's membership following 12 years of talks.

vii. **UAE**: Sheikh Khalifa plans the UAE's first elections.

viii. **Turkey**: New lira currency introduced as six zeroes are stripped from old lira, ending an era in which banknotes were denominated in millions. EU membership negotiations officially launched after intense bargaining.

B) Till the mid of 2006 spillover is not that high but rose the second half of 2006.

i. **Bahrain:** Shia wins 40% of the vote in the general election.

ii. **Egypt:** In April, 20 people are killed by a bomb attack in the Red Sea resort of Dahab. In November, Egypt became one of the Arab countries that started developing nuclear programmes to diversify energy sources.

iii. **Jordan:** The Leader of Al Qaeda in Iraq has been killed in an air strike.

iv. **Kuwait:** The emir Sheikh Jaber dies and Sheikh Sabah Al-Ahmed is sworn in as emir.

v. **Oman** and the US sign a free trade deal.

vi. **Saudi Arabia:** 363 Hajj pilgrims are killed in a crush during a stone-throwing ritual in Mecca. And more than 70 pilgrims are killed when a hostel in the city collapses.

vii. **UAE:** Political storm in the US forces state-owned Dubai Ports World to relinquish control of terminals at six major American ports

viii. **Turkey:** Gunman opens fire in Turkey's highest court, killing a prominent judge and wounding four others. Baku-Tbilisi-Ceyhan oil pipeline opened at ceremony in Turkey. EU partially freezes Turkey's membership talks because of Ankara's failure to open its ports and airports to Cypriot traffic.

C) Some weak fluctuations took place in 2007.

i. **Bahrain:** Illegal foreign workers rush to take advantage of a government sanctioned amnesty.

ii. **Jordan:** First local elections since 1999. The main opposition party, the Islamist Action Front, withdraws after accusing the government of vote-rigging.

iii. **Kuwait:** Oil Minister Sheikh Ali resigns amid a political standoff between the government and parliament.

iv. **UAE:** Dubai and Qatar become the two biggest shareholders of the London Stock Exchange, the world's third largest stock exchange.

v. **Turkey:** Tens of thousands of supporters of secularism rally in Ankara, aiming to pressure Prime Minister Erdogan not to run in presidential elections because of his Islamist background. Turkey launches a series of air strikes on fighters from the Kurdish PKK movement inside Iraq.

D) 2008 started high then gets weaker.

i. **Bahrain:** Appointing the first Jewish women as the USA ambassador in the Arab world.

ii. **Jordan:** King Abdallah becomes the first Arab leader to visit Iraq since US invasion in 2003.

iii. **Oman:** The Cyclone Gonu, the strongest storm to hit the Gulf for decades, kills more than 50 people and disrupts oil production was in June 2007 but its effect is seen in 2008.

iv. **Saudi Arabia:** British House of Lords reverses High Court decision and says their government acted lawfully in dropping investigation into the Al-Yamamah defense deal, as the Saudis had threatened to withdraw cooperation with London on security matters. Saudi Arabia and Qatar agree final delineation of border.

v. **UAE:** France and the UAE sign a deal allowing France to set up a permanent military base in the UAE's largest emirate, Abu Dhabi. The UAE cancels the entire debt owed to it by Iraq - a sum of almost $7bn.

vi. **Turkey**: Thousands protest at plans to allow women to wear the Islamic headscarf to university.

vii. Within the countries no major effect took place that may lead to that high boom, which makes it clear that it could be the effect of the financial crisis and its effect on the countries and on oil too.

E) Towards the end of 2008 and the beginning of 2009 a huge boom took place.

i. **Bahrain:** King Hamad pardons more than 170 prisoners charged with endangering national security.

ii. **Jordan:** the king dissolves the parliament half way through its four-year term, and appoints new premier to push through economic reform.

iii. **Kuwait:** Emir dissolves parliament after it demands to question his nephew and PM, Sheikh Nasser Mohammad al-Ahmad al-Sabah, about corruption allegations.

iv. **Saudi Arabia:** A court issues verdicts in the first explicit terrorism trial for al-Qaeda militants in the country.

v. **UAE:** Dubai sold $10bn in bonds to the UAE in order to ease liquidity problems. The UAE withdraws from plans for Gulf monetary union, dealing a blow to further economic integration in the region.

F) The volatility began to rise in 2010, major events that took place that could be explaining this increase are:

i. **Jordan:** Parliamentary elections, boycotted by the opposition Islamic Action Front.

ii. **Bahrain:** In September, 20 Shia opposition leaders - accused of plotting to overthrow monarchy by promoting violent protests and sabotage - arrested in run-up to elections. In October: Parliamentary elections. Main Shia opposition group, Islamic National Accord Association, makes a slender gain.

iii. **Egypt:** During 2010 was President Mubarak's rise and fall. President ruled for three decades before being swept aside by a popular uprising

iv. **Saudi Arabia:** In December- Diplomatic cables revealed by whistle-blowing website Wikileaks suggest US concern that Saudi Arabia is the "most significant" source of funding for Sunni terrorist groups worldwide.

v. **Turkey:** Constitutional reform

vi. **UAE:** In January- Burj Khalifa tower opens in Dubai as the world's tallest building and man-made structure.

G) Volatility in 2011 is high at the beginning then began to decline till right before 2012, it begins to rise again, reasons behind this is:

i. **Bahrain:** Protests. In February- Thousands of protesters gather in Manama, inspired by popular revolts that toppled rulers in Tunisia and Egypt. A security crackdown results in the death of several protestors. In November - Government concedes that "excessive force" is used by security forces in Bahrain against pro-democracy protesters.

ii. **Egypt:** In February - President Mubarak steps down and hands power to the army council. Goes on trial in August, charged with ordering the killing of demonstrators. From April to August - Protests continue in Cairo's Tahrir Square over slow pace of political change. Islamist groups come to the fore. In November - Violence in Cairo's Tahrir square as security forces clash with protesters accusing the military of trying to keep their grip on power.

iii. **Jordan:** Protests in Tunisian streets are found in other countries including Jordan.

iv. **Kuwait:** In March - Hundreds of young people demonstrate for reform, inspired by a wave of protests across the Arab world. In December- Emir dissolves parliament and replaces his prime minister following protests and a showdown over allegations of high-level corruption.

v. **Oman:** Protesters demand jobs and political reform. One demonstrator is shot dead by police. Sultan Qaboos reacts by promising jobs and benefits. Unrest inspired by the Arab Spring made the Sultan grant the council more power.

vi. **Saudi Arabia: In** March - Public protests banned, after small demonstrations in mainly Shia areas of the east. King Abdullah warns that threats to the nation's security and stability will not be tolerated. King Abdullah announces increased welfare spending, as 'Arab Spring' unrest continues in the region. Saudi troops participate in crackdown on unrest in Bahrain.

vii. **Turkey:** In June- Thousands of refugees fleeing unrest in Syria stream into Turkey. Ankara demands reform in Syria. In October - PKK rebels kill 24

Turkish troops near the Iraqi border, the deadliest attack against the military since the 1990s.

viii. **UAE:** UAE joins international military operation in Libya.

H) In 2012 the volatility is not as high as before. The ups and downs were not that sharp. Egypt is the only country that has major events going on that could explain these fluctuations.

i. **Bahrain:** In October - Protesters clash with riot police in Manama at funeral of Ali Ahmed Mushaima, who died in prison after being jailed for taking part in pro-democracy demonstrations. The authorities indefinitely ban all protests and gatherings.

ii. **Egypt:** In January - Islamist parties emerge as victors of drawn-out parliamentary elections. In May - Military leaders announce the end of the state of emergency in place since Anwar al-Sadat's assassination in 1981. In June - Muslim Brotherhood candidate Mohammed Morsi narrowly wins presidential election. Court sentences ex-President Mubarak to life in prison for complicity in the killing of protesters during the 2011 uprising. In August - Islamist fighters attack an army outpost in Sinai, killing 16 soldiers, and mount a brief incursion into Israel, beginning new insurgency.

iii. **Jordan:** Clashes between protesters and the king's supporters against lifting the fuel subsidies.

iv. **Kuwait:** At least 5,000 protesters clash with security forces outside parliament over opposition fears that the government is trying to redraw constituency boundaries.

v. **Turkey:** Tension rises with Damascus. After Syrian mortar fire on a Turkish border town kills five civilians, parliament authorizes military action inside Syria, and the armed forces respond with artillery fire into Syria.

vi. **UAE:** The UAE begins operating a key overland oil pipeline which bypasses the Strait of Hormuz. Iran has repeatedly threatened to close the strait at the mouth of the Gulf, a vital oil-trade route. Mindful of protests in nearby Bahrain, the UAE outlaws' online mockery of its own government or attempts to organize public protests through social media.

I) After the start of 2013 there is a boom in volatility due to several reasons happening in each country.

i. **Bahrain:** In March - King Hamad appoints his son, Crown Prince Salman bin Hamad bin Isa al-Khalifa, as deputy prime minister.

ii. **Egypt:** In January – More than 50 people are killed during days of violent street protests. Army chief Abdul Fattah al-Sisi warns that political strife is pushing the state to the brink of collapse. In July- army overthrows President Morsi amid mass demonstrations calling on him to quit. In August - Hundreds killed as security forces storm pro-Morsi protest camps in Cairo. In December - Government declares Muslim Brotherhood a terrorist group after a bomb blast in Mansoura kills 12.

iii. **Kuwait:** Parliamentary elections, with liberals and candidates from the smaller tribes making gains.

iv. **Oman:** In March - Sultan Qaboos pardons around 30 people, including online activists and protesters.

v. **Turkey:** In May-June - Mass anti-government protests spread to several cities, sparked by plans to develop one of Istanbul's few green spaces. The police respond with violence, and two protestors die. In December - Government sacks numerous police chiefs over arrests of pro-government public figures on corruption charges.

vi. **UAE:** Trial in UAE of Egyptians and Emiratis accused of starting a branch of the Muslim Brotherhood, which is outlawed in the Gulf state.

J) Towards the end of 2013, the Markets where down again, but just after few months of 2014, major events took place to make them boom again.

In 2014, the oil prices collapsed affecting the GCC countries mainly.

i. In March**- Bahrain, Saudi Arabia and UAE** temporarily withdraw their ambassadors from Qatar after alleging that it has been meddling in their internal affairs.

ii. **Bahrain**. In July - Bomb blast kills police officer, the latest in a series of attacks on security forces. In December - Leader of Al-Wefaq opposition movement Sheikh Ali Salman is arrested. Protests and clashes between his supporters and security forces ensue.

iii. **Egypt:** In January - New constitution bans parties based on religion. In May - Former army chief Abdul Fattah al-Sisi wins presidential election.

iv. **Jordan:** In September - Jordan is one of four Arab states to take part, together with the US, in air strikes on Islamic State militants in Syria. Jordanian authorities arrest the deputy head of the country's Muslim Brotherhood organization.

v. **Kuwait:** Several TV channels banned from airing programmes about an alleged plot against the ruling system.

vi. **Turkey:** In August- Prime Minister Erdogan wins the first direct popular election for president.

vii. **Oman:** In May - Former Omani commerce minister Mohammed al-Khusaibi is sentenced to three years in prison for corruption.

viii. In September - **Saudi Arabia, and UAE** take part together with the United States in air strikes against Islamic State militant strongholds in Syria.

K) 2015 started with a rise in the market then fell and not after so long it rose again.

i. In March – **Kuwait, Bahrain, UAE, Jordan and Saudi Arabia** states take part in Saudi-led air strikes on Houthi rebels in Yemen.

ii. **Egypt:** In May - Ousted President Morsi sentenced to death over 2011 mass breakout of Muslim Brotherhood prisoners, along with more than 100 others. In June - Prosecutor-General Hisham Barakat and three members of the public killed in suspected Islamist car bombing in Cairo. In July - Islamic State launches wave of attacks in North Sinai. In October - Islamic State claims responsibility for destruction of Russian airliner in Sinai, in which all crew and 224 tourist passengers were killed.

iii. **Saudi Arabia:** In January - King Salman ascends to the throne after King Abdullah dies. In May - Two suicide bomb attacks on Shia mosques in Eastern Province kill at least 25 people, claimed by Saudi branch of Islamic Group Sunni extremist group. In September - Hundreds die in stampede near Mecca during annual Hajj pilgrimage, days after 109 people perished when a crane collapsed at the Grand Mosque, raising further concerns about safety standards during these mass events.

iv. **Turkey:** Turkey shoots down a Russian military jet on Syria bombing mission. Russia, Turkey's second-largest trading partner, imposes economic sanctions.

L) In 2016 the volatility is not major unlike previous year, but there are major events happening.

i. **Bahrain:** A UN-appointed panel accused the authorities of carrying out a systematic campaign of harassment against the country's Shia Muslim population.

ii. **Egypt:** In January - Islamic State carries out attack at Giza tourist site and is suspected of attack on tourists in Hurghada. In May - Egypt Air flight from Paris to Cairo crashes into the Mediterranean Sea. In November - IMF approves a three-year $12bn loan to Egypt designed to help the country out of its deep economic crisis. In December - A bomb attack on a Cairo church kills 25. The blast is claimed by Islamic State militants who threaten more attacks on Christians.

iii. In April - **Egypt** announces that it is going to hand over to **Saudi Arabia** two strategic Red Sea islands, sparking public outrage and unrest.

iv. **Saudi Arabia:** Government approves a plan for far-reaching reforms to diversify the economy away from oil.

v. **Jordan:** In December - Ten people, including a tourist, are killed in an attack claimed by the Islamic State group at a Crusader castle in the town of Karak.

vi. **Oman:** The national newspaper Azaman is forced to close after publishing an article about alleged pressure on judges from officials. The editor is sentenced to jail.

vii. **Turkey:** Bomb attack on military convoy in the capital Ankara kills at least 38 people and a suicide car bomb attack in Ankara kills 37 people, both the Kurdistan Freedom Hawks (TAK) claims responsibility of.

M) With the start of 2017, the market rose high due to:

i. **Bahrain:** Execution of three Shia activists for killing three policemen in bomb attack of 2014. Isa Qassim the most prominent Shia cleric is found guilty of illegal fundraising and money laundering.

ii. **Egypt:** In April - State of emergency declared after suicide bombers kill dozens at two churches where worshippers celebrate Palm Sunday. In May - Egyptian military carries out a series of airstrikes against alleged jihadist training camps in Libya, after the Islamic State group claimed responsibility for ambushing and killing Christians on a bus in Minya province. In November - Jihadists attack mosque in Bir al-Abed village in North Sinai, killing 305.

iii. **Turkey:** In April - President Erdogan narrowly wins referendum to extend his powers.

iv. In June - Diplomatic crisis in Qatar as **Saudi Arabia** leads an air, land and sea blockade to get Qatar to cut its alleged connections with terrorism and distance itself from Iraq, **Egypt** and **UAE** joined Saudi led campaign. Which made Qatar start using ports in **Oman** to carry cargo.

v. **Jordan:** In August - Jordan and Iraq reopen their main border crossing for the first time in two years after Islamic State militants were driven from the main highway to Baghdad.

N) Some peaks are found in 2018.

i. **Bahrain:** Bahrain discovered the kingdom's largest oilfield in more than 80 years. The opposition leader of the banned Al Wefaq party is sentenced to jail for spying for Bahrain's arch-rival, Qatar.

ii. **Egypt:** President Sisi wins a second term in elections against a sole minor position candidate. More serious challengers either withdraw or were arrested. In October, 17 people were sentenced to death over the 2016-2017 wave of Islamic state group attacks on churches.

iii. **Jordan:** Protests in the streets against tax hikes which led to the fall of the Prime Minister.

iv. **Kuwait:** The Philippines bans its citizens from taking up jobs in Kuwait following reports of sexual abuse and the deaths of Filipino women there.

v. **Saudi Arabia:** The killing of emigre reporter Jamal Khashoggi in the Saudi consulate in Istanbul causes an international outcry.

vi. **Turkey:** Turkish lira plunges to record lows, having shed more than 40% of its value against the dollar in the past year. US-imposed sanctions, linked to Ankara's refusal to release a jailed US pastor, exacerbate the situation and prompt fears of an economic crisis.

After mentioning all the major events that took place in the eight countries and numerically showing the spillover between them total and directional, several points can be drawn from them. Firstly, the most influential events that took place during the sample period are the financial crisis in 2008 and the Arab Spring started in 2011. This can be seen from the individual graphs of each of the markets that in 2008 there is a major burst some of the countries recovered from and some didn't. This again is reflected in the total volatility spillover figure the global financial market turmoil in 2008 and actually not getting better till after 2010. This may be due to the effect of the crisis along with the Arab Spring both together. The Arab Spring started in 2010, it is expected that the effect would be higher than the financial crisis effect since several MENA region countries experienced it. It is not as high but for the latter years the stability is not that good, several ups and downs. As if seeing the market trying to recover but cannot.

From the Spillover table we concluded that Egypt is not a receiver. This can be one of the reasons behind not seeing a major effect of the Egyptian revolution on the graph. This does not mean that it didn't affect other neighbouring markets, it just means that it affected itself more than other, which is confirmed by the 77.44% spillover on itself. Concluding from the spillover results that Egypt is not a receiver nor a giver. Unlike UAE who is a receiver by 76.6% not a giver, which makes sense since no major events took place in UAE that can be transmitted to other countries.

Jordan and Oman are the two major receivers from other markets. Looking closely at their contribution from others, we can see that Jordan receives from Oman 25.08% and Oman receives from Jordan 19.28% which is the highest for both countries. Consider when Qatar was boycotted from other countries, it used Oman's port to carry cargo, making Oman a receiver of the transmitted event. Furthermore, the events mention that both Jordan and Oman had political instability nearly around the same time.

Kuwait can be considered both a receiver and giver by 63.6% and 56.2% respectively. Kuwait experienced some political instability, and also joining the Saudi-led air strikes on Houthi rebels in Yemen. Likewise, Bahrain can be considered a receiver and giver, also joining the Saudi-led air strikes, and political instability whether protestors or governmental changes. Saudi Arabia is like Egypt, receiver and giver of itself more than other markets, even though it joined other countries in strikes and actions like the Saudi-led air strikes and the Saudi campaign of blockade against Qatar. Likewise, Turkey receives and gives itself the most, also receives spillover from Jordan, Kuwait, and Oman.

It can be concluded that the Global Financial Crisis is one of the most influential events that took place. Furthermore, the Arab Spring effect cannot be seen clearly, how long it lasted, and when the countries recovered. To prove this, it is helpful to divide our sample into three categories, ‘pre-crisis’ 2003 to 2007, ‘during the events’ 2008 to 2013, and ‘post-events’ 2014 to 2018 and analyse volatility spillover for each. The next section estimates volatility spillover of each of the three categories.

6.5 Examining Spillover of the Divided Sample

The two important major events that took place and had a strong effect from 2003 till 2018 are the Global financial turmoil in 2008 and then the Arab Spring starting 2010. In order to see the effect of these events, we divide our sample into three categories. The first category is representing the sample from 2003 to 2007 which is pre-crisis period, the second category is during the major events from 2008 to 2013, then the post-events from 2014 to 2018, reflected in Table 6.14, 6.15, and 6.16 respectively.

After splitting the sample into three categories, one can see that the spillover between the countries in the MENA region increased during the major events that took place, whether the financial crisis or the Arab Spring. The pre-crisis period has a spillover index of 36.8%, on the other hand during the events that took place the spillover index reached 75.9%. However, post-events period's spillover index decreased more than pre-crisis period showing 29%.

Looking at each country separately, Jordan can be seen as a country that is influenced by other markets throughout the three categories. However, who influences Jordan differ. Before the events Bahrain and UAE are the most influential on Jordan, during the events, Jordan is a receiver from Bahrain, Kuwait, Oman and UAE, and after the events, Jordan became a receiver from Turkey. On the other hand, Jordan is not really a giver before and after the events, but during the events it becomes a transmitter to other markets by 100.1%. As it was mentioned above, Jordan has several protests and events, along with joining the three Arab states to take part, together with the US, in air strikes on Islamic State militants in Syria. Moreover, reopening the border to Iraq, these events and several others are the reason behind transmitting information to the other MENA region countries.

Bahrain is a transmitter of spillover before and during the events by 76.2% and 65.1% respectively, mainly to Jordan, Saudi Arabia, and UAE. However, Bahrain is not a receiver either before or after the events, but becomes a receiver during the events by 76% from Jordan, Kuwait, Oman, Saudi Arabia, and UAE. Having a relation with Saudi Arabia up until the end of the events can be due to the kingdom's largest oilfield that Bahrain found in 2018.

Egypt's spillover results are very close the full sample results; it is an independent country that is neither receiver nor transmitter. However, during the events Egypt becomes a receiver from Jordan, Kuwait, Oman, and Saudi Arabia, and a transmitter to Turkey. Likewise, Kuwait is not a receiver nor a transmitter pre-crisis and post-events, however during the events it became a receiver from Jordan, Oman, and Saudi Arabia, and a transmitter to almost all markets. Turkey becomes a transmitter to Jordan and Saudi Arabia post-events, and a receiver from Egypt, Jordan, Kuwait, Oman and Saudi Arabia during the events.

UAE is a receiver and transmitter of spillover pre-crisis and during the events, but not in post-events. A receiver from Jordan and Oman pre-crisis, and Bahrain and Oman during the events. A transmitter to Jordan, Kuwait, and Oman in pre-crisis, and Bahrain and Jordan during the events. Therefore, there is a back and forth transmission between UAE and Jordan pre-crisis period. There is also a back and forth relation between Oman and UAE pre-crisis, but this relation gradually disappears over time. This can be due to political reasons like Oman helping out Qatar while UAE bans it.

Saudi Arabia is a receiver from Bahrain by 23.19% pre-crisis. During the events Saudi Arabia can be seen as a receiver and transmitter from almost all countries with different percentages. This can be due to several events that occurred either the campaigns or strikes led by Saudi Arabia or revolutions in nearby countries like Egypt. As for post-events, Saudi Arabia had a back and forth relation with Oman and Turkey.

Table 6.14: Spillover “Pre-crisis” from 2003 to 2007

	Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	76.42	0.60	5.22	6.84	6.17	0.54	0.41	3.82	23.6
Egypt	0.61	90.01	1.68	0.38	4.11	0.95	1.30	0.96	10.0
Jordan	26.11	0.90	34.18	0.89	5.00	2.70	4.83	25.40	65.8
Kuwait	5.20	1.10	0.63	69.25	9.75	0.86	0.50	12.71	30.8
Oman	4.19	0.84	2.18	2.26	56.26	2.45	0.16	31.65	43.7
Saudi Arabia	23.19	0.62	1.42	0.52	8.20	59.09	1.97	4.98	40.9
Turkey	1.21	2.16	4.25	0.46	4.12	4.01	78.79	5.01	21.2
UAE	15.69	1.12	16.56	2.30	18.78	0.75	3.46	41.35	58.7
Contribution to others	76.2	7.3	31.9	13.6	56.1	12.3	12.6	84.5	294.7
Contribution including own	152.6	97.3	66.1	82.9	112.4	71.3	91.4	125.9	36.8%

Note: Monthly real returns from Jan 2003 to Dec 2007, volatility measured by GJR-GARCH. Volatility Spillover Index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. The ith row and the jth column figures are the contribution of country j to country i.

Table 6.15: Spillover “During the events” from 2008 to 2013

	Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	23.98	5.79	14.05	14.91	15.56	10.21	4.85	10.64	76.0
Egypt	1.97	32.62	12.40	13.56	13.89	13.52	8.58	3.46	67.4
Jordan	14.48	5.43	15.82	15.25	17.04	9.40	5.42	17.16	84.2
Kuwait	5.94	8.58	16.43	21.76	18.19	15.47	8.45	5.18	78.2
Oman	8.05	7.88	17.88	17.77	19.67	13.70	6.69	8.36	80.3
Saudi Arabia	6.19	9.16	16.76	16.87	16.07	18.52	9.87	6.55	81.5
Turkey	5.08	11.81	12.58	14.12	11.74	14.88	25.10	4.68	74.9
UAE	23.39	2.81	9.95	9.55	13.50	3.90	1.88	35.02	65.0
Contribution to others	65.1	51.5	100.1	102.0	106.0	81.1	45.7	56.0	607.5
Contribution including own	89.1	84.1	115.9	123.8	125.7	99.6	70.8	91.1	75.9%

Note: Monthly real returns from Jan 2008 to Dec 2013, volatility measured by GJR-GARCH. Volatility Spillover Index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. The ith row and the jth column figures are the contribution of country j to country i.

Table 6.16: Spillover "Post-events" from 2014 to 2018

	Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	86.61	0.29	2.47	1.29	0.65	0.68	5.36	2.66	13.4
Egypt	1.85	79.24	1.60	3.33	1.78	9.90	1.99	0.33	20.8
Jordan	9.99	0.25	41.53	1.65	2.05	1.80	39.11	3.63	58.5
Kuwait	0.88	4.39	0.99	80.60	2.05	6.92	2.25	1.92	19.4
Oman	4.56	0.22	4.04	1.92	60.99	22.73	3.04	2.50	39.0
Saudi Arabia	2.63	3.48	6.34	2.32	18.32	49.41	15.68	1.82	50.6
Turkey	1.73	0.39	3.43	0.67	0.56	11.98	79.87	1.37	20.1
UAE	0.76	0.89	0.26	0.88	2.22	0.79	4.50	89.71	10.3
Contribution to others	22.4	9.9	19.1	12.0	27.6	54.8	71.9	14.2	232.0
Contribution including own	109.0	89.1	60.7	92.6	88.6	104.2	151.8	103.9	29.0%

Note: Monthly real returns from Jan 2014 to Dec 2018, volatility measured by GJR-GARCH. Volatility Spillover Index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. The ith row and the jth column figures are the contribution of country j to country i.

Generally, we can interpret that the contribution from other countries to any one of the countries in our sample increased during the events period. This proves that the two major events that took place during these years were very influential on the MENA region markets. Last section gives an overview and summarizes the output of this chapter.

6.6 Conclusion

This chapter provides the descriptive statistics of the Stock Market nominal returns of the MENA region markets (Bahrain, Egypt, Jordan, Kuwait, Oman, Saudi Arabia, Turkey, and UAE). By analysing these results, several observations can be highlighted. Consistent with Harvey (1995) who argues that emerging markets are characterized by high returns and high volatility, which is seen in the nominal returns of our sample markets.

After finding ARCH effects in the nominal returns of the markets, we analysed volatility using symmetric model. Taking into consideration the currency devaluation effect of the market's activity, real returns is more applicable in order to capture this effect. After providing the descriptive statistics of real returns then modelling volatility using symmetric model GARCH, then using asymmetric models EGARCH, and GJR GARCH the ARCH effect test is used in order to capture any remaining ARCH effects. After testing the three models on our eight MENA region countries, GJR GARCH is found to be the best model that captured all the ARCH effects and was also chosen by the information criteria for almost all the markets.

The GJR-GARCH model shows how the MENA region markets are very volatile, also indicating which affects it more positive or negative events. Bahrain, Jordan, Kuwait, Oman and UAE are affected by negative shocks producing higher volatility in the future than positive shocks of the same magnitude. Meanwhile, Egypt, Saudi Arabia and Turkey are affected by positive shocks producing higher volatility in the future than negative shocks of the same magnitude. Graphically, Jordan, Oman, and UAE seem to have high volatility becomes relatively stable in the latter years. Bahrain and Kuwait have several shocks at the beginning of our sample but later on becomes less unstable with fewer less volatile shocks taking place. Meanwhile, Egypt, Saudi Arabia, and Turkey do not show any kind of stability, shocks are found throughout the sample. Even through, Saudi Arabia seemed to be stable around 2013, but did not last for long. Egypt has several shocks around 2015 to 2017 that can be the post-revolution effect.

Furthermore, volatility spillover is measured using the Diebold and Yilmaz framework, which provides Spillover Table and Spillover Plots. The spillover table provides a summary or description of the average behaviour but does not show the secular and cyclical movements of spillover, while the Spillover Plots estimates the model using 24-rolling samples and assess the extent and nature of spillover variation over time via the corresponding time series of Spillover indexes graphically. Looking at the Spillover tables it is clear that there is a strong transmission between the eight MENA region countries. The total spillover index for the represented sample of the MENA region is 57.5%. The spillover table gives a brief summary of the transmission that took place during these years. Looking at the Spillover Plots, the first one is the Total Volatility Spillover which shows the peaks and fluctuations that took place and linking them to the events that took place in the sample countries in order to understand its effect. It is clear that the most influential events were the Global Financial turmoil and the Arab Spring.

Additionally, in order to see the effect of these two major events, we divided our sample into three categories, before the events 2003 to 2007, during the events 2008 to 2013, and after the events 2014 to 2018. The results were interesting for some of the countries, while for other countries it was expected. Generally, it was expected to see that the total spillover index be the highest during the years in which these major events happened. Meanwhile it was not expected that Saudi Arabia becomes a receiver and transmitter to almost all countries during the events. Moreover, finding Egypt not a receiver nor a transmitter except during the events. In general, whether the countries were a receiver or transmitter or neither before and after the events, they all became both during the events. Therefore, these few years were very critical for the MENA region with a lot of spillover transmissions.

In order to confirm these results, further examinations are needed. As discussed in chapter 4, the DY Index is criticized for its lack of finding the accuracy of its outcome. The next chapter provides the outcome of using the bootstrapping method in order to test the significance of the index results.

Chapter 7

Bootstrapping the Volatility Spillover Index

7.1 Introduction

Financial globalization has altered the relationship between international capital markets. Markets have become more intertwined, and the concept of one financial market spilling over another market has become relevant (Choi and Shin, 2018). Not surprisingly, this topic has attracted a great deal of research recently. These studies developed insights that are useful in explaining financial market spilling over globally. Ng (2000) analyses volatility spillover from Japan and the US to six Pacific–Basin equity markets. Baele (2005) investigates the equity markets interdependence in Western Europe, and Christiansen (2007) analyses the US and European bond markets spillover to individual European bond markets. Finally, Du *et al.* (2011) inspect the volatility spillover among crude oil, corn, and wheat markets. The above mentioned studies document the existence of spillover between different markets whether across or within markets.

Although the literature shows a wide array of methods that are used to test volatility spillover, there was no unified framework that considers the relevance of different dimensions. Prior studies that use, for example, cointegration tests, Granger causality, or correlation, show only correlation levels and ignore the directions of connectedness. This motivated Diebold and Yilmaz (2012) to develop their volatility spillover index to address these limitations and provide a unified framework for conceptualizing and empirically measuring total and directional spillover in a generalized VAR framework. Since then, the Diebold and Yilmaz (DY) framework is considered as the most commonly used approach to measure volatility spillover (Zhou *et al.*, 2012, Lucey *et al.*, 2014 and Sugimoto *et al.*, 2014).

In Chapter 6, the volatilities of eight markets from the MENA region were estimated using the GJR GARCH model. Subsequently, the volatility spillover among these markets was analysed using the Diebold and Yilmaz approach. However, one of the criticisms facing the Diebold and Yilmaz approach is that it does not identify whether or not the spillover from one market to another is significantly different from zero. Thus, in order to determine the significance of this estimated spillover index, the standard errors of the estimated index as well as its sampling distribution are required. Despite the importance of identifying the significance of spillover estimates, there are no available estimation methods for the standard errors of the volatility spillover indexes. This, in turn, motivated Choi and Shin (2018) to apply bootstrapping to estimate standard errors and confidence interval estimations of the Diebold and Yilmaz index. Choi and Shin (2018) apply bootstrapping as it is considered as one of the commonly used approaches in the literature to estimate standard errors and confidence interval of the results better than the usual methods.

This chapter aims to demonstrate the usefulness of bootstrapping in estimating standard errors and confidence interval for the volatility spillover index. It aims to reinvestigate the results of Diebold and Yilmaz (2012) to ascertain whether the conclusions they reached are correct. Furthermore, the results of Chapter 6 are reanalysed to determine whether considering the significance of the results can have an impact on the conclusions reached.

The outline of this chapter is as follows. Section 7.2 presents an overview of the volatility spillover index and the appropriate method of bootstrapping to be used. Section 7.3 reports the significance of the Diebold and Yilmaz (2012) index and provide an overview on how the conclusions may change when the significance of the estimates is considered. Section 7.4 reports the estimates significance of the reinvestigated volatility spillover index of the MENA region. Section 7.5 reports the significance of the DY index of the reinvestigated volatility spillover index of the divided sample of the MENA region. Section 7.6 concludes the chapter outcomes.

7.2 Volatility Spillover Index

In Chapter 6, volatility was estimated using different ARCH/GARCH methods. The GJR-GARCH was chosen as the best model for modelling volatility for the eight selected MENA markets based on the Information Criteria and its ability to capture all the ARCH effects. Subsequently, the Diebold and Yilmaz volatility spillover index was used to investigate the spillover between these eight markets, taking into consideration the recent events that took place and analysing their effects on the region.

Consistent with the research hypotheses, there is a volatility spillover between the eight countries in the MENA region. The results show that there is a total spillover of 57.5% in the region. However, these results should be interpreted with caution, as they do not necessarily mean that the estimates of the spillover are statistically significant. The DY approach does not provide the significance of its output statistics, which makes the spillover percentages hard to interpret. Thus, to test the significance of these results and determine whether the high spillover estimates between the eight countries are not due to chance, bootstrapping is used. The bootstrapping is deemed appropriate to use according to Choi and Shin (2018) because of the absence of a clear measurement of the standard errors of volatility spillover index. Bootstrapping requires few assumptions, and provides higher accuracy than classical methods as mentioned in the methodology Chapter 5. Thus, the next section highlights the specific bootstrapping method used to test the volatility spillover index.

7.2.1 Bootstrapping Method Choice

There is a wide variety of bootstrapping methods as highlighted in Chapter 4. However, this study uses the stationary block bootstrapping to test the significance of the volatility spillover estimates. This approach is considered as appropriate because the underlying data are likely to be serially correlated. The stationary block bootstrap with random block length is appropriate in this study since it works well with dependent data (Choi and Shin, 2018). Indeed, the stationary block bootstrap is used with almost all cases of dynamic models. Finally, the stationary bootstrap can handle heteroscedasticity (Politis and Romano, 1994). In this thesis, the underlying data, volatility, is likely to be dependent and serially correlated, which motivates our choice of block bootstrapping.

The next section aims to use the stationary bootstrapping method to estimate the significance of the Diebold and Yilmaz volatility spillover index applied on their original data. By estimating the significance of their estimates, the importance of estimating the significance of the spillover results is highlighted. The section explains whether the conclusion they drew can change when the significance of their estimates are determined. By doing this, we contribute to the literature by being the first to formally test the significance of volatility spillover indexes. Indeed, existing studies have followed the steps of DY by producing spillover indexes without giving any attention to the statistical properties of these estimates.

7.3 Bootstrapping Volatility Spillover Index of DY (2012)

Diebold and Yilmaz (2009) develop a framework for measuring connectedness at various levels. However, this framework was criticized due to its dependency on the Cholesky-factor identification of the VARs where the results are dependent on the ordering of the variables. Later, Diebold and Yilmaz (2012) introduced an extension to solve this disadvantage and based their extension on Pesaran and Shin (1998), to overcome the impact of ordering of the variables on the results. Diebold and Yilmaz (2012) use a generalized impulse response function that does not require orthogonalization by Cholesky decomposition and construct directional indices.

By using the generalised VAR framework that produces variance decompositions invariant to ordering, Diebold and Yilmaz (2012) overcome the main criticism facing their paper in 2009. Instead of attempting to orthogonalize shocks, this generalized approach allows for correlated shocks. It accounts for them appropriately, using historically observed distribution of the errors. As the shocks to each variable are not orthogonalized, the sum of the contributions to the variance of forecast error is not necessarily equal to one.

Diebold and Yilmaz (2012) analyse the volatility spillover across US Stocks, Bonds, Commodities, and Foreign exchange market from January 1999 to January 2010. They addressed the total spillover and examined the directional spillover (from/to a specific market). Generally, the estimates show that the spillover across markets was very small until 2007 when the global financial crisis began to emerge. Furthermore, they highlight that the spillover from stock market to other markets started to take place after the 2008 Crisis. Generally, the high spillover is usually connected to a certain event happening, whether during or after the event.

Despite the ability of the DY (2012) framework to overcome the criticism facing their initial paper in 2009, it is criticized by its failure to identify the significance of the estimates. Thus, in order to get more reliable results, stationary block bootstrapping method is used to identify whether the spillover index is significant or not. By reinvestigating Diebold and Yilmaz (2012) study and identifying the statistical significance of their estimates, conclusions drawn from their estimates may change which may lead to different interpretations and decisions.

In applying the stationary bootstrapping to test the significance of the DY (2012) volatility spillover estimates, the volatility data set $\{x_1, \dots, x_t\}$, represents the volatilities of the US Stocks, Bonds, Commodities, and Foreign exchange market. In addition, L the block length is chosen randomly from a geometric distribution , representing the rate of increase of L as m increases (MacKinnon, 2007). The stationary bootstrap procedure is as follows:

Step 1: Draw L randomly from a geometric distribution. Let m be the minimum integer such that $mL \geq T - 1$. Make m random draw $\{i_1, i_2 \dots, i_m\}$ from $\{2,3 \dots, T\}$.

Step 2: Let $B_j = \left\{x_{i_j}, \dots., x_{i_{j+L-1}}\right\}$, be the jth block of size L_j starting from x_{i_j}, $j = 1, \dots, m$. Here B_j represents the new random draw set from the original volatility data.

Step 3: By combining m blocks, $\{B_1, \dots., B_m\}$ and deleting the last $\sum_{j=1}^{m} L_j - (T-1)$ elements in order to form a sample length of T, attaining $\{x, t = 1, \dots., T\}$.

By repeating steps 1 to 3, the bootstrap samples $\{x_t^*, t = 1, \dots., T\}$ are generated for 1000 times with the exception that for each block, the block size L is generated randomly from a geometric distribution with success probability $\tau \in (0,1)$ from the generated block sizes $L_1 + L_2 + \cdots + L_m \geq T - 1$. These bootstrapping samples that are drawn from the daily variance, using prices are then estimated by the VAR equation in order to calculate volatility spillover. For each bootstrap, sample $\{x_t^*, t = 1, \dots., T\}$ is estimated through VAR model equation $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$ from which H-step volatility indexes. Total volatility spillover index:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \times 100; \tag{7.1}$$

Directional volatility spillover received by market i from all other markets j:

$$S_{i\cdot}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H)} \times 100; \tag{7.2}$$

Directional volatility spillover transmitted by market i to all other markets j:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100; \tag{7.3}$$

Net volatility spillover from market i to all other markets j:

$$S_{i}^{g} = S_{\cdot i}^{g}(H) - S_{i \cdot}^{g}(H); \tag{7.4}$$

$i = 1, \dots, N$. We interpret each of the above spillover indexes as a statistic, $\hat{\theta}$. The standard error of $\hat{\theta}$ representing the volatility index estimator is $se(\hat{\theta})$. Since no method is directly applicable in the literature for estimating the standard error, an alternative is replacing $se(\hat{\theta})$ by a bootstrapping approximation $se^{*}(\hat{\theta}^{*})$. The bootstrap confidence interval (pivot with normal quantile) is given by:

$$CI_{NorP} = \hat{\theta} \pm 1.96\, se^{*}(\hat{\theta}^{*}) \tag{7.5}$$

where $se^{*}(\hat{\theta}^{*})$ is the standard deviation of, B say, bootstrapped volatility indexes $\{\hat{\theta}^{*(b)}, b = 1, \dots, B\}$. The interval is constructed from the asymptotic normality of the pivot $z = \frac{\hat{\theta} - \theta}{se^{*}(\hat{\theta}^{*})}$, giving the normal quantile 1.96 for 95% confidence interval in Equation 7.5.

The following section applies bootstrapping to the DY framework in order to get the significance of their estimates and see if different conclusions can be drawn.

7.3.1 Bootstrapping the DY (2012) Estimates

The significance of the Diebold and Yilmaz (2012) volatility spillover index is estimated using the stationary bootstrap and presented in Table 7.1. The Table gives the spillover estimates from/ to the four markets examined by DY along with total spillover index, the contribution from others, and the contribution to others. The total spillover index is reported at the lower right corner. Let i represent the rows and j represent the columns. In Table 7.1 the contribution to the forecast error variance of the volatility i coming from innovations to volatility j is represented by the $ijth$ entry. Below each estimate in the table the Z-stat is reported along with the p-value in brackets. The diagonal elements $(i = j)$ measure own market volatility spillover, and the off diagonal elements $(i \neq j)$ provides the cross market volatility spillover within two markets.

The table reveals that the total spillover index is statistically significant. It confirms that there is a significant 12.6% total spillover across the four markets (p-value<0.001). The contributions from other and contributions to others are all highly significant at the 1% level. The biggest receiver (18.6%) and transmitter (18.0%) is the bond market, while the commodities market receives from (6.3%) and gives to (4.6%) others the least spillover. Without formal testing, we would probably be satisfied, albeit heuristically, that the large spillover estimates are significant. However, the small figures were not considered by DY, they only mentioned the two largest figures of 18.5% and 14.24% as being ‘relatively large’ (2012, pp.61). Since their test could not justify if these figures can be considered as noise or not, only formal testing by finding the significance of these small figures confirms the existence of the spillover.

Overall, the tests in Table 7.1 confirm that aggregate transmission ‘to’ and ‘from’ each of the four markets is highly significant. However, there remains the question of whether the aggregate ‘to’ and ‘from’ transmissions are due to all other markets or some of them. Because they could not formally test individual spillover indexes, DY (2012, pp.61) conclude that “both the total and directional spillover over the full sample period were quite low.” However, ‘low’ does not necessarily mean significant or insignificant. Thus, despite the richness of the results, DY remain mostly silent, being hindered by the lack of formal testing. We therefore go further and formally test each individual, market to market, spillover index.

First, the insignificant spillover from commodities market to stock market (Index=0.35%, p-value=0.318) being one of the small figures across the markets. The spillover from the FX market to the stock market (Index=3.61%, p-value=0.14) is also insignificant, despite being relatively large. Thus, the stock market only receives from the bonds market (Index=7.29%, p-value<0.001).

Second, the bond market is the biggest receiver as it receives from all three markets (10.21%, 2.73% and 5.61% for stocks, commodities and FX respectively). All three indexes are significant at the 5% level or lower. This is reflected in the 'from' aggregate index of 18.6%. Third, commodities do not receive from stocks (Index=0.47%, p-value=0.248) or FX (Index=2.14%, p-value=0.07). This market, however, receives from the bonds market but only 3.70% (p-value=0.018). Clearly, commodities market is the least susceptible to volatility transmission from others. Finally, the spillover from commodities market to the FX market is statistically insignificant (Index=1.55%, p-value=0.133). However, the FX market is the second highest receiver, with 5.69% from stocks, and 7.03% from bonds (both p-values < 0.001).

Overall, Bonds receive from all three markets, FX receives from Stocks and Bonds, Commodities from Bonds only, and Stocks from Bonds only. In terms of giving, the Bonds market is again the most important, giving to all three markets, followed by stocks which give to Bonds and FX. Both Commodities and FX give to Bonds only. The above conclusions could only be drawn thanks to the availability of formal testing, which demonstrates the usefulness of our proposed procedure for testing volatility spillover indexes.

The net directional volatility spillover is reported in Table 7.2. These net directional measures are calculated from Table 7.1 as the 'contribution to others' minus 'contribution from others'. In discussing these important net spillover, DY (2012, p.61) simply state that "… the largest are from the stock market to others (16.29-11.24 = 5.05%) and from others to the FX market (11.41- 14.24 = -2.8%)." Unfortunately, this is not evidence as to whether or not it is 'better to give than to receive' as DY's paper title indicates. Indeed, if we look at the raw net directional spillover, we would be led to believe that stocks give to others, while bonds, commodities, and FX receives from others. The formal test demonstrates that this is not the case.

The largest net directional volatility spillover is from the Stock market to others (5.05%) which is statistically significant (p-value=0.014). Thus stocks give about 5% spillover than they receive from the other three markets. The second largest net spillover is from others to FX market (-2.8%). However, the formal testing reveal that it is statistically insignificant (p-value=0.126). Thus, contrary to the implicit suggestion by DY, there is no evidence of net spillover from others to FX market. The 'contribution to FX' is statistically indistinguishable from the 'contribution from FX'. In other words, the FX gives as much as it receives.

The commodities market net directional spillover is small (-1.68%) but statistically insignificant (p-value=0.327). The bond market net directional spillover figure is the lowest (-0.54%) and also highly insignificant (p-value=0.814). Thus, there is no evidence of net directional spillover in three out of the four markets. Nevertheless, the lack net directional spillover does not mean weak spillover. It simply means that a market gives to others as much as it takes from others. For example, the bonds market's net directional spillover is close to zero. Yet, bonds are significant transmitters to all three markets, and significant receivers from all three markets.

Table 7.1 Volatility Spillover of DY (2012) with P-value

		Stocks	Bonds	Commodities	FX	From Others
Stocks	Index	88.79	7.29	0.35	3.61	11.2
	Z-stat	40.32	4.86	0.99	2.80	5.10
	P-value	(0.000)	(0.000)	(0.318)	(0.14)	(0.000)
Bonds	Index	10.21	81.45	2.73	5.61	18.6
	Z-stat	5.92	28.92	1.42	4.55	6.58
	P-value	(0.000)	(0.000)	(0.034)	(0.000)	(0.000)
Commodities	Index	0.47	3.70	93.69	2.14	6.30
	Z-stat	1.15	2.35	40.61	1.79	2.72
	P-value	(0.248)	(0.018)	(0.000)	(0.07)	(0.003)
FX	Index	5.69	7.03	1.55	85.73	14.3
	Z-stat	3.31	4.89	1.50	27.30	4.47
	P-value	(0.000)	(0.000)	(0.133)	(0.000)	(0.000)
Contribution to others	Index	16.4	18.0	4.6	11.4	50.4
	Z-stat	5.45	5.35	2.32	4.06	
	P-value	(0.000)	(0.000)	(0.009)	(0.000)	
Contribution including own	Index	105.1	99.5	98.3	97.1	TSI: 12.6%
	Z-stat					5.67
	P-value					(0.000)

Note: TSI: Total Spillover Index. Daily returns from January 25, 1999 to January 29, 2010. Volatility spillover index based upon a VAR of order 4, and generalized variance decomposition of a 10-day ahead volatility forecast errors. Stationary bootstrapping the volatility spillover index, bootstrapped 1000 times. The ith row and the jth column figures are the contribution of country j to country i. Under each of the four markets in the table, the estimates, z-statistics, and the p-value is reported.

Table 7.2 Net Directional Spillover for DY (2012) with P-value

	Stocks	Bonds	Commodities	FX
Index	5.13	-0.54	-1.68	-2.90
Z-stat	2.42	-0.23	-0.97	-1.49
P-value	(0.014)	(0.814)	(0.327)	(0.126)

Note: Net directional volatility spillover is calculated as contribution to others minus contribution from others in Table 7.1. Under each of the four markets in the table, the estimates, z-statistics, and the p-value is reported.

Table 7.3 gives net pairwise spillover estimates. Net pairwise spillover between X and Z is simply the difference between gross volatility shocks transmitted from X to Z minus gross volatility shocks transmitted from Z to X. For example, in Table 7.1, the transmission from stocks to bonds is 10.21%, while the transmission from bonds to stocks is 7.29%, giving a net pairwise spillover of 2.92%.

The only statistically significant net pairwise spillover is between Stocks and Bonds (Index=2.92%, p-value=0.031) which is reflected by the statistically significant spillover from Stocks to Bonds (Index=10.21%, p-value<0.001) and from Bonds to Stocks (Index=7.29%, p-value<0.001). The insignificance found for the net pairwise spillover between Stocks and Commodities (Index=0.12%, p-value=0.730) can be due to the insignificant spillover from Commodities to Stock (Index=0.35%, p-value=0.318). Likewise, the net pairwise between Stocks and FX (Index=2.08, p-value=0.070) is statistically insignificant reflecting the insignificance found from FX to Stock market (Index=3.61%, p-value=0.14). Similarly, the net pairwise between Commodities and FX (Index=-0.59%, p-value=0.496) is statistically insignificant which is the result of having insignificant spillover from FX to Commodities (Index=2.14%, p-value=0.07). However, the net pairwise spillover between Bonds and Commodities and between Bonds and FX

(Index=0.96%, p-value=0.420; Index=1.41%, p-value=0.140) are statistically insignificant although the directional spillover analysis shows statistically significant spillover for both directions.

Overall, pairwise, there are three groups of transmissions. First, Stocks and Bonds transmit to each other significantly, but Stocks give more than they receive. Second, Bonds-Commodities and Bonds-FX have insignificant pairwise transmissions, but they give and receive equally. Finally, the remaining pairs do not show significant pairwise transmission, hence their net pairwise spillover is also insignificant.

To sum up, the introduction of formal testing has created a richness of results that was not possible without knowing whether figures and indices are statistically meaningful. Thus, it is essential to reinvestigate the results of Chapter 6 to test the accuracy of the drawn conclusions and interpretations. The outcome of such analysis is important to investors, portfolio managers, and other practitioners looking for diversifying their portfolio.

Table 7.3 Net Pairwise Spillover for DY (2012) with P-value

	Index	Z-stat	P-value
Stocks – Bonds	2.92	2.07	(0.031)
Stocks – Commodities	0.12	0.33	(0.730)
Stocks – FX	2.08	1.74	(0.070)
Bonds – Commodities	0.96	0.80	(0.420)
Bonds – FX	1.41	1.45	(0.140)
Commodities – FX	-0.59	-0.67	(0.496)

Note: Net Pairwise Spillover is the spillover between two markets. Beside each pair markets in the table, the estimates, z-statistics, and the p-value are reported.

7.4 Bootstrapping Volatility Spillover within MENA Countries

This section aims to explore the previously investigated volatility spillover of the MENA region in Chapter 6. To estimate the significance of the spillover index, this section follows the same steps outlined in the previous section. Specifically, it assumes that the volatility data set $\{x_1, \ldots, x_t\}$ is the output of the GJR-GARCH and the block length L is chosen randomly from a geometric distribution, representing the rate of increase of L as m increases. The stationary bootstrapping procedure is the same as in the previous section. Consequently, each of the following sections reports and discusses the bootstrapping of the volatility spillover estimates in details. Section 7.4.1 discusses the bootstrapping results of the total spillover which refers to the spillover in general across the region, Section 7.4.2 interprets the bootstrapping results of the individual markets spillover for each of the eight markets looking at a narrower scope of the spillover from and to each of the eight markets. Then, Section 7.4.3 assesses the bootstrapping results of net pairwise spillover in order to understand the transmission and relations between markets.

7.4.1 Total Spillover Index

As shown in Table 7.4, the total spillover index is estimated to be 57.5%, this result proves to be statistically significant (p-value<0.001), which describes the portion of the forecast error variance that comes from all of the spillovers, and is an average impact of connectedness. A high percentage of total spillover index reflects the relationship within the MENA region and can be attributed to three main factors. The first factor is trading relationships between these countries. Specifically, in the MENA region, the main trading commodities are oil, gas, and agricultural products. The major trading nations for oil and gas are the UAE, Saudi Arabia, and Kuwait. Because much of the wealth within the MENA region is driven by these natural resources, it is tempting to speculate that this total measure of interconnectedness and dependency within the region comes from these three countries. However, as we shall see later, this is not the case.

The second factor is cross border investments which again reflects the dependency within the region. Specifically, investments like the UAE Al-Futtaim Corporation in several countries across the region like Saudi Arabia, Oman, Kuwait, Bahrain, Turkey and Egypt (whether retail, real estate, or financial services) (Al-Futtaim-Our Global Presence, 2020). Other investments like the Emaar Developments (originally based in the UAE) in the region (Kuwait, Jordan, and Turkey) in the real estate field. Another investment like the Kuwait Corporation, Americana Group, in various countries (the UAE, Saudi Arabia, and Egypt) in the region did not just invest in countries but also affected the culture of these countries by introducing a new concept of quick serving restaurants in the region (Americana Group - Who We Are, 2020). All these different types of investments provide evidence of the dependency with the region which is again supported by the statistically significant total spillover.

The third factor that reflects the relationship within the MENA region is the occurrence of various political and economic events. The Global Financial Crisis in 2008 affected the MENA region as much as it affected the whole world. The 2011 Arab Spring, which started in Tunisia and spread to other countries in the region (Schraeder, 2012) significantly influenced the political stability of the region. Moreover, the establishment of the Gulf Cooperation Council in the Gulf area to foster the economic and political relations between the different nations in the area also provides further explanation for the significant spillover between countries in the MENA region.

To sum up, the results of Table 7.4 that there is a significant spillover between countries in the MENA region of 57.5% are supported by the strong relations between these countries in different areas, and the fact that these countries share similar political, economic, social conditions. In the following sections, the directional spillover ‘to’ and ‘from’ individual markets are analysed in depth to identify which of these countries contribute more to the observed total spillover in the MENA region.

7.4.2 Spillover from Individual Markets

This section aims to test the significance of the volatility spillover statistics for each of the eight selected markets individually. The significance level makes the spillover percentages easier to interpret, which gives the analysts or policy makers greater confidence in using these results to draw conclusions and recommendations. Each market is discussed separately in order to clarify each individual market’s contribution to and reception of spillover. In the discussion, we mention whether the spillover reported between pairs of markets is significant or not and accordingly whether previously drawn conclusions remain valid. In addition, we pinpoint which markets are receivers, transmitter, both or neither, along with the net spillover between markets.

This section revisits the results of the directional volatility spillover for each individual market and discusses the different outcomes after testing the significance of the estimates. In Table 7.4 Jordan seems to be the most influential market. The spillover from Jordan to the other seven markets are all highly significant and large varying from a low 2.65% (p-value=0.021) for Egypt to a high 19.28% (p-value<0.001) for Oman. This is in line with the findings of Öztürk and Volkan (2015) who find that in the stock market, the volatility spillover is transmitted from Jordan to the rest of the MENA region. In terms of FDIs, Jordan is considered one of the major destinations of massive investments by the Gulf countries due to the following reasons. First, Jordan plans large scale infrastructure projects to become a regional logistics hub for electric and transport networks. Second, the quality of its infrastructure, its solid banking system, and its level of economic openness that allows for establishing trade zones are considered among the main factors affecting the number of FDIs in Jordan. Third, after the implementation of a comprehensive economic adjustments and reform program in both the monetary and financial sectors, Jordan is placed as the highest financial developed among the MENA countries (Creane *et al*., 2003) which, in turn, explain the strong spillover from Jordan to other MENA region countries. Another potential reason is the strong political ties that Jordan manages to hold with all MENA countries, in addition to, Jordan being severely affected by the amount of Syrian refugees which lead to increasing the usage of local services, rent and food prices (World Bank, 2020) leading to increasing its imports.

Oman is the second most influential market, spilling over to all markets except Egypt (7.4%, p-value=0.113). Judging by the scale of individual spillover indexes in the DY study, a spillover of 7.4% is not low since the highest index in DY is 10.21% (see Table 7.1). Again the possible explanation for this insignificant spillover is the instability in the Egyptian economy due to the Arab Spring revolution. Given that Oman to own spillover is high (Index=34.73%, p-value=0.01), the spillover to others are highly significant and generally large, varying between a low of 12.36% for (p-value=0.03) Turkey to a high of

25.08% (p-value<0.001) for Jordan. This can be attributed to Oman being one of the largest oil and natural gas producers in the Middle East and not a member of the OPEC, and considered one of the major benchmarks in the international oil market (Energy Information Administration, 2017). Moreover, Oman being a member of more than one trading bloc, like GCC and GAFTA, which constitutes financial links between the members.

Kuwait is the third most influential market, significantly impacting five of the seven countries, specifically Jordan (9.45%, p-value<0.001), Oman (14.42%, p-value=0.042), Saudi Arabia (9.45%, p-value=0.013), Turkey (10.04%, p-value=0.014), and the UAE (7.43%, p-value<0.001). This spillover can be attribute to more than one reason. First, Kuwait is a member of GAFTA and OPEC, which can help the country to establish strong relationships with the members. Second, Kuwait invests heavily in the aforementioned countries such as Americana Group which is considered as one of the major Kuwaiti investments. The spillover from Kuwait to own market is 43.75% (p-value=0.011). However, the spillover from Kuwait to Bahrain is high but insignificant (Index=9.71%, p-value=0.113), possibly due to relative stability of Kuwait market and the small size of Bahrain market. The strongest evidence is found against Egypt. Despite the strong historical relations between Egypt and Kuwait, the spillover to Egypt (Index=3.04%, p-value=0.456) is statistically insignificant. One possible explanation is that Egypt has experienced massive instability in its economy due to the Arab Spring revolution. Kuwait being relatively stable, had little to transmit to an already volatile market.

Jordan, Oman, and Kuwait are the most influential markets, reporting the highest spillover estimates. Additionally, there is a bidirectional relation between these three markets. First, a bidirectional spillover between Jordan and Kuwait is supported by a significant spillover from Jordan to Kuwait (11.95%) and from Kuwait to Jordan (9.45%). Second, a bidirectional relation between Kuwait and Oman can be explained by, the large and significant spillover from Kuwait to Oman (14.42%) and from Oman to Kuwait (22.24%). Third, there is a bidirectional spillover between Jordan and Oman since Jordan spills over Oman (19.28%) and Oman spills over Jordan (25.08%). Overall, the influence of these three markets point to an unexpected but important feature of these countries. All three countries are relatively stable and politically neutral to the regional and international conflicts. The economic and political stability of these countries lowers market volatility such that when there is a local shock the impact of the surprise would be perceived strongly in foreign markets. Similarly, local investors would also react relatively strongly to external shocks.

Turkey is the least influential market, spilling over to Kuwait (Index=4.79%, p-value=0.078) only. Given the significant spillover from Turkey to Kuwait (4.79%) and from Kuwait to Turkey (10.04%), the results of Table 7.2 show that there is a bidirectional spillover between the two countries. This can be attributed to the economic partnership between the two countries. Specifically, Kuwait is considered as Turkey's gateway into the Gulf, while Turkey is Kuwait's route into Europe and central Asia (Pervez Bilgrami, 2019). Turkey has attempted to strengthen its trade exchange with the MENA region since 2007, by increasing its exports of manufactured goods (Marouane and Mezghani, 2013). Nevertheless, the spillover from Turkey to the other six markets are statistically insignificant varying from high to Saudi Arabia (4.79%, p-value=0.202) and too low to the UAE (1.77%, p-value=0.455). This result reveals that Turkey can be nominally grouped among MENA countries while trades mainly outside the region as Aksoylar and Altug (2020) argued. In addition to, having political tensions between Turkey and Egypt especially after the Arab spring, where Turkey is interfering Egypt's domestic affairs (Fox News, 2015).

Although Saudi Arabia is considered as the largest capital market in the Gulf region with strong economic ties with Egypt and Turkey (Uludag and Ezzat, 2017). Saudi Arabia seems to be the second least influential market in the MENA region. In this regard, the results of Table 7.2 show that Saudi Arabia only has a significant spillover to Oman (Index=8.34%, p-value=0.03), while it has a weakly significant spillover to Egypt (Index=3.96%, p-value=0.065) and to Kuwait (Index=7.02%, p-value=0.053). These weak spillover relations are hard to explain given the exchanges in trade and services along with the investments between these countries. Furthermore, Saudi Arabia, Oman and Kuwait are members of the GCC which boosts the cooperation between these countries. One possible explanation is the large scale of the Saudi market and its history as the source of major crises in the past (Bowen, 2007). As a result, investors in other markets factor in these potential risks such that when a shock takes place in Saudi Arabia it has little effect since it was mostly anticipated.

Although Saudi Arabia, Bahrain, and the UAE are members of the GCC, the spillover from Saudi Arabia to Bahrain (Index=5.51%, p-value=0.140), from Saudi Arabia to the UAE (Index=4.49%, p-value=0.232) are all statistically insignificant. These results are counterintuitive, since, Bahrain depends heavily on the Saudi market, with more than quarter of its non-oil exports going to Saudi market (IMF, 2018). Furthermore, Saudi Arabia is one of the main oil exporting country in the region which means that trading countries should be affected by the oil price fluctuation. However, the formal testing shows that the estimates are insignificant, rejecting the spillover due to oil argument. The result of Saudi market contradicts the previous finding of Awartani *et al*. (2013) who argue that the Saudi market spills over all the GCC countries, and plays a leading role among the GCC markets. Since they used DY index to measure spillover, then the difference between the results could be the formal testing implemented in this study to reveal the significance of the estimates.

Although the UAE is becoming an important investment hub in the Middle East through embracing international economic integration and alignment with global financial standards (Central Bank of UAE, 2004), it seems to be the third least influential market, spilling over to Bahrain (Index=4.68%, p-value=0.009), and to Jordan (Index=9.67%, p-value<0.001) significantly. Although there are several financial and political ties between the UAE and Egypt, as they are known for being close allies and collaborating in several issues like the Saudi Blockade of Qatar, there is a weak significant spillover from the UAE to Egypt (Index=1.57%, p-value=0.075). This is unexpected since the UAE is one of the top Arab countries supporting the Egyptian economy after the revolution and offering great financial support (ADFD, 2020). Nevertheless, this shows that spillovers across financial markets are not necessarily driven by economic and/or political ties.

Saudi Arabia, Turkey, and the UAE are not just the least influential markets. These markets are amongst the most affected by other markets. Interestingly, these three markets do not spillover ‘to’ or ‘from’ each other (no directional spillover between them). Saudi Arabia receives spillover from all markets except Turkey and the UAE. Similarly, the UAE receives spillover from all markets except from Saudi Arabia and Turkey. Turkey receives spillover from all markets except for Saudi Arabia, the UAE, and Bahrain. Another interesting point is that, the spillover 'from others' is larger than the spillover 'to others' for the three markets. For example, Saudi Arabia spills over to four markets, the largest of which is 8.34% for Oman. Meanwhile, it receives from five markets, the largest of which is 14.6% for Oman. Thus, Saudi Arabia both transmits to and receives from Oman. Turkey spillover to Kuwait is only 4.79%, while it receives from four markets the largest of which is 12.36% for Oman. As for the UAE, the spillover is significant to three markets, the largest of which is 9.67% for Jordan. Meanwhile, it receives from five markets, the largest of which is 20.18% for Oman.

Overall, while Saudi Arabia, Turkey, and the UAE do not spillover to each other, all three markets receives the largest significant spillover from Oman. The insignificant spillover between these markets is found despite the UAE and Saudi Arabia having political conflicts with Turkey, condemning Turkey's military actions in Iraq, along with Turkey being close to Qatar knowing the diplomatic conflicts with the UAE and Saudi Arabia (Al-Monitor, 2020). Furthermore, the formal testing shows no significant spillover between the UAE and Saudi Arabia, despite the strong ties between them. One potential explanation for this strange result is the heavy involvement of all three countries in regional conflicts, which increases risk perception and anticipation by local and foreign investors. Thus, additional shocks within these three countries add little to the volatility of other markets as investors have mostly anticipated political risks inherent in these markets. On the other hand, local investors may not factor-in excessive risk in foreign (and more stable) markets. When a shock realises in these markets the surprise to local investors is therefore high, explaining the significant reception of spillover from other markets.

The spillover from Bahrain to own market is weakly significant (Index=36.76%, p-value=0.080) shown in Table 7.4. In Chapter 6, this spillover was attributed to the participation of Bahrain in the Yemen conflict in 2015 and the discovery of the kingdom's largest oilfield in 2018. However, the argument that these events have led to spillover within the Bahrain market are not supported by strong statistical evidence. Furthermore, there is statistically weakly significant spillover from Bahrain to Kuwait (Index=8.06%, p-value=0.099), but a strongly significant spillover from Bahrain to Jordan (17.98%, p-value<0.001), to Oman (14.3%, p-value=0.047), to Saudi Arabia (9.47%, p-value=0.014), and to the UAE (19.26%, p-value<0.001). This significant spillover cannot be attributed to the trade agreements between these countries. One could argue that Bahrain, Saudi Arabia, Oman and the UAE are all members in the Gulf Cooperation Council (GCC) design similar regulations in finance, trade, and encourage their private sectors to cooperate with each other (Öztürk and Volkan, 2015). However, this does not explain why there is no spillover from either Saudi Arabia or Kuwait to Bahrain. This is counterintuitive since Bahrain is a much smaller market than Saudi Arabia or Kuwait. So it should normally be the opposite; the direction should be from the big market to the small market and not vice versa. The explanation is again political instability. Bahrain is highly unstable locally because of the recent social unrest that obliged Saudi Arabia to intervene directly. Because Saudi Arabia and Kuwait have Shia minorities, a shock in Bahrain has a greater chance to resonate in Saudi Arabia and Kuwait since there is always a chance that the source of turmoil is Shia driven social unrest.

This line of argument is in contradiction with to Alkulaib *et al*. (2009) who find that the interaction and linkages in the GCC region is possibly the result of the higher level of political and economic integration of the GCC countries. Finally, from Table 7.4, there are insignificant spillover from Bahrain to Egypt and to Turkey (p-value=0.484, and 0.174 respectively). This is not surprising as Bahrain is a much smaller economy that these two countries and has weaker economic links with them.

As for Egypt, there is a strongly significant spillover to Jordan (2.36%, p-value=0.004) and the UAE (2.60%, p-value<0.001). Although these results may show that the spillover from Egypt to Jordan and the UAE are not too high despite being statistically significant, these results can reflect the relation between Egypt and these countries, given the amount of investments by different corporations from the UAE in Egypt – The Emaar developments (real estate) and Al-Futtaim Corporation (whether retail, real estate, or financial services). In addition, Egypt, Jordan, and the UAE are members in the Great Arab Free Trade Area (GAFTA) which explains part of the interdependence between these countries. Furthermore, the results show that the strongest spillover is from Egypt to its own market (77.6%, p-value<0.001). This strongly significant spillover can be attributed to the economic and political instabilities that Egypt witnessed during the sample period. Specifically, in 2008, the whole world and accordingly the Egyptian economy was affected by the Global Financial Crisis. In addition, in 2011 and 2013, Egypt was affected by the eruption of the Egyptian revolutions that resulted in political and economic turmoil.

However, despite the well-known economic, political, and social relations between Egypt and Saudi Arabia, the results of Table 7.2 show that the spillover from Egypt to Saudi Arabia is only weakly significant (2.6%, p-value=0.092). Even though, Rouis and Tabor

(2013) state that Turkey is an important trading partner for Egypt, a weakly significant spillover from Egypt to Turkey (4.15%, p-value=0.053) is found. This is surprising since we would expect no connectedness between Egypt and Turkey thanks to the escalating tensions between the two countries since the Arab Spring which is impacting the political, situations of Libya, Sudan, and the threatening the stability of the Middle East (Maher and Tsukerman, 2019). On the other hand, there is no spillover from Egypt to Bahrain (p-value=0.406), Kuwait (p-value=0.502), and Oman (p-value=0.287). This suggests that financial volatility in Egypt has little influence on these three GCC markets. This could be explained by Bahrain market being relatively small, Kuwait being relatively shielded by economic strength, and Oman being distant in terms of financial and economic links.

There is a clear absence of bidirectional spillover between Egypt and Bahrain, where the spillover from Egypt to Bahrain (1.85%) and from Bahrain to Egypt (1.28%) are both insignificant. Both of these markets are low transmitters as well as low receivers. The only two markets that transmit to and receive from Egypt are Jordan and the UAE. Therefore, there is a bidirectional spillover between Egypt and Jordan, since there is a significant spillover from Egypt to Jordan (2.36%) and from Jordan to Egypt (2.65%). This is attributed to both Egypt and Jordan receiving more than half of the remittance inflows of the GCC, and Egypt is an important export market for Jordan (Rouis and Tabor, 2013). Another bidirectional spillover is between Egypt and the UAE, since there is spillover from Egypt to the UAE (2.6%) and from the UAE to Egypt (1.57%). This can be attributed to Egypt exporting mostly to the UAE, as well as both being members of GAFTA, in addition to, the UAE and Egypt have strong growing political, economic, and cultural ties, and ranks first among Arab and foreign countries investing in Egypt (Ismail and Bashir, 2019).

Similar to Egypt, Bahrain being a low transmitter and low receiver, it transmits and receives from Jordan, Oman, and the UAE significantly indicating that there is bidirectional spillover between Bahrain and these three countries. Bahrain spills over to Jordan (17.98%) and Jordan spills over to Bahrain (15.59%) resulting in a bidirectional spillover between Bahrain and Jordan. There is bidirectional spillover between Bahrain and Oman since there is spillover from Bahrain to Oman (14.3%) and from Oman to Bahrain (23.81%). This can be attributed to the fact that being members of the GCC as previously mentioned, increases the interdependence, along with enhancing the cooperation between these countries (Öztürk and Volkan, 2015).

On the other hand, although the UAE is one of the least influential markets, the UAE is the most affected by the other markets, receiving from all other markets except Saudi Arabia (4.49%, p-value=0.232) and Turkey (1.77%, p-value=0.455). The significant spillover from Bahrain to the UAE is 19.26% (p-value<0.001), and from the UAE to Bahrain 4.68% (p-value=0.009), suggesting that there is a bidirectional spillover between the UAE and Bahrain. This can be attributed to both being members of the GCC and GAFTA. Additionally, the UAE is one of the major exports partner of Bahrain (World Bank, 2018). Another significant spillover from the UAE to Jordan 9.67% (p-value<0.001) and from Jordan to the UAE 2.6% (p-value<0.001) indicating that there is bidirectional between the UAE and Jordan. This can be accredited to both being members of the GAFTA, along with both trying to be a regional hub. Moreover, the UAE is becoming an investment hub while Jordan becoming a logistic hub.

Similarly, Saudi Arabia is one of the least influential markets, and one of the most affected by others as mentioned previously, it has bidirectional spillover with two of the most influential markets, Kuwait and Oman. There is a bidirectional spillover between Kuwait and Saudi Arabia since there is spillover from Kuwait to Saudi Arabia (9.45%) and from Saudi Arabia to Kuwait (7.02%). Along with a bidirectional spillover between Oman and Saudi Arabia since there is spillover from Oman to Saudi Arabia (14.6%) and from Saudi Arabia to Oman (8.34%). This can be attributed to the three markets being members of the same trading bloc like GCC and GAFTA representing the interdependence between them, along with Oman exporting to Saudi Arabia, and Kuwait importing from Saudi Arabia, and in addition to Saudi Arabia bordering with Kuwait and Oman by land which represents the stronger ties between the three countries.

Without the formal testing of the significance the bidirectional relations would have not been detected since the DY index only gives estimates of spillover without indicating its significance, and therefore making it hard to interpret which estimates are significant and which estimates are insignificant. Another contribution from testing the significance is classifying the markets. The markets can be classified by the number of markets they transmit to and receive from. Bahrain can be classified as a transmitter, despite its small market size, since it transmits to five markets (Jordan, Kuwait, Oman, Saudi Arabia, and the UAE) while receives only from three markets (Jordan, Oman, and the UAE). This is confirmed by having Bahrain 'contribution to others' larger than (Index=79.3%, p-value<0.001) 'contribution from others' (Index=63.2%, p-value=0.001), then Bahrain is a transmitter to other markets. Even though the contribution 'to' and 'from' others are significant, Table 7.5 shows that the net spillover for Bahrain is 13.09% (p-value=0.236) and it is insignificant. Despite Bahrain's small size, it is a highly connected markets which is probably due to its own internal social instability, to which neighbouring GCC countries are highly sensitive.

Egypt is a transmitter since it transmits to four markets (Jordan, Saudi Arabia, Turkey, and the UAE) and receives only from three markets (Jordan, Saudi Arabia, and the UAE). Since the period of study includes a major event that took place in Egypt like the Egyptian revolution, it is expected to see Egypt as a transmitter to neighbouring countries. However, the opposite is found from the contribution 'to' and 'from' others. Egypt 'contribution to others' (Index=18%, p-value=0.042) is smaller than 'contribution from others' (Index=22.6%, p-value=0.037). However, the contribution 'to' and 'from' are not significantly different. As Table 7.5 shows, the net directional spillover for Egypt is -4.59% (p-value=0.452) and highly insignificant.

Jordan transmits to seven markets (Bahrain, Egypt, Kuwait, Oman, Saudi Arabia, Turkey, and the UAE) and receives from five markets (Bahrain, Egypt, Kuwait, Oman, and the UAE). Confirmed by the 'contribution from other' (Index=71.8%, p-value<0.001) being smaller than the 'contribution to other' (Index=91.1%, p-value<0.001). The net directional spillover for Jordan 19.29% (p-value=0.066) is weakly significant confirming Jordan being a transmitter. This can be attributed to Jordan being the highest financial developed among the region, along with being a major destination for investments by Gulf countries (Creane *et al*., 2003). This can also be attributed partly to Jordan's economy depending on the GCC, leading Jordan to have a security relationship with these countries, like having their military officers serving as advisors in the armed forces of the UAE and

Oman. Around 11% of the Jordanian population are working abroad, mostly in the GCC countries (Aftandilian, 2020).

Similarly, Oman is a transmitter since it transmits to six markets (Bahrain, Jordan, Kuwait, Saudi Arabia, Turkey, and the UAE) and receives only from four markets (Bahrain, Jordan, Kuwait, and Saudi Arabia). By inspecting Oman contribution from others (Index=64.3%, p-value<0.001) it is smaller than the contribution to other (Index=125.7%, p-value<0.001) and both are highly significant, confirming that Oman is a transmitter. According to Table 7.5, Oman has the highest significant net directional spillover 60.38% (p-value<0.001) confirming Oman being a transmitter. As said earlier, this can be attributed to Oman being relatively stable and political neutral.

Saudi Arabia receives from five markets (Bahrain, Egypt, Jordan, Kuwait, and Oman) and transmits to three markets (Egypt, Kuwait, and Oman). Saudi Arabia appears to be a receiver, since the 'contribution to others' (Index=39.1%, p-value<0.001) is smaller than the 'contribution from others' (Index=54.1%, p-value<0.001) both statistically significant. However, Table 7.5 shows that the net directional spillover for Saudi Arabia is -15.02% but insignificant (p-value=0.195). Although there is evidence of Saudi Arabia being transmitter and receiver, it is well below expectation given its economic and market size and its position as the biggest oil producing country in the world. As explained earlier, the explanation may lie in the fact that the Saudi financial market is highly unstable. Saudi Arabia has been hit by several adverse events during the recent years. For example, Saudi Arabia led air strike on Yemen; Saudi Arabia blocked air, land, and sea ports to Qatar; and faced unrest in other markets due to the Arab Spring (Matthiesen, 2015).

Turkey receives from four markets (Egypt, Jordan, Kuwait, and Oman) yet transmits only to Kuwait. Turkey proved to be a receiver, since the 'contribution from others' (Index=50.2%, p-value<0.001) is larger than 'contribution to others' (Index=21.8%, p-value=0.040) both statistically significant. In Table 7.5, Turkey has a negative significant net directional spillover (-28.32%, p-value=0.015) indicating that Turkey is a receiver.

The UAE receives from five markets (Bahrain, Egypt, Jordan, Kuwait, and Oman) and transmits to three markets (Bahrain, Egypt, and Jordan). This is in line with having the UAE 'contribution from other' 76.6% (p-value<0.001) larger than 'contribution to others' 24.5% (p-value=0.008). The UAE being a receiver is also confirmed in Table 7.5, where the UAE net directional spillover (-52.13%, p-value=0.000) is significant.

Finally, Kuwait transmits to five markets (Jordan, Oman, Saudi Arabia, Turkey, and the UAE) and receives to five markets (Bahrain, Jordan, Oman, Saudi Arabia, and Turkey) as well, therefore Kuwait is a transmitter as much as a receiver. This is confirmed by having Kuwait 'contribution to others' 63.6% (p-value=0.002) larger than 'contribution from others' 56.2% (p-value<0.001). Even though the contribution 'to' and 'from' others are significant, Table 7.5 shows that the net directional spillover for Kuwait is 7.3% (p-value=0.503) and is insignificant.

Table 7.4 Bootstrapping Volatility Spillover Index

		Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	Spill	36.76	1.85	15.59	9.71	23.81	5.51	2.09	4.68	63.2
	Z-stat	1.74	0.83	7.49	1.58	2.57	1.47	0.59	2.59	3.00
	P-value	(0.080)	(0.406)	(0.000)	(0.113)	(0.009)	(0.140)	(0.549)	(0.009)	(0.001)
Egypt	Spill	1.28	77.44	2.65	3.04	7.40	3.96	2.67	1.57	22.6
	Z-stat	0.69	6.10	2.30	0.74	1.58	1.84	1.62	1.77	1.77
	P-value	(0.484)	(0.000)	(0.021)	(0.456)	(0.113)	(0.065)	(0.103)	(0.075)	(0.037)
Jordan	Spill	17.98	2.36	58.17	9.45	25.08	4.94	2.35	9.67	71.8
	Z-stat	12.20	2.81	8.77	7.13	18.30	1.17	0.88	3.31	22.36
	P-value	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.241)	(0.377)	(0.000)	(0.000)
Kuwait	Spill	8.06	1.62	11.95	43.75	22.24	7.02	4.79	0.57	56.2
	Z-stat	1.64	0.67	6.43	2.52	2.68	1.93	1.75	0.244	3.24
	P-value	(0.099)	(0.502)	(0.000)	(0.011)	(0.007)	(0.053)	(0.078)	(0.806)	(0.000)
Oman	Spill	14.30	2.78	19.28	14.42	34.73	8.34	3.66	2.49	64.3
	Z-stat	1.98	1.06	6.78	1.94	2.55	2.15	0.88	0.69	4.80
	P-value	(0.047)	(0.287)	(0.000)	(0.042)	(0.010)	(0.030)	(0.373)	(0.489)	(0.000)
Saudi Arabia	Spill	9.47	2.60	10.48	9.45	14.60	45.90	4.51	2.99	54.1
	Z-stat	2.45	1.68	2.27	2.47	3.04	5.60	1.27	0.71	6.60
	P-value	(0.014)	(0.092)	(0.022)	(0.013)	(0.002)	(0.000)	(0.202)	(0.472)	(0.000)
Turkey	Spill	5.98	4.15	10.26	10.04	12.36	4.83	49.84	2.54	50.2
	Z-stat	1.35	1.92	2.33	2.44	2.16	1.07	3.72	0.66	3.75
	P-value	(0.174)	(0.053)	(0.019)	(0.014)	(0.030)	(0.281)	(0.000)	(0.505)	(0.000)
UAE	Spill	19.26	2.60	20.11	7.43	20.18	4.49	1.77	23.36	76.6
	Z-stat	15.33	3.70	7.39	5.81	13.92	1.19	0.74	7.79	25.56
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.232)	(0.455)	(0.000)	(0.000)
Contribution to others	Spill	79.3	18.0	91.1	63.6	125.7	39.1	21.8	24.5	460.0
	Z-stat	3.82	1.72	8.59	2.75	4.74	3.03	1.74	2.40	
	P-value	(0.000)	(0.042)	(0.000)	(0.002)	(0.000)	(0.001)	(0.040)	(0.008)	
Contribution including own	Spill	113.1	95.4	119.3	107.3	160.4	85.0	71.7	47.9	57.5%
	Z-stat									6.02
	P-value									(0.000)

Note: Monthly real returns from Jan 2003 to Dec 2018, volatility measured by GJR-GARCH. Volatility spillover index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. Stationary bootstrapping the volatility spillover index, bootstrapped 1000 times. The ith row and the jth column figures are the contribution of country j to country i.Under each of the eight markets in the table, the estimates, z-statistics, and the p-value is reported. Insignificant highlighted in pink, weakly significant highlighted in yellow, and highly significant is not highlighted.

Table 7.5 Bootstrapping Net Directional Spillover

	Spill	Z-stat	P-value
Bahrain	13.09	1.18	(0.236)
Egypt	-4.59	-0.75	(0.452)
Jordan	19.29	1.83	(0.066)
Kuwait	7.30	0.66	(0.503)
Oman	60.38	3.80	(0.000)
Saudi Arabia	-15.02	-1.29	(0.195)
Turkey	-28.32	-2.42	(0.015)
UAE	-52.13	-5.11	(0.000)

Note: Net directional volatility spillover is calculated as contribution to others minus contribution from others statistics in Table 7.4. Beside each of the eight markets in the table, the estimates, z-statistics, and the p-value is reported.

7.4.3 Net Pairwise Spillover

Table 7.6 illustrates the net pairwise spillover among the eight markets. Net pairwise spillover between X and Z is simply the difference between gross volatility shocks transmitted from X to Z minus gross volatility shocks transmitted from Z to X. For example, the net pairwise spillover between Egypt and Bahrain is the difference between gross volatility shocks transmitted from Egypt to Bahrain and gross volatility shocks transmitted from Bahrain to Egypt. The results of Table 7.6 show that most of the net pairwise spillover are statistically insignificant which clarifies the importance of this formal testing in order to prove whether there is pairwise spillover between the markets or not. Specifically, without this formal testing of the statistical significance of the results, one can interpret that there is pairwise spillovers between the countries in the MENA region and draw inaccurate conclusions accordingly. Out of the twenty-eight possible net pairwise spillover, there are only seven statistically significant net measures at the 5% level and four weakly significant net pairwise spillovers at the 10% level. Generally, the seven significant pairwise spillovers can be divided into two categories. The first category includes cases in which the net pairwise spillover between two markets is statistically significant and directional spillover transmission between these markets is also significant. On the other hand, the second category includes cases in which the net pairwise spillover between two markets is statistically significant and one of the directional spillover transmission between these markets is insignificant.

The first category includes the significant net pairwise spillover between Bahrain and the UAE (14.58%, p-value<0.001). This significant pairwise spillover can be attributed to the significant spillover from Bahrain to the UAE (19.26%) rather than the spillover from the UAE to Bahrain (4.68%). Similarly, the significant net pairwise spillover is between Jordan and the UAE (11.24%, p-value<0.001). This is attributed to a significant spillover from Jordan to the UAE (20.11%) rather than the significant spillover from the UAE to Jordan (9.67%). Kuwait being one of the most influential markets, has significant net pairwise spillover between Kuwait and Oman (-7.81%, p-value=0.016). The negative sign of the net pairwise spillover between Kuwait and Oman indicates that the spillover from Oman to Kuwait is larger as highlighted in Section 7.4.2. Specifically, the results of Section 7.4.2 show that the spillover from Oman to Kuwait (22.24%) is larger than that from Kuwait to Oman (14.42%). Oman and Kuwait are the most neutral countries in the GCC area, especially in their position with Qatar and Yemen.

The second category includes the significant net pairwise spillover between Oman and the UAE (17.69%, p-value<0.001). Even though the directional spillover from the UAE to Oman (2.49%, p-value=0.489) is insignificant, the directional spillover from Oman to the UAE (20.18%, p-value<0.001) is much larger and statistically significant. Therefore, Oman seems to be a strong transmitter. Turkey, as previously mentioned, seems to be one of the least influential markets. According to the net pairwise spillover Turkey is involved in two significant net pairwise spillovers only. First, the net pairwise spillover between Jordan and Turkey (7.9%, p-value=0.033) which can be attributed to a significant spillover from Jordan to Turkey (10.26%) as the spillover from Turkey to Jordan (2.35%) is insignificant (p-value=0.377) as indicated in Section 7.4.2. This, in turn, indicates that Jordan transmits to Turkey but Turkey does not transmit to Jordan. Second, the net pairwise spillover between Oman and Turkey (8.69%, p-value=0.032) which can be attributed to a significant spillover from Oman to Turkey (12.36%, p-value=0.03) but an insignificant spillover from Turkey to Oman (3.66%, p-value=0.373). Similarly, the net pairwise spillover between Kuwait and the UAE (6.86%, p-value<0.001). The significant net pairwise spillover between Kuwait and the UAE is attributed mainly to the significant spillover from Kuwait to the UAE (7.43%).

The results of Table 7.6 also show that there are four weakly significant net pairwise spillovers which are Bahrain-Oman, Egypt-Oman, Kuwait-Turkey, Oman-Saudi Arabia. The common feature between these spillovers is that both the net pairwise spillovers and the directional spillovers between the countries are significant which indicate that these countries give and receive from each other. Nonetheless, the only exception is the pairwise spillover between Egypt and Oman (-4.62%, p-value=0.082). Although, the net pairwise spillover between them is weakly significant, the directional spillover between these countries is statistically insignificant.

Finally, the results of Table 7.6 show that all the rest of the net pairwise spillover is statistically insignificant, while having at least one of the directional spillover between the two markets insignificant. However, there are six net pairwise spillover that are insignificant, but the two markets give and receive normally. The six pairwise spillover are Bahrain-Jordan, Egypt-Jordan, Egypt-UAE, Jordan-Kuwait, Jordan-Oman, and Turkey-Saudi Arabia. All these insignificant pairwise spillover have a significant bidirectional spillover. These drawn interpretations would not have been found without the formal testing of the significance of the estimates. In other words, interpreting the estimates without the formal testing would lead to the conclusion that, all the pairwise spillovers and directional spillovers exits. However, after finding the significance of the estimates, it is easier to interpret the estimates and find which estimates actually exist.

The sample period of this study is from 2003 to 2018. During this period, two major events took place: the 2008 financial crisis and the 2011 Arab Spring. From this study's analysis of the volatility and volatility spillover for the eight countries (illustrated in Chapter 6), it is noticeable that the MENA region markets have been affected during these events. This study sought to confirm the spillover from/to each market, and to recognize the market that holds the highest spillover during this period. From the results of the bootstrapping, it can be concluded that there is spillover between most of the markets during the full sample period. This outcome is clarified between the MENA markets during the 2008 financial crisis and the 2011 Arab Spring. Nevertheless, this study seeks to clarify the relations between the markets during the post era of the events. It pursues to find the real estimates of spillover and build the right interpretations about MENA markets. Thus, the next sections test the significance of spillover for three sub-periods, namely pre-crisis, crisis period, and post-crisis.

Table 7.6 Bootstrapping Net Pairwise Spillover

	Index	Z-stat	P-value
Bahrain – Egypt	-0.57	-0.37	(0.707)
Bahrain – Jordan	2.39	1.26	(0.205)
Bahrain – Kuwait	-1.65	-0.45	(0.652)
Bahrain – Oman	-9.50	-1.79	(0.072)
Bahrain – Saudi Arabia	3.96	1.60	(0.108)
Bahrain – Turkey	3.88	1.38	(0.166)
Bahrain – UAE	14.58	8.01	(0.000)
Egypt – Jordan	-0.29	-0.27	(0.780)
Egypt – Kuwait	-1.42	-0.703	(0.481)
Egypt – Oman	-4.62	-1.737	(0.082)
Egypt – Saudi Arabia	-1.35	-1.07	(0.281)
Egypt – Turkey	1.48	0.93	(0.348)
Egypt – UAE	0.03	1.17	(0.239)
Jordan – Kuwait	2.49	1.40	(0.159)
Jordan – Oman	-5.79	-2.16	(0.030)
Jordan – Saudi Arabia	5.54	1.29	(0.194)
Jordan – Turkey	7.90	2.12	(0.033)
Jordan – UAE	11.24	3.79	(0.000)
Kuwait – Oman	-7.81	-2.40	(0.016)
Kuwait – Saudi Arabia	2.42	0.99	(0.320)
Kuwait – Turkey	5.25	1.77	(0.075)
Kuwait – UAE	6.86	3.36	(0.000)
Oman – Saudi Arabia	6.26	1.72	(0.084)
Oman – Turkey	8.69	2.13	(0.032)
Oman – UAE	17.69	5.76	(0.000)
Saudi Arabia – Turkey	0.32	0.11	(0.906)
Saudi Arabia – UAE	1.49	0.356	(0.721)
Turkey – UAE	-0.77	-0.232	(0.815)

Note: Net Pairwise Spillover is the spillover between two markets. Beside each pair markets in the table, the estimates, z-statistics, and the p-value is reported.

7.5 Bootstrapping Volatility Spillover of MENA of The Split Sample

The aim of this section is to better understand the implications of the Arab Spring on the markets of this politically unstable region. We control for the global financial crisis, as well as macroeconomic and governance settings. To this end, the sample is divided into three sub-samples. The first subsample is from 2003 to 2007, which reflects the pre-crisis period. The second subsample is from 2008 to 2013. During this period, two major events took place, the 2008 Global Financial Crisis and the 2011 Arab Spring. Lastly, the third subsample represents the post-crisis period that is from 2014 to 2018.

Analysing the sub-samples helps assessing how the spillover between the countries in the MENA region changed during the major events. The same procedure applied in earlier sections is followed.

7.5.1 Pre-crisis Bootstrapping Outcome

In Table 7.7, Bahrain seems to be the most influential market, transmitting to four out of the seven markets. The spillover from Bahrain to the other four markets (Jordan, Oman, Saudi Arabia, and the UAE) are all highly significant varying from a low 4.19% (p-value=0.008) for Oman to a high 26.11% (p-value<0.001) for Jordan. This is in line with Abraham and Seyyed (2006) who report the existence of volatility spillover from the small but accessible Bahrain market to the larger but less accessible Saudi market. This spillover can possibly be due to the fact that Bahrain has several foreign policies activities with Saudi Arabia and the UAE. Furthermore, Saudi Arabia, the UAE, and Oman are considered as its main exporting partners. Comparing to the estimates of the full sample in Table 7.4, it seems that the results of Bahrain are almost the same. Specifically, Bahrain still spills over significantly to the same markets. Although, Bahrain is the most influential, it only receives shocks from Jordan but with a weak statistical evidence (5.22%, p-value=0.069). These results indicate that there is a bidirectional spillover between Bahrain and Jordan, as was previously elaborated in Section 7.4.2. This bidirectional spillover between Kuwait and Jordan during the sample period 2003-2007 can be attributed to the argument of Byman (2007) who highlights that during this sample period, both Bahrain and Jordan suffered a lot due to having large number of Iraqi refugees seeking their help. This, in turn, resulted in asking for aids and technical assistance from the United States to overcome the social, political and financial pressures that they faced.

The UAE in the full sample, seemed to be one of the least influential markets as mentioned in Section 7.4.2. However, the UAE in 'pre-crisis' seems to be the second most influential market, transmitting to three markets (Jordan, Kuwait, Oman). The spillovers from the UAE to the three markets are all highly significant varying from a low 12.71% (p-value=0.007) for Kuwait to a high (31.65%) (p-value<0.001) for Oman. The UAE also receives from Jordan (16.56%) and Oman (18.78%), indicating that there is a bidirectional spillover between the UAE and Jordan, and between the UAE and Oman. From 2003 to 2006 Jordan was a recipient of heavily subsidised crude oil from the UAE (Refworld, 2006). This is in line with the results of Bouri and Azzi (2014) who found that there is volatility transmission from the UAE to Jordan from 2005 to 2012.

As for Jordan and Oman, both transmit to two markets and receives from two markets as well. Like the full sample, Jordan and Oman transmit and receive from the UAE. In addition, Jordan has a bidirectional spillover with Bahrain. Oman transmits to Saudi Arabia (8.2%, p-value=0.018).

The most interesting yet surprising outcome is that of Egypt and Turkey, as the results of Table 7.7 show that they neither receive nor transmit to any of the markets. All the spillovers 'to' and 'from' Egypt and Turkey are statistically insignificant. Furthermore, Egypt and Turkey have no 'contribution to others' (p-values=0.219, and 0.148

respectively). Despite the strong economic and political ties with several neighbouring countries, along with official development assistance, investments, trade exchange in the Egyptian market, it is a vital finding for investors to see that the Egyptian market is not a transmitter nor a receiver. Likewise, despite the investment and trade exchanges with Turkey, the formal testing revealed no transmission between Turkey and the other seven markets. However, Turkey has a significant 'contribution from others' (p-value=0.016). Unlike the full sample, where Egypt transmits and receives from at least three markets, whereas Turkey transmits to Kuwait only and receives from other markets shown in Table 7.4.

Kuwait and Saudi Arabia do not transmit to any of the other markets in the 'pre-crisis' subsample; unlike the full sample, where both transmit to and receive from other countries. In addition, despite Kuwait having significant contribution to others while Saudi Arabia insignificant in the full sample (Table 7.4), the results of Table 7.7 show that Kuwait and Saudi Arabia have insignificant 'contribution to others' (p-values= 0.122 and 0.170 respectively) in the 'pre-crisis' subsample. Kuwait did not receive spillover from the UAE, however in 'pre-crisis' subsample it receives from the UAE significantly 12.71%. Whereas Bahrain in the full sample receives from Jordan, Oman, and the UAE, in 'pre-crisis' subsample it receives weakly from Jordan 5.22% only.

Generally, in this sample period, it is noticeable that Bahrain, Jordan, Oman, and the UAE are the only markets transmitting and receiving risk in the region, while other markets are relatively isolated during this period. Overall, the behaviour of the MENA region markets is mostly calm and have minimal spillover. This is not surprising since there were no major events taking place during this period. On the contrary, the world markets have seen unprecedented growth following the dot com crisis.

Compared to the full sample, the results of the ‘pre-crisis’ subsample contains fewer significant transmission between the markets. These results imply that the significant transmissions observed in the full sample can be attributed to the volatile period that the full sample includes. Thus, to provide formal tests for this argument, the next section analyses the volatility spillover between the MENA region countries in the ‘crisis’ subsample.

7.5.2 Crisis Sub-Sample Bootstrapping Outcome

This section represents the results of stationary bootstrapping for the second subsample from 2008 to 2013. During this period, two major events took place: the 2008 Global Financial Crisis and the Arab Spring that started in 2011. Thus, this section aims to analyse whether the spillover between the eight countries in the MENA region changed during the crisis period as compared to the full sample period analysed in Section 7.4.2 and the pre-crisis period analysed in Section 7.5.1.

The results of Table 7.8 show that the total spillover 75.9% is highly significant (p-value<0.001), indicating the existence of total spillover within the MENA region in the ‘during the crisis’ period. By comparing this result to the results in Table 7.4 and Table 7.8, it is apparent that the highest significant spillover is recorded in the crisis period. This outcome is expected since the crisis period is considered a highly volatile period for the region and research results provide evidence that political instability strongly affects the economic growth and financial markets.

Table 7.7: Bootstrapping Pre-crisis volatility spillover

		Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	Spill	76.42	0.60	5.22	6.84	6.17	0.54	0.41	3.82	23.6
	Z-stat	3.00	0.14	1.17	0.84	1.08	0.13	0.15	0.70	1.17
	P-value	(0.000)	(0.827)	(0.069)	(0.400)	(0.128)	(0.894)	(0.857)	(0.213)	(0.011)
Egypt	Spill	0.61	90.01	1.68	0.38	4.11	0.95	1.30	0.96	10.0
	Z-stat	0.14	3.07	0.45	0.11	0.77	0.23	0.25	0.29	0.55
	P-value	(0.807)	(0.000)	(0.527)	(0.849)	(0.191)	(0.748)	(0.652)	(0.638)	(0.115)
Jordan	Spill	26.11	0.90	34.18	0.89	5.00	2.70	4.83	25.40	65.8
	Z-stat	3.19	0.19	2.18	0.19	0.81	0.42	0.76	2.02	2.61
	P-value	(0.000)	(0.625)	(0.000)	(0.725)	(0.192)	(0.309)	(0.206)	(0.000)	(0.000)
Kuwait	Spill	5.20	1.10	0.63	69.25	9.75	0.86	0.50	12.71	30.8
	Z-stat	0.63	0.21	0.14	2.96	1.17	0.25	0.17	1.97	1.39
	P-value	(0.498)	(0.606)	(0.831)	(0.000)	(0.209)	(0.717)	(0.804)	(0.007)	(0.002)
Oman	Spill	4.19	0.84	2.18	2.26	56.26	2.45	0.16	31.65	43.7
	Z-stat	0.89	0.16	0.37	0.54	2.75	0.51	0.04	3.13	2.02
	P-value	(0.008)	(0.738)	(0.585)	(0.588)	(0.000)	(0.384)	(0.966)	(0.000)	(0.000)
Saudi Arabia	Spill	23.19	0.62	1.42	0.52	8.20	59.09	1.97	4.98	40.9
	Z-stat	2.04	0.15	0.20	0.13	1.37	2.78	0.29	0.68	1.67
	P-value	(0.000)	(0.818)	(0.728)	(0.830)	(0.018)	(0.000)	(0.726)	(0.284)	(0.000)
Turkey	Spill	1.21	2.16	4.25	0.46	4.12	4.01	78.79	5.01	21.2
	Z-stat	0.22	0.38	0.60	0.12	0.74	0.57	3.30	0.76	0.95
	P-value	(0.605)	(0.492)	(0.367)	(0.812)	(0.247)	(0.493)	(0.000)	(0.306)	(0.016)
UAE	Spill	15.69	1.12	16.56	2.30	18.78	0.75	3.46	41.35	58.7
	Z-stat	2.23	0.27	1.34	0.51	2.24	0.13	0.59	2.83	2.37
	P-value	(0.000)	(0.483)	(0.000)	(0.464)	(0.000)	(0.801)	(0.344)	(0.000)	(0.000)
Contribution to others	Spill	76.2	7.3	31.9	13.6	56.1	12.3	12.6	84.5	294.7
	Z-stat	2.45	0.30	1.43	0.66	2.35	0.54	0.63	4.32	
	P-value	(0.000)	(0.219)	(0.003)	(0.122)	(0.000)	(0.170)	(0.148)	(0.000)	
Contribution including own	Spill	152.6	97.3	66.1	82.9	112.4	71.3	91.4	125.9	36.8%
	Z-stat									3.902
	P-value									(0.000)

Note: Monthly real returns from Jan 2003 to Dec 2007, volatility measured by GJR-GARCH. Volatility spillover index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. Stationary bootstrapping the volatility spillover index, bootstrapped 1000 times. The ith row and the jth column figures are the contribution of country j to country i. Under each of the eight markets in the table, the estimates, z-statistics, and the p-value is reported. Insignificant highlighted in pink, weakly significant highlighted in yellow, and highly significant is not highlighted.

In this regard, Abdelbaki (2013) highlights that the Arab Spring has an effect on macroeconomic variables and stock markets of the countries that experienced it. In addition, Rouis and Tabor (2013, p.132) provide evidence on the impact of the political instability in the MENA region on the economic conditions of the region as follows:

"*recent conflicts and security issues in the MENA region may affect the economies of neighbouring countries and are of increasing concern to policymakers*".

Similar to the results of the full sample, Oman, Jordan, and Kuwait are the most influential markets. Specifically, Oman is still the most influential market, like the full sample, transmitting to all the other markets significantly. On the other side, Oman receives from Egypt 7.88%, Jordan 17.88%, Kuwait 17.77%, and Saudi Arabia 13.7%. This can be attributed to the Omani protests in 2011 demanding employment, higher salaries along with calling for anti-corruption measures and reform which was considered as a reflection of the Arab Spring over the political realm in Oman (Al Jazeera English, 2011). Therefore, the results show that protests in Oman affected other countries in the MENA region and the political instability that hit other countries in the MENA region also affected Oman. These spillovers indicate that there are bidirectional relations between Oman and Egypt, Oman and Jordan, Oman and Kuwait, and Oman and Saudi Arabia. There is no doubt that the media has played a major role in transmitting the protests pictures to Oman, which lead to escalating the protests in it. As Worrall (2013) notes the Arab Spring has shaken Oman more than predicted.

Likewise, Jordan transmission increased in the 'during the crisis' subsample than in 'pre-crisis' subsample. In this regard, the results show that Jordan is the second most influential market in the during the crisis' subsample as it transmits to all other markets except the UAE (9.95%, p-value=0.306). This is possibly due to the protest in the streets of Jordan by middle-class incomes, the shortage of formal sector jobs, and corruption rather than poverty and income inequality were at the root of the protests (Ianchovichina, 2018). Leading to Jordan becoming a volatile market and transmitting to other markets. Even though Jordan used to spillover the UAE in the full sample and in 'pre-crisis' subsample, in the 'crisis' subsample the only market that Jordan does not transmit to is the UAE. On the other side, Jordan receives from all markets except Saudi Arabia (9.4%, p-value=0.143) and Turkey (5.42%, p-value=0.328). However, Jordan in the full sample and 'pre-crisis' did not receive any spillover from Saudi Arabia and Turkey. Like the 'pre-crisis' subsample there is a bidirectional spillover between Jordan and Bahrain. However, unlike the 'pre-crisis' subsample there is bidirectional spillover between Egypt and Jordan, Kuwait and Jordan, and Oman and Jordan in 'during the crisis' subsample. This can be attributed to the Arab Spring effect, since all four countries had protests during this period of time.

The third influential market is Kuwait, transmitting to all other markets. Although in the 'pre-crisis' subsample, the results show that Kuwait transmit to own market only, the results in the 'crisis' subsample surprisingly show that the spillover from Kuwait to own market is insignificant (21.76%, p-value=0.138). This can be due to the amount of spillover coming from other countries, transmitting the Arab Spring effect. On the other hand, Kuwait receives from Jordan 16.43%, Oman 18.19%, Saudi Arabia 15.47%, and Turkey 8.45%. Indicating a bidirectional spillover between Kuwait and Jordan, Kuwait and Oman, Kuwait and Saudi Arabia, and Kuwait and Turkey. This is attributed to reforms inspired by the protests across the Arab World, along with Kuwait participation in the Saudi-led air strike in Yemen (Darwich, 2018) which resulted in stronger ties with the strike participant and political problems with Oman which was taking Qatar's side. Although in 'pre-crisis' subsample no transmission from Kuwait was found, while only receiving from UAE.

The least influential markets are the UAE, Bahrain, and Turkey. The UAE transmits weakly to Bahrain (10.64%, p-value=0.072) and Jordan (17.16%, p-value=0.082), although the UAE did not transmit to Bahrain in 'pre-crisis' subsample, while transmitting to Jordan in 'pre-crisis' and 'during the crisis' subsamples. On the other hand, the UAE is not a high receiver as well, receiving only from Bahrain 23.39%, Kuwait 9.55%, and Oman 13.5%, indicating that there is a bidirectional spillover between the UAE and Bahrain. This can be attributed to the UAE and Bahrain being members of GCC, which in 2011 lead the UAE to send troops to Bahrain as a response to the Bahrain government request from the GCC to intervene (Katzman, 2017).

Bahrain transmits only to the UAE and Jordan. However, Bahrain spillover to own market is insignificant. While it receives from Jordan 14.05%, Kuwait 14.91%, Oman 15.56%, Saudi Arabia 10.21%, and weakly from the UAE 10.64%, unlike the 'pre-crisis' subsample, where Bahrain spills over to Jordan, Oman, Saudi Arabia, the UAE, and own market. This can be attributed to the effect of the Global Financial Crisis and Arab Spring being transmitted to Bahrain. Since Bahrain is a small market, the amount of spillover 'to' was large enough that Bahrain could not affect itself. In addition, Bahrain was not able to control the protests alone, which led Saudi Arabia and the UAE to intervene to help restore order (Beser and Kilic, 2017).

In the ‘pre-crisis’ subsample, Turkey had no spillover ‘to’ or ‘from’ other markets, making it the most isolated market. Yet, during the crisis, Turkey seems to be the most influenced by other markets. Turkey transmits to Egypt 8.58%, Kuwait 8.45% and Saudi Arabia 9.87% significantly, while it receives from all markets except from Bahrain and the UAE. This indicates that there is bidirectional spillover between Turkey and Egypt, between Turkey and Kuwait, and Turkey and Saudi Arabia. The bidirectional spillover between Turkey and Egypt could be attributed to the Egyptian revolution, the Muslim brotherhood ruling which Turkey was supporting, and the political problems that arose afterwards. The bidirectional spillover between Turkey and Saudi Arabia is attributed to the strong economic ties between the two markets along with knowing that both had been affected by the Financial Crisis (Uludag and Ezzat, 2017). Turkey considered a receiver more than a transmitter is supported by Kalin (2011) stating that the Arab Spring strengthened rather than weakened Turkey’s position in the Arab World.

Saudi Arabia is a transmitter as much as a receiver, unlike ‘pre-crisis’ subsample where Saudi Arabia did not transmit to any of the markets, while receives from Bahrain and Oman only. Despite the strong economic and political ties between Saudi Arabia and the UAE, Saudi Arabia transmits to all markets except for Jordan and the UAE, while receives from all markets except for Bahrain and the UAE. Indicating bidirectional spillover between Saudi Arabia and Egypt, between Saudi Arabia and Kuwait, between Saudi Arabia and Oman, and between Saudi Arabia and Turkey. Generally, bidirectional spillover is found between Saudi Arabia and the countries that have experienced the Arab spring and had protests.

Finally, Egypt transmits to all markets except for Bahrain, Kuwait and the UAE, and receives from all markets except for Bahrain and the UAE. Note that Egypt in the 'pre-crisis' subsample did not transmit nor receive from any of the markets. Furthermore, the 'contribution to other' markets are all highly significant, signifying that the spillover from a market to all other markets exists, which was not the cause in the pre-crisis sample. Similarly, the 'contribution from other' markets are highly significant (p-value<0.001), confirming the significance of the spillover from all markets to each individual market. The reason for this significant change is that Egypt was the actual centre of the Arab Spring revolution. Although the Arab Spring started in Tunisia, it is Egypt where the turmoil had the biggest impact, both because Egypt is a large economy and military power (thus plays an important part in the security of the GCC countries against Iran and possibly Iraq) and because it has close economic and financial ties with the GCC countries.

As previously mentioned, the formal testing of the significance of the estimates reveals several interpretations about the MENA region. In the pre-crisis period there were only three bidirectional spillovers between the markets, while during the crisis period there are thirteen bidirectional spillovers.

The financial crisis in 2008 and the Arab Spring that started in 2011 effects can be perceived in the MENA region markets. From interpreting the results' significance of stationary bootstrapping, it is clear that the crises have increased the spillover between markets in the MENA region (when compared to the pre-crisis period). The total spillover index moved up from 36.8% to 75.9%, obtaining more significant relations during the crisis period rather than pre-crisis period. Without the formal testing, some of the spillovers would have not been interpreted properly and different conclusions could have been drawn. The following section provides the significance results of the ‘post-crisis’ period.

7.5.3 Post-crisis Bootstrapping Outcome

This section presents the outcome of the significance of the volatility spillover for the ‘post-crisis’ period (January 2014 to December 2018). The significance levels are shown in Table 7.9. The total spillover index is 29% and highly significant (p-value<0.001), which confirms that the spillover is found within the region post-crisis. However, the total spillover percentage is not as high as during the crisis (75.9%) or the pre-crisis period (36.8%). This is not surprising since, out of the maximum 56 spillovers, only 8 are significant. Clearly, transmission across the market is minimal after the turmoil of the credit crunch and Arab Spring. One obvious reason is that the markets themselves were relatively calm during the post-crisis period. A second reason could be that, following the significant shocks of the crisis period, investors reaction to the post crisis period was less acute.

Table 7.8: Bootstrapping During events volatility spillover

		Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	Spill	23.98	5.79	14.05	14.91	15.56	10.21	4.85	10.64	76.0
	Z-stat	1.25	1.52	2.17	2.95	2.73	2.10	1.19	1.79	3.92
	P-value	(0.208)	(0.128)	(0.029)	(0.003)	(0.006)	(0.035)	(0.232)	(0.072)	(0.000)
Egypt	Spill	1.97	32.62	12.40	13.56	13.89	13.52	8.58	3.46	67.4
	Z-stat	0.61	1.47	2.88	1.78	2.16	3.37	2.86	1.03	3.07
	P-value	(0.538)	(0.039)	(0.003)	(0.074)	(0.030)	(0.000)	(0.004)	(0.300)	(0.001)
Jordan	Spill	14.48	5.43	15.82	15.25	17.04	9.40	5.42	17.16	84.2
	Z-stat	5.49	2.79	2.23	5.16	4.39	1.46	0.97	1.73	10.81
	P-value	(0.000)	(0.005)	(0.025)	(0.000)	(0.000)	(0.143)	(0.328)	(0.082)	(0.000)
Kuwait	Spill	5.94	8.58	16.43	21.76	18.19	15.47	8.45	5.18	78.2
	Z-stat	1.37	1.60	2.77	1.48	3.29	3.82	2.45	1.00	5.12
	P-value	(0.168)	(0.108)	(0.005)	(0.138)	(0.000)	(0.000)	(0.014)	(0.317)	(0.000)
Oman	Spill	8.05	7.88	17.88	17.77	19.67	13.70	6.69	8.36	80.3
	Z-stat	1.48	1.79	2.66	3.16	2.04	3.24	1.60	1.41	7.45
	P-value	(0.136)	(0.072)	(0.007)	(0.001)	(0.040)	(0.001)	(0.109)	(0.156)	(0.000)
Saudi Arabia	Spill	6.19	9.16	16.76	16.87	16.07	18.52	9.87	6.55	81.5
	Z-stat	1.34	2.58	3.05	4.13	3.92	3.54	2.24	1.27	11.17
	P-value	(0.177)	(0.009)	(0.002)	(0.002)	(0.000)	(0.000)	(0.024)	(0.202)	(0.000)
Turkey	Spill	5.08	11.81	12.58	14.12	11.74	14.88	25.10	4.68	74.9
	Z-stat	1.12	3.21	2.48	3.72	2.72	3.58	2.96	0.995	7.81
	P-value	(0.259)	(0.001)	(0.012)	(0.000)	(0.006)	(0.000)	(0.003)	(0.319)	(0.000)
UAE	Spill	23.39	2.81	9.95	9.55	13.50	3.90	1.88	35.02	65.0
	Z-stat	8.95	1.43	1.02	2.87	3.62	0.68	0.42	4.74	8.04
	P-value	(0.000)	(0.150)	(0.306)	(0.003)	(0.000)	(0.490)	(0.673)	(0.000)	(0.000)
Contribution to others	Spill	65.1	51.5	100.1	102.0	106.0	81.1	45.7	56.0	607.5
	Z-stat	3.19	2.52	3.29	4.43	5.93	5.31	2.69	2.08	
	P-value	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.018)	
Contribution including own	Spill	89.1	84.1	115.9	123.8	125.7	99.6	70.8	91.1	75.9%
	Z-stat									8.86
	P-value									(0.000)

Note: Monthly real returns from Jan 2008 to Dec 2013, volatility measured by GJR-GARCH. Volatility spillover index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. Stationary bootstrapping the volatility spillover index, bootstrapped 1000 times. The ith row and the jth column figures are the contribution of country j to country i.Under each of the eight markets in the table, the estimates, z-statistics, and the p-value is reported. Insignificant highlighted in pink, weakly significant highlighted in yellow, and highly significant is not highlight

The post-crisis period is important to analyse in order to see how the markets react after crisis and how long the effect of the crisis lasts. These conclusions are vital to investors who want to invest in a specific market in the MENA region. With the emerged insights, investors now know that other markets spillover to nations, impacting their behaviours. For example, investors who want to invest in Bahrain will need to not just look at Bahrain market only, but to also examine other markets that spillover to Bahrain to gain accurate predictions and forecasts of Bahrain market future performances. Furthermore, the stability after the turmoil in the MENA region will not only allow countries to benefit from deepening trade and finance, but will also consolidate market stability and, consequently, boost investor confidence within the region.

All markets are mostly non-receivers. The biggest receivers are Jordan (from Bahrain (9.99%) Turkey (39.11%)), and Saudi Arabia (from Oman (18.32%) and Turkey (15.68%)). Bahrain, Oman and Turkey receive from a single country each. Finally, Kuwait and UAE receive from no other country. In terms of transmission, only Turkey is a clear transmitter (to Bahrain, Egypt, Jordan and Saudi Arabia). The second transmitter is Saudi Arabia (to Oman and Turkey).

The results are markedly different from the 'crisis' and pre-crisis subsamples. Most of the transmissions are clearly due to the volatility periods, driven by economic crises and social unrest. Following crises, volatility transmission dampens significantly. Overall, transmission is accentuated by crises. For example, in the 'pre-crisis' subsample Egypt was not a transmitter, while in 'during the crisis' it transmits to Jordan, Oman, Saudi Arabia, and Turkey. Indicating that Egypt is not a transmitter except in the volatile periods. Similarly, Jordan is more of a transmitter in 'during the crisis' subsample than in the other two subsamples.

However, Turkey is an important exception. It is the only clear transmitter in the region with a single reception from Saudi Arabia. This is unlike the 'pre-crisis' subsample where Turkey is neither a transmitter nor a receiver, or the 'crisis' subsample where it is both a receiver and a transmitter. Being both transmitter and receiver during the crisis indicates that Turkey did get affected by the Arab Spring. The most likely channel is the Syrian Crisis and the ensuing refugee crisis. Unfortunately, we cannot find a viable explanation as to why Turkey is virtually the only source of volatility spillover after the crisis. Perhaps, contrary to the official attitude of governments, individual investors were driven by flight to quality and were investing heavily in Turkey during the crisis as Turkey was shielded from the Arab Spring before the Syrian crisis. Investors in Bahrain, Egypt, Jordan and Saudi Arabia, and consequently their respective markets, became sensitive to events in Turkey.

To sum up, after emphasising the importance and advantages of the formal testing of the significance of the estimates, a richer set of conclusions can be drawn from analysing the three divided samples.

By finding the statistical significance of the estimates of the divided samples, gave a more accurate insight of the spillover within the region and how economic and social instabilities affect volatility spillover. The spillovers confirmed by the significant levels are meaningful and can be explained by actual events that took place at that time.

Table 7.9: Bootstrapping Post-crisis volatility spillover

		Bahrain	Egypt	Jordan	Kuwait	Oman	Saudi Arabia	Turkey	UAE	From others
Bahrain	Spill	86.61	0.29	2.47	1.29	0.65	0.68	5.36	2.66	13.4
	Z-stat	9.80	0.06	0.53	0.60	0.24	0.22	2.10	0.89	1.56
	P-value	(0.000)	(0.947)	(0.595)	(0.548)	(0.809)	(0.825)	(0.035)	(0.369)	(0.058)
Egypt	Spill	1.85	79.24	1.60	3.33	1.78	9.90	1.99	0.33	20.8
	Z-stat	0.47	9.84	0.45	1.00	0.79	1.70	0.86	0.14	2.61
	P-value	(0.634)	(0.000)	(0.646)	(0.314)	(0.426)	(0.088)	(0.046)	(0.885)	(0.003)
Jordan	Spill	9.99	0.25	41.53	1.65	2.05	1.80	39.11	3.63	58.5
	Z-stat	3.38	0.10	6.50	0.56	0.63	0.51	4.21	0.54	9.20
	P-value	(0.000)	(0.916)	(0.000)	(0.572)	(0.526)	(0.608)	(0.000)	(0.588)	(0.000)
Kuwait	Spill	0.88	4.39	0.99	80.60	2.05	6.92	2.25	1.92	19.4
	Z-stat	0.47	1.07	0.35	6.34	0.23	1.35	1.02	0.61	1.54
	P-value	(0.633)	(0.283)	(0.721)	(0.000)	(0.810)	(0.176)	(0.307)	(0.540)	(0.061)
Oman	Spill	4.56	0.22	4.04	1.92	60.99	22.73	3.04	2.50	39.0
	Z-stat	1.09	0.10	1.25	0.26	6.31	3.50	1.04	0.60	4.06
	P-value	(0.274)	(0.917)	(0.211)	(0.790)	(0.000)	(0.000)	(0.294)	(0.542)	(0.000)
Saudi Arabia	Spill	2.63	3.48	6.34	2.32	18.32	49.41	15.68	1.82	50.6
	Z-stat	0.80	0.82	2.02	0.47	3.17	8.17	2.80	0.38	8.26
	P-value	(0.421)	(0.411)	(0.143)	(0.636)	(0.001)	(0.000)	(0.005)	(0.698)	(0.000)
Turkey	Spill	1.73	0.39	3.43	0.67	0.56	11.98	79.87	1.37	20.1
	Z-stat	0.81	0.18	0.50	0.23	0.22	2.12	9.20	0.17	2.32
	P-value	(0.413)	(0.849)	(0.616)	(0.811)	(0.819)	(0.033)	(0.000)	(0.857)	(0.010)
UAE	Spill	0.76	0.89	0.26	0.88	2.22	0.79	4.50	89.71	10.3
	Z-stat	0.26	0.31	0.04	0.30	0.66	0.17	0.54	7.28	0.84
	P-value	(0.791)	(0.752)	(0.964)	(0.762)	(0.503)	(0.857)	(0.585)	(0.000)	(0.199)
Contribution to others	Spill	22.4	9.9	19.1	12.0	27.6	54.8	71.9	14.2	232.0
	Z-stat	2.08	1.00	1.69	0.82	1.98	4.57	4.51	0.86	
	P-value	(0.018)	(0.157)	(0.045)	(0.206)	(0.023)	(0.000)	(0.000)	(0.193)	
Contribution including own	Spill	109.0	89.1	60.7	92.6	88.6	104.2	151.8	103.9	29.0%
	Z-stat									6.62
	P-value									(0.000)

Note: Monthly real returns from Jan 2014 to Dec 2018, volatility measured by GJR-GARCH. Volatility spillover index of DY (2012) based upon a VAR of order 1 and generalized variance decompositions of 10-day-ahead volatility forecast errors. Stationary bootstrapping the volatility spillover index, bootstrapped 1000 times. The ith row and the jth column figures are the contribution of country j to country i. Under each of the eight markets in the table, the estimates, z-statistics, and the p-value is reported. Insignificant highlighted in pink, weakly significant highlighted in yellow, and highly significant is not highlighted

7.6 Conclusion

Studying volatility spillover helps to understand how information is transmitted across markets. It also aids in understanding the market efficiency and the level of integration. This study investigates the spillover of the stock market of the eight selected markets representing the MENA region by building on the DY framework and considering the statistical properties of the estimates using the bootstrap. To our knowledge, this is the first time formal tests have been carried out on volatility spillover. This chapter aims to provide an overview on the importance of using bootstrapping to estimate standard errors and confidence interval for the volatility spillover index. With the acceleration of global integration, rapid progress of developing markets, expansion of the markets scale, the conclusions drawn from the bootstrap volatility spillover index are important to improve the trade between markets, as well as increasing the ties between their financial markets.

Stationary bootstrapping is used to calculate the statistical significance of the estimates in order to find the accuracy of the DY framework results. The research first reviewed the aim and importance of the significance of the index estimates. Since there is no clear measurement of the standard errors of volatility spillover index, the study follows Choi and Shin (2018) steps, applying bootstrapping to get the standard error and confidence interval of the index. Choosing the stationary bootstrapping complies with data and model type. Stationary bootstrapping is similar to block bootstrapping where it resamples and impose fewer assumptions. It basically divides the quantities that are being resampled into blocks of b consecutive observations. Stationary bootstrapping solves the problem of block bootstrapping for observations.

Secondly, this research reinvestigates Diebold and Yilmaz (2012) study and finding the significance by the stationary bootstrapping method in order to be certain of the drawn conclusions. The statistical significance results of Diebold and Yilmaz spillover statistics are not all significant, which leads to different interpretations. The conflicting outcomes of the significance of estimates highlight the importance of testing the significance of DY Index.

Thirdly, after finding the importance of testing the significance of the index estimates, this research re-analyses the results of Chapter 6 by applying stationary bootstrapping. The results that emerged showed that the total spillover index is significant validating that the spillover in the region as a whole actually exists. However, there are some estimates that were statistically insignificant between individual markets invalidating the dependency between some markets. The formal testing provides more details about the markets, finding the bidirectional spillover between the markets, along with classifying the market as a transmitter, receiver, both or neither. Without this formal testing it would not have been possible to draw out these interpretations.

Based on the full sample, not all markets have significant spillover. Jordan, Kuwait, and Oman are the most influential markets, while Saudi Arabia, Turkey and UAE are the least influential. Overall the contribution 'to' and 'from' others are all significant indicating that there is spillover in the region. Which is also shown by the significant total spillover index 57.5%.

These results are inconsistent with the expectations derived from observing the strong ties between the selected countries due to the aforementioned reasons and the richness of the sample period that includes several political, economic and financial events. Thus, these results warrant further analysis to identify the reasons behind the deviations between the results and the observations. To provide more in depth analysis of the results, in Section 7.4.2, the sample period is split into 3 subsamples (pre-crisis, during the crisis, post-crisis) to analyse how the spillover between these markets change in different periods and different economic and political conditions.

The 'pre-crisis' subsample contains fewer significant spillovers than the full sample indicating that the spillover is possibly attributed to the volatile period included in the full sample, while in the 'crisis' subsample clearly the crisis has increased the spillover, obtaining more significant spillover. In the 'post-crisis' subsample the transmissions are accentuated by crises. Overall, by finding the statistical significance of the estimates of the divided samples, gave a more accurate insight of the spillover within the region and how economic and social instabilities affect volatility spillover.

Table 7.10 provides each market's classification whether transmitter, receiver, both, or neither during the three divided samples. This gives a sum up of how markets changed from one period to another. It is clear from the Table how markets change during crisis periods. The full sample can be the summation of the three period effect.

To sum up, this chapter not only contributes to the academic literature by providing an efficient way to test the significance of the volatility spillover index of DY (2012), but also shows how ignoring this measure of accuracy can have a severe impact on the decisions of investors, policy makers, and practitioners. The results provide clarity to investors and portfolio managers.

Table 7.10: Markets Classification

Market	Full Sample	Pre-crisis	During Crisis	Post-Crisis
Bahrain	Transmitter	Transmitter	Receiver	Both
Egypt	Transmitter	Neither	Receiver	Receiver
Jordan	Transmitter	Both	Transmitter	Receiver
Kuwait	Both	Receiver	Transmitter	Neither
Oman	Transmitter	Both	Transmitter	Both
Saudi Arabia	Receiver	Receiver	Both	Transmitter
Turkey	Receiver	Neither	Receiver	Transmitter
UAE	Receiver	Both	Receiver	Neither

Note: Each market is provided its classification in the same row for the three divided sample pre-crisis, during crisis, and post crisis. Transmitter means 'spilling over' more number of markets than 'spilled to'. Receivers means 'spilling to' by more number of markets than 'spilled over'. Both reflects being a transmitter as well as a receiver. Neither reflects being neither a receiver nor a transmitter.

Chapter 8

Herding in the Egyptian Stock Market

8.1 Introduction

One of the main factors that affects investors' decision in stock markets is the condition of the market. In stable periods, investors can think rationally in analysing the market, have enough time to gather adequate information and therefore make informed decisions. On the other hand, in crisis periods, investors start to make decisions that are biased and rather follow others' investors' actions. When investors do not follow their own rational thinking and follow other investors' trading behaviour this is classified as herding behaviour. However, market condition is not the only factor that affects investors' herding behaviour. Information asymmetry and transparency are also considered among the main factors that induce investors to herd. Specifically, when investors do not have the amount of information needed to take rational decisions, they are more likely to follow others and this may lead to biased decisions. In addition, the reliability and the credibility of information may as well affect investors decisions where the information needed to make a rational decision is not available to the public (Mertzanis and Allam, 2018).

Given the above argument that investors herding behaviour depends on the prevailing market conditions, the Egyptian stock market provides an interesting case to analyse the herding behaviour and how it varies in different market conditions given the wide array of events that the Egyptian market witnessed during the sample period of this thesis. Specifically, the results of Chapter 7 show that from 2005 to 2007, the market witnessed a calm and stable period. The market performance was strong and no major economic or political concerns were seen in the Egyptian market or within the region. On the other hand, the period from 2008 to 2016 was mostly unstable. The market in this period witnessed major adverse events, such as the Global Financial Crisis, the Egyptian Revolution, and the Egyptian Military takeover of the country by the Army in 2013. Lastly, from 2017 to 2019 the market started to recover from the events that took place in the previous period. However, the recovery was not very easy, in the process of stabilizing the economy, the Central Bank of Egypt decided to float the Egyptian pound in an attempt to get rid of the black market that was prevailing in that period. Furthermore, the recovery process was affected badly by the shortage of foreign currency inflows due to a decline in foreign investments and exports, a decline in Suez Canal revenues, a decline in tourism sector revenues and political instability. As Gabbori *et al.* (2020) argue, investors most probably herd when they are under stress. Therefore, several researchers have investigated market behaviour during extreme market conditions and crises. Lam and Qiao (2015) examine the Hong Kong market and find significant herding during the Asian Crisis in 1997. Güvercin (2016) studies the Egyptian market during the period when the Egyptian military took over the country in 2013, and finds significant herding in the market.

Moreover, Christie and Huang (1995) argue that herding can cause higher volatility due to uncertainty about the market and asymmetry of information. The results of Chapter 7 show that the Egyptian stock market is a highly volatile market, indicating that this can be due to the presence of herding in the market. The directional volatility spillover from Egypt to its own market is 77.44% for the full sample, while reaching its highest spillover at 90.01% during the crisis period. Therefore, these results may imply the existence of herding in the market, especially so given that the Egyptian stock market is an emerging market that is more subject to behavioural biases as it is dominated by small investors (Schmitz *et al.*, 2006).

From the literature, it is expected to find herding in the Egyptian stock market since Thornton (2010) states that herding is found in emerging countries, nonetheless, there is a significant paucity in research that tests herding behaviour in the Egyptian stock market. Most of the studies focus mainly on developed countries and only a handful on emerging markets. Lao and Singh (2011) examine herding behaviour in emerging markets (Chinese and Indian markets), concluding that herding is found in both markets and that it depends on different market conditions. One of the studies that examined the Egyptian market is El-Shiaty and Badawi (2014) who examine the Egyptian stock market from 2006 to 2010 using the Christie and Huang (1995) model, and find no evidence of herding in the Egyptian market during this period. A more recent study by Mertzanis and Allam (2018) examines the existence of herding in the Egyptian stock market during the revolution period using the cross-sectional absolute deviation (CSAD), and although the results fail to provide evidence of herding in the market yet there is evidence of adverse herding behaviour that exhibits non-linearity.

Despite the availability of some research studies testing the existence of herding in the Egyptian stock market, none of these studies attempt to differentiate between intentional and unintentional herding. Thus, to fill in this gap, this chapter aims to examine herding behaviour in the Egyptian stock market along with examining whether the presence of herding behaviour is explained by fundamental factors. In other words, whether herding is intentional or unintentional. Moreover, the Fama-French-Carhart four factors as a measure of fundamental risk factors have been applied on the Gulf region and Saudi Arabia by Gabbori *et al.* (2020). However, it has not been applied on the Egyptian stock market. In addition, the previous research examining herding in the Egyptian stock market did not take this wide span of years analysed in this study covering the numerous events that took place. To our knowledge this is the only study that considers the full set of crises in Egypt since 2005. This chapter therefore contributes to the literature analysing the herding behaviour in the Egyptian stock market, examining herding in different market conditions by dividing the sample and examining each subsample separately. In other words, this chapter provides a comprehensive analysis of the herding behaviour in the Egyptian Stock Market.

The remainder of the chapter is organised as follows. Section 8.2 provides an overview of total herding, and differentiating between unintentional and intentional herding in the stock market. Section 8.3 presents the descriptive statistics for CSAD and the Fama-French-Carhart factors. Section 8.4 investigates total herding for the full sample period and then this total herding is divided into intentional (fundamental) and unintentional (non-fundamental) herding separately to differentiate between fundamental (intentional) herding that results from exposures to the common risk factors and non-fundamental (unintentional) herding that ignores these factors (Galariotis *et al*., 2015). Furthermore, given the fact that herding differs between market conditions, Section 8.5 aims to test herding in six subsamples which are the pre-crisis, the Global Financial Crisis (GFC), the Arab Spring, the second Egyptian Revolution, the Economic Reform, and the post-crisis period. Finally, Section 8.6 concludes the chapter.

8.2 Herding

The aim of this section is to provide a brief overview of the approaches employed to analyse herding behaviour in the Egyptian stock market. To achieve this aim, this section analyses how herding can be measured, and identifies how the total herding can be divided into fundamental and non-fundamental herding. Differentiation between rational and irrational herding reflects trading noise in financial markets as suggested by prior research (DeLong *et al*., 1990; Admati, 1991). On the one hand, rational herding moves prices toward the fundamental value of assets and the price movement is not likely to reverse. On the other hand, irrational herding, where investors with insufficient information blindly follow other investors' actions, might lead to market inefficiencies, driving away asset prices from fundamental values and causing mispricing (Hung *et al*., 2010). As mentioned in Chapter 5, to test the existence of herding, following Chang *et al.* (2000), the cross-sectional absolute deviation of returns (henceforth, CSAD), as measured in Equation 8.1, is regressed on the absolute and squared market returns as in Equation 8.2.

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{8.1}$$

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + e_t \tag{8.2}$$

where $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is the cross-sectional average return of N stocks in the portfolio at time t, and N is the number of stocks in the portfolio. In Equation 8.2 the relationship between $CSAD_t$ and $R_{m,t}$ is used to detect herding behaviour. Hence, if β_2 is significant and negative, this implies the existence of herding, where increasing the correlation among individual asset returns and the dispersion among asset returns will either decrease or increase at a decreasing rate. Markets herd when dispersions are expected to be low despite a big possible change in the market which is reflected by a negative association between dispersion and absolute returns. In normal conditions, firm returns are expected to move with the market according to their betas, and the CSAD is expected to increase linearly with market returns.

However, the existence of herding does not necessarily imply inefficiency, herding may occur due to the flow of fundamental information or similar investors' reactions towards the same information. Therefore, to differentiate between both types of herding, the CSAD is regressed on Fama-French-Carhart common risk factors as in Equation 8.3 to eliminate their influence and identify the fundamental and non-fundamental herding. Awwaliyah and Husodo (2011) argue that the Fama-French-Carhart factors seem capable in explaining the variation of the stock returns and applying them provides guidance for investors in understanding the market conditions, especially for the emerging markets.

The Fama-French-Carhart factors include (i) $R_{m,t} - R_f$ which represents the market-oriented investment style that establishes exposure to the general market, (ii) the HML_t factor, which is the return on the portfolio that longs the high book to market (value) stocks and shorts the low book to market (growth) stocks, (iii) the SMB_t factor, which is the return on the portfolio that invests in small companies and sells big ones, which is expected to capture small-cap investment style, and (iv) the MOM_t (momentum) factor, which represents the return on a portfolio that buys previous winners and sells previous losers.

Specifically, the conditional CSAD for these four risk factors symbolizes the part of the deviation that is due to similar investment styles or same investor responses to the common information as measured in Equation 8.5, which is the fundamental and the rest of the CSAD can be recognized as non-fundamental CSAD in Equation 8.4, which is proxied by the error term in Equation (8.3).

$$CSAD_t = \beta_0 + \beta_1(R_{m,t} - R_F) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + e_t \tag{8.3}$$

where $CSAD_{NONFUND,t} = e_t$ (8.4)

and

$$CSAD_{FUND} = CSAD_t - CSAD_{NONFUND,t} \tag{8.5}$$

In order to test for unintentional herding or the non-fundamental herding, the $CSAD_{NONFUND,t}$ is regressed on absolute and squared returns as in Equation 8.6. To test for intentional (or fundamental) herding , the $CSAD_{FUND,t}$ is regressed on the absolute and squared market returns as in Equation 8.7. In the following sections, these tests are carried out at market-level over the full sample and then over six subsamples (pre-crisis, Global Financial Crisis (GFC), Arab Spring, second Egyptian Revolution, Economic Reform, and post-crisis) in order to check for total herding as well as differentiate between unintentional and intentional herding under six different market conditions.

$$CSAD_{NONFUND,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t \tag{8.6}$$

$$CSAD_{FUND,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t \tag{8.7}$$

Given the importance of testing herding behaviour in an emerging market like the Egyptian stock market, the next section aims to provide the descriptive statistics of the CSAD and the Fama-French-Carhart risk factors to provide some preliminary results about the existence of herding in the Egyptian stock market.

8.3 Full Sample Descriptive Statistics

The aim of this section is to analyse the descriptive statistics of the CSAD and the Fama-French-Carhart factors which may provide new insights to add to the vast empirical evidence on the characteristics of the Egyptian stock market.

The first variable considered is CSAD, which is calculated using Equation 8.1 as described in Section 8.2. However, to ensure the reliability of the measure and since the market return is defined differently by different studies, it is calculated in two different ways. In the first way, the market return is calculated as the value-weighted average return of all listed stocks in the Egyptian stock market, while in the second way, the market return is calculated as the return of the main market index in Egypt which is the EGX30. Figure 8.1 compares the two ways of estimating the market returns. Although both ways capture the same trends in the market, the EGX return is always higher than the value-weighted market return. This can be attributed to the argument of Pae and Sabbaghi (2015) that equally-weighted market index returns may overweight small-cap stocks that can be subject to higher fluctuations. Similarly, Whited and Wu (2006) argue that the market premium of an equally weighted market index is higher than the market premium of a value-weighted market index. However, they argue that the value-weighted market return is more representative of the actual market fluctuations. Thus, in this chapter, the results for both the value-weighted market and the EGX index returns are reported for the full sample. When the results are similar the chapter will proceed using value-weighted market returns only to avoid repetition.

Table 8.1 provides the descriptive statistics of the CSAD using both weighted average returns and the EGX30 index returns. The Egyptian equities' daily average dispersion around the market is 1.4% for weighted returns and 1.5% for the index returns, which is close to the range reported by Mertzanis and Allam (2018) for the Egyptian stock market for sample period 2003 to 2014 which is 2%. The CSAD ranges from around 0.3% to 14.6% for the weighted returns. This indicates that in certain days, movement around the market shrinks significantly and potentially investors could be herding, providing a hint of the presence of herding behaviour. Table 8.1 also shows that the CSAD is positively skewed and leptokurtic for both weighted and index returns indicating that many returns fall at the tails of the distribution, and therefore the null hypothesis of normality is rejected by the Jarque-Bera statistics. This implies that the cross sectional absolute deviation departs from the normal distribution which is a common characteristic of emerging markets (Harvey, 2001).

In order to see the dynamics of dispersion across time, Figure 8.2 plots a time series of the CSAD during the full sample period, along with the average of the CSAD as a point of reference. Generally, dispersions tend to move closely with the market consensus, which is not seen where the spikes are found around the main events that took place in Egypt, such as the Global Financial Crisis in 2008, the start of the Egyptian Revolution at the end of 2010 and up the second Egyptian Revolution in 2013, the floatation of the Egyptian pound in 2016. These spikes of CSAD that occur around the major events that faced the

Egyptian stock market gives some indications of the presence of herding around these periods, consistent with the results of Caparrelli *et al.* (2004) who find that herding in the Italian stock market occurs mainly during extreme market conditions. Furthermore, Balcilar *et al.* (2013) find that there is evidence of herding in the Gulf countries in extreme market conditions except for Qatar which herds only under low and high volatility conditions.

Table 8.1 also provides the descriptive statistics of the Fama-French and Carhart risk factors, in order to give some indication about the performance of different investment strategies in the Egyptian stock market. First, the market factor has an average return of 0.017% per day which is equivalent to about 6.2% per year. However, it is statistically insignificant. This insignificance can be attributed to the numerous events and instability that the market experienced during most of the years of the sample, which is apparent from the high standard deviation of 1.5% daily. These results are consistent with Harvey (1995) argument that emerging markets are characterized by high return and volatility. He also argues that the variance of the market factor in markets like Egypt is normally high since the market portfolio is not highly diversified due to the small number of listed firms in the market. Similarly, Ragab *et al.* (2019) examine the performance of the Fama and French three and five factor models in Egypt from 2005 to 2016 and they argue that the market factor is insignificant due to the remarkable events that the market experienced.

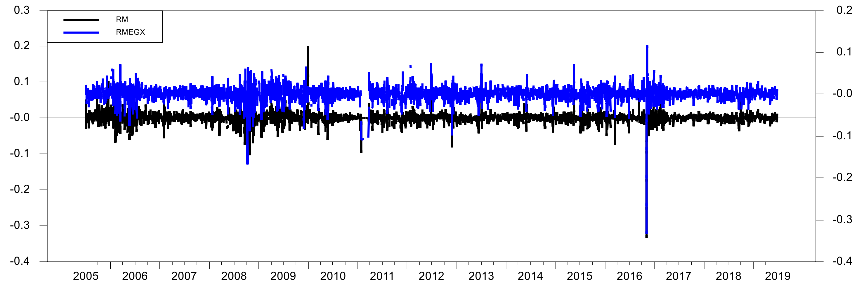

Figure 8.1: Weighted Market returns and EGX30 market returns

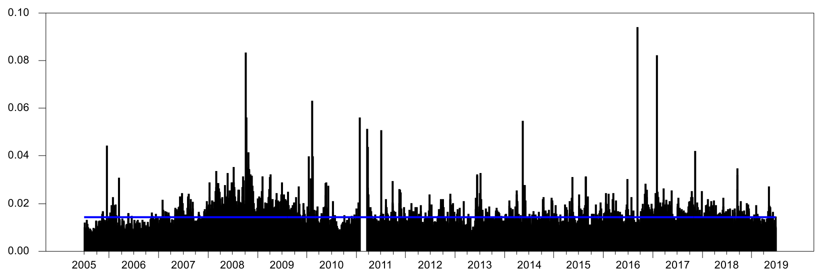

Figure 8.2: CSAD and the average of the CSAD

Table 8.1: Descriptive Statistics of CSAD and Market Returns

	CSAD	CSAD (EGX)	Market Factor	Market Factor (EGX)	SMB	HML	MOM
Sample Mean	0.014	0.015	0.0002	0.0002	-0.0003	0.0008	0.0001
P-value	0.000	0.000	0.0000	0.0010	0.0000	0.0003	0.8471
Standard deviation	0.006	0.006	0.015	0.018	0.013	0.017	0.009
Standard error	0.0001	0.0001	0.0003	0.0003	0.0002	0.0003	0.0002
Skewness	7.552*	5.362*	-2.416*	-2.496*	0.746*	-2.793*	3.556*
Kurtosis (excess)	120.654*	61.786*	73.544*	41.051*	18.488*	51.339*	76.0612*
Jarque-bera	1990528.9*	529917.6*	826136.4*	242557.6*	39048.2*	302697.1*	662374.7*
Minimum	0.0037	0.0002	-0.3332	-0.3336	-0.1389	-0.3198	-0.0595
Maximum	0.146	0.122	0.201	0.116	0.158	0.136	0.184

Note: This table presents descriptive statistics on the cross-sectional absolute deviation measure to proxy daily Egyptian stock market herding from (1/7/2005 to 27/6/2019). It is estimated using the following expression: $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$. *Provided also a summary statistics of the market factor for Egyptian stock market using weighted average returns and EGX index returns. In addition to summary statistics on the Fama-French-Carhart factors which are constructed using stocks from the Egyptian stock market. These factors are size factor (SMB), value factor (HML) and momentum factor (MOM).*

The SMB factor, which aims to mimic the risk factor in returns related to firm size, has an average return of -0.028% (significant at the 1% level) daily which is equivalent to -10.22% annually. According to Abdou (2020) the significant negative average returns of SMB indicates that during this period small firms underperformed big firms, which is expected to happen during stress periods. Moreover, the SMB portfolio seems to be volatile in Egypt having a daily standard deviation of 1.27%, though less volatile than the market (1.5%). Although these results indicate the absence of the size effect in the Egyptian stock market, they can be attributed to the fact that the sample period of this thesis is dominated by negative events which can explain why small stocks underperformed the big ones during this period. According to Perez-Quiros and Timmermann (2000), in periods of stress or when the economy is facing recession, small firms tend to underperform big ones or otherwise no investor will be inclined to hold big stocks.

The HML factor, which aims to mimic the risk factor in returns related to the book-to-market ratio, has an average returns of 0.081% daily which is equivalent to 29.5% annually and is statistically significant. These results imply the presence of the value effect in the Egyptian stock market and that value strategies can yield a positive and significant return in the Egyptian stock market. Moreover, the return of the HML factor is highly volatile compared to other factors, having 1.7% daily standard deviation. This can be attributed to the fact that the factor is not well diversified due to the limited number of stocks in the market or to the highly volatile market conditions that the whole market witnessed during the sample period.

The presence of the value effect in the Egyptian stock market is inconsistent with the results of Ragab *et al.* (2019) who provide evidence about the existence of the size effect rather than value effect. Their study shows that the value stock returns are significant and negative indicating that the value stocks underperform growth stocks. This is unlike our results where value stocks are significant and positive, indicating that the growth stocks underperform value stocks. This difference of results can be due to the difference in the time span, as this study covers a wider span of years. It could also be due to using different data frequency, as this study uses daily data while Ragab *et al.* (2019) use monthly data. An important motivation of the presence of value effects is that it can describe some of the fundamental risk in the market which is important in this study since this differentiates between intentional and unintentional herding trying to be analysed.

The last factor to analyse is the MOM factor, which refers to the tendency of stocks with high short-term past returns (past winners) to perform well, while stocks with low past returns (past losers) to continue to underperform. According to Cakici *et al.* (2013) the momentum effect tends to be stronger than size and value effects in developed markets, while weak in most of emerging markets. The results of the MOM statistics confirm this argument. The results show that the average return of the MOM factor is positive but insignificant (0.014%, p-value=0. 847). Indicating that there is no evidence of the presence of momentum effect in the Egyptian stock market. This outcome is supported by the previous findings of Sakr *et al*. (2014) examining the presence of momentum in the Egyptian stock market as a growing emerging market and finding no evidence of the momentum in the market.

Comparing between the size, value, and momentum portfolios, the maximum daily drawdown of MOM strategy is 18.4%, which is higher than the 15.8% and 13.6% of the SMB and HML portfolios' respectively. The lowest daily drawdown is experienced by the HML strategy with a maximum daily drop of 31.9%, while the daily drop of the SMB and the MOM is 13.8% and 5.9% respectively.

Figure 8.3 and 8.4 presents a scatter plot of the CSAD against market returns showing the movement of dispersion with the market returns using the weighted average returns and using index returns respectively. Although Figure 8.3 shows that the dispersion increases with market returns, the increase in dispersion is at a decreasing rate indicating a negative relationship between CSAD and the market returns. Hence, it is expected to find a significant presence of herding. Specifically, the apparent concavity in Figure 8.3 implies the existence of herding in the Egyptian stock market as argued by Gabbori *et al.* (2020).

Figure 8.5 compares the performance of 1 dollar invested in each of the Egyptian market factor portfolios. The figure shows that a $1 investment in the HML portfolio has ended with a value of below $0.5 while investing $1 in the SMB portfolio ended with almost $3.5 by the end of the sample period. However, looking at the figure, the HML has been high throughout the sample and just the last few years the drop happened, which explains why the returns of the HML is positive. On the other hand, SMB ended with a higher than HML yet the portfolio had huge fluctuations and a lot of drops throughout the sample which again explains the negative returns of SMB. The investments in the market and MOM are ambiguous, where investing $1 ended with a value of almost $1 as well. Although the market had several fluctuations similar to the SMB.

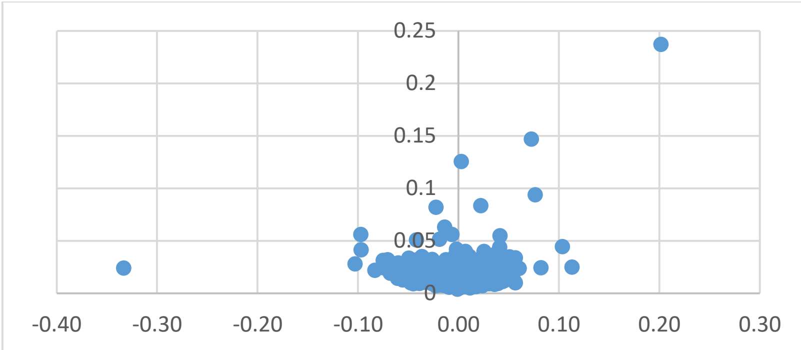

Figure 8.3: Scatter Plot CSAD against weighted market returns

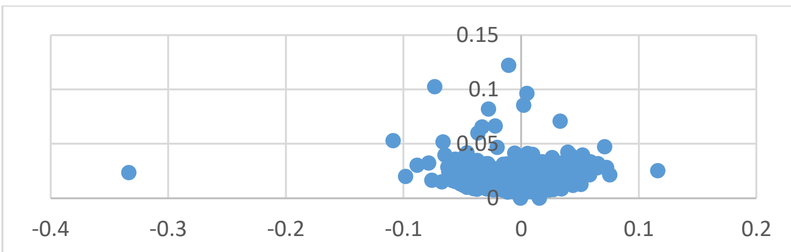

Figure 8.4: Scatter Plot CSAD against EGX market returns

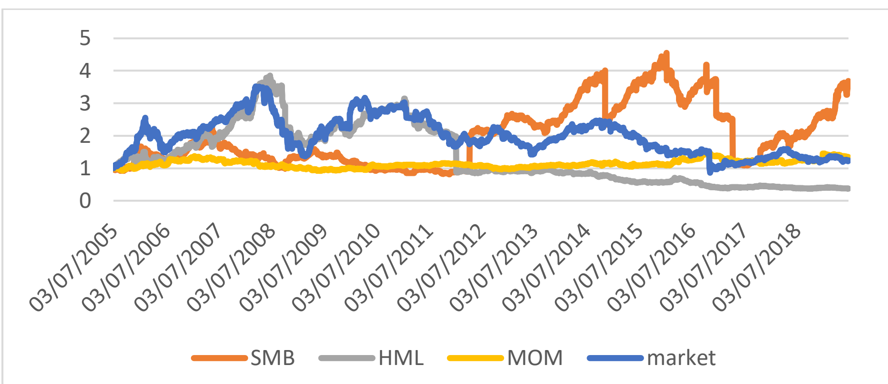

Figure 8.5 The growth of a 1 USD invested in the Egyptian market factor portfolios (1/7/2005 – 27/6/2019)

Table 8.2 shows the correlation matrix where the correlation between the four Fama-French-Carhart factors are almost all weak which is consistent with the portfolio construction method that ensures that the factors are weakly correlated. The market factor is positively correlated to all the three factors. However, the correlation coefficient between the value risk premium HML and market risk premium is 0.731, which indicated that both are highly positively correlated implying that the variation in the marker factor have a strong effect on the HML factor estimation. The MOM factor is positively related to the HML (0.050) while negatively correlated to the SMB (-0.019). Finally, with SMB and HML factors are negatively correlated (-0.392).

Overall the descriptive statistics point to the existence of dispersion in the market and indicates the probability of finding herding behaviour in the Egyptian stock market. The next section aims to provide more formal tests on the presence of herding in the Egyptian stock market.

Table 8.2: Correlation Matrix

	SMB	HML	MOM	Market factor
SMB	1			
HML	-0.392	1		
MOM	-0.019	0.050	1	
Market Factor	0.161	0.731	0.046	1

Note: The table presents the correlation matrix between the four Fama-French-Carhart factors.

8.4 Full Sample Herding Outcome

The results of the previous section provide some evidence on the existence of herding in the Egyptian stock market. However, in order to provide more formal evidence about the existence of herding in the Egyptian market, this section aims to regress CSAD on market absolute returns and squared returns to identify whether there is significant evidence on the existence of herding. As previously explained in Chapter 5, total herding can be due to fundamental and non-fundamental factors. Rational investors with similar stock preferences adopt the same response to similar information about company characteristics and fundamentals. Hence, intentional herding represents the herding part that arises from identical investment strategies or similar investor responses to the same information. On the other hand, non-fundamental factors which is attributed to the unintentional herding occurs when investors with insufficient information and inadequate risk evaluation disregard their prior beliefs and blindly follow other investors' actions, which is found when the impact of fundamental risk factors is partialled out.

Table 8.3 shows the results of total herding. The results show that the linear parameter β_1 of absolute return is highly significant and positive (β_1 equals 0.297 and 0.277 for the weighted portfolio and EGX respectively), indicating that there is a linear relationship between stock market returns and their dispersion which is in line with the assumption of rational asset pricing models (Pennacchi, 2008). The non-linear parameter β_2 associated with the squared market returns is significant and negative (β_2 equals -0.223 and 0.693 for the weighted portfolio and EGX respectively). Thus, even though the relationship between CSAD and the absolute returns is increasing (positive β_1), it is increasing at a decreasing rate. Hence, this should be considered as evidence of herding in the Egyptian stock market especially that both parameters are statistically significant. Therefore, herding exists in the Egyptian market during the full sample period where there is negative and non-linear relationship between market returns and CSAD.

Although the results of Table 8.3 provide evidence of herding in the Egyptian stock market, it is important to analyse whether this herding is due to fundamental risk factors or non-fundamental risk factors. To achieve this aim both $CSAD_{FUND,t}$ and $CSAD_{NONFUND,t}$ are regressed on absolute and squared market returns. Consistent with the results of total herding, Table 8.3 shows that when $CSAD_{NONFUND}$ is regressed on absolute and squared returns, β_2 remains negative (coefficient for weighted portfolio=-0.644, coefficient for EGX=-0.785) and significant indicating that when the effect of fundamental risk factors is eliminated, there is still evidence of negative non-linearity between cross sectional absolute dispersion and squared market returns. The Egyptian stock market is an emerging market, which is not fully open and smaller in size compared to developed markets. According to Solakoglu and Demir (2014), sentimental herding is more likely to be found in markets that are smaller where investors are less informed. In the Egyptian market investors are not completely informed about the market fundamentals and it is, therefore, more likely to observe sentimental herding or as named here unintentional herding.

However, when $CSAD_{FUND}$ is regressed on both absolute and squared market returns, β_2 turned to be positive (coefficient for weighted portfolio= 0.009, coefficient for EGX= 0.063) and significant indicating that herding of equity returns observed is not induced by investors' similar styles in the Egyptian stock market. In other words, most of the non-linear negative relation found between dispersion and market returns stems from investors ignoring their information and following the herd.

Generally, in normal conditions investors would have enough time to collect the required information, think rationally, analyse the market and make decisions. In distress periods, however, investors are more biased towards others' opinions and would rather follow other investors' actions. Hence, market distress decreases the time for proper information gathering, leading investors to follow rumours and herd (Mertzanis and Allam, 2018). In order to see the effect of the distress periods on the existence of herding, in the next section the sample is divided into six subsamples to analyse whether the existence of herding is affected by market conditions. Since the weighted and index returns reported similar results, the chapter proceeds using the weighted returns only in order to avoid repetition.

Table 8.3: Full Sample Herding Outcome

	β_0	p-value	β_1	p-value	β_2	p-value	R^2
Total Herding							
Weighted	0.0112	0.000	0.2975	0.000	-0.2235	0.002	0.216
EGX	0.0119	0.000	0.2779	0.000	-0.6934	0.000	0.195
Non-Fundamental							
Weighted	-0.002	0.000	0.2537	0.000	-0.6442	0.000	0.763
EGX	-0.00307	0.000	0.2848	0.000	-0.7854	0.000	0.606
Fundamental							
Weighted	0.0147	0.000	0.0046	0.000	0.0096	0.000	0.335
EGX	0.0148	0.000	0.0017	0.000	0.0630	0.001	0.288

Note: This table presents the estimates of the model specification in equation (8.2): $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + e_t$ *for the full sample period 1/7/2005 to 27/6/2019. This specification retains total herding where both fundamental and non-fundamental components in the CSAD for the Egyptian stock market herding and provides estimates for linear and non-linear herding parameters* β_1 *and* β_2 *respectively. The estimates of the model specification in Equation (8.4):* $CSAD_{NONFUND,t} = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + e_t$*. This specification runs the regression on non-fundamental CSAD removing the Fama-French-Carhart factors. We replicate the estimation of this regression using fundamental CSAD where we replace non-fundamental CSAD with fundamental CSAD as the dependent variable in equation (8.4). The estimates for linear and non-linear herding parameters* β_1 *and* β_2 *respectively. Each estimate is run twice, once for weighted returns and the other for the index returns.*

8.5 Herding in Different Market Conditions

Given the vast amount of evidence that herding differs in different market conditions, it is significant to divide the sample into subsamples in order to analyse the presence of herding in different market conditions. In the previous chapters (Chapters 6 and 7) the sample is divided into three sub-samples (Pre-crisis, During the Crisis, and Post-crisis). However, since the analysis is on the MENA region, each country in our sample is experiencing different events at different time periods, which makes it hard to divide the sample according to each country's events. Therefore, a general division is made pointing out the major events of the region such as Global Financial Crisis and the Arab Spring (during the crisis from 2008 to 2013). The pre-crisis period in the previous chapters' ranges from 2003 to 2007 and it reflects a generally stable period for most of the countries in the region. However, this chapter focuses only on Egyptian market, this, in turn, provides an opportunity to make an in-depth analysis of market conditions and its relationship with herding. Since Egypt in this period witnessed several major events, this can enable us to divide the sample period into more categories to reflect more faithfully the various political and economic events that took place in Egypt.

Thus, the sample is divided into six subsamples. The first subsample is the pre-crisis period which covers the period from 2005 to 2007 which is considered a stable period, where no major events took place, except for the Gulf stock market crash in 2006, which is not expected to have severely affected the Egyptian market. The second subsample is the Global Financial Crisis (GFC) period which covers the period from 2008 to 2009 which was tough on all economies due to the global nature of the crisis. The third subsample is the Arab Spring period which represents the period from early 2010 to 30

June 2013. This crisis affected many MENA economies not just Egypt. It is possible to specify the end of this subsample because the specific date of 30 June 2013 is a turning point for Egypt where the start of the second crisis begins. Therefore, the fourth subsample is the second Egyptian revolution which covers the period from 1 July 2013 to end of 2014, which may have a different impact on the economy than the first revolution. The fifth subsample is the economic reform which represents the period from beginning of 2015 to the end of 2016 where the government carried out a number of reform policies in an attempt to boost the economy. The most important of these reforms was the floating of the Egyptian Pound. Finally, the sixth subsample is the post-crisis period which represents the period from the early of 2017 to the mid of 2019, where no major events are taking place, the economy is recovering and nearly stable, along with investments and agreements are nourishing. More details about each subsample are given in the following section along with evidence graphically and numerically. Since the weighted and index returns reported in the full sample have similar results, the chapter proceeds using the weighted returns only in order to avoid repetition.

8.5.1 Individual Sample Descriptive Statistics

This sections provides the descriptive statistics of each of the six subsamples, along with graphical illustration in order to provide a hint about the existence of herding in the Egyptian stock market over different market conditions.

Table 8.4 provides the descriptive statistics for the six subsamples for the CSAD and the Fama-French-Carhart factors. The Egyptian equities' daily average dispersion around the market shows the highest daily average dispersion in the second Egyptian Revolution period reporting 1.6% and the lowest in the post-crisis period reporting 1.1%. Looking at the CSAD range for the subsamples, it is clear that the widest range is found during the Arab Spring period with a minimum of 0.5% and maximum of 12.5% as the movement around the market shrinks significantly indicating the presence of herding. From the six subsamples, the next highest ranges are for Economic Reform, the Global Financial Crisis, and the second Egyptian Revolution with span of 8.6%, 7.5% and 5.1% respectively. Hence, herding is expected to be present during these subsamples. While the pre-crisis and post-crisis period span is not wide therefore it's not expected to find herding during these periods.

Table 8.4 shows that the CSAD for all the six subsamples are positively skewed and leptokurtic, indicating that many deviations fall at the tails of the distribution, and therefore the null hypothesis of normality is rejected by the Jarque-Bera statistics, which is consistent with the full sample statistics. This implies that the cross sectional absolute deviation departs from the normal distribution which is expected given that CSAD is calculated in terms of absolute values.

Table 8.4 also provides the descriptive statistics of the Fama-French-Carhart factors of the Egyptian stock market for the six subsamples. First, the market portfolio average return is significant and positive for the pre-crisis (0.17%) and post-crisis (0.03%) periods with low standard deviation, thus reflecting the relative stability of the Egyptian financial market during these two periods. On the other hand, the GFC, the Arab Spring, the second Egyptian revolution, and the Economic Reform periods show negative returns and high standard deviation, implying the negative impact of the events experienced by Egypt during these periods.

For the SMB factor, we first note that small stocks are expected to underperform large ones during recessions, as credit conditions are tighter and investors pessimistic (Hur *et al*., 2014). Across all periods the average return of the SMB portfolio is significant and negative, except for the pre-crisis period where the average return is significant and positive 0.07%. The negative average returns for the rest of the periods are significant, indicating that during stress periods small firms underperformed big firms. In contrast, the significant and positive average returns in the pre-crisis indicates that small firms over perform relative to big firms when markets are stable. The statistical significance of the SMB returns during the first five periods is evidence of the presence of size effect in the Egyptian stock market. However, the SMB average return is negative but insignificant for the post-crisis periods, indicating the absence of the size effect. The SMB standard deviation is the highest during the GFC (1.7%) period followed by the Economic Reform (1.1%), the Arab Spring (0.8%), and the second Egyptian Revolution (0.8%). Therefore, subsamples with ongoing events have low returns while stable and calm subsamples have higher returns. This is consistent with Perez-Quiros and Timmermann (2000), who argues that markets are expected to earn lower returns during stress or recession times when credit conditions are tighter and investors are pessimistic. While earning higher returns in periods of distress risk where the market is in good conditions and investors are more optimistic.

Third, the HML factor, Zhang (2005) argue that value firms are more loaded with unproductive capital than growth firms in periods of unstable economic conditions, indicating that value firms are expected to underperform growth firms during these time periods. The HML average returns are significant and negative for GFC (-0.05%), the second Egyptian Revolution (-0.26%), and Economic reform (-0.05%) periods, while there are significant positive average returns pre-crisis (0.22%), and post-crisis (0.15%). This confirms the argument by Zhang (2005) and it is clear that during the instability periods growth firms outperformed value firms, while in stable periods growth firms underperformed value firms. These results provide evidence of the existence of the value effect in the Egyptian stock market during these subsamples. However, in the Arab Spring period the HML average return is positive but insignificant, hence neither growth nor value outperformed one another, indicating that the value effect does not exist in this subsample. The pre-crisis period reports the highest average excess rate of return and a reliable value premium in return (0.22% daily), indicating that there is a strong value premium in rate of return for this subsample.

Fourth, the MOM portfolio has positive average returns for all subsamples except for the GFC and the post-crisis period. The MOM factor is highly volatile during the pre-crisis period having the highest standard deviation of 1.1% compared to other subsamples. An important point is that the MOM portfolio average returns are insignificant throughout all the subsamples, indicating that there is no evidence of momentum in the Egyptian stock market throughout different market conditions. This outcome is supported by the findings of Rouwenhorst (1999) who finds no evidence of intermediate horizon momentum returns in 14 out of 20 emerging markets studied over the period 1982 to 1997.

Table 8.4: Divided Sample Descriptive Statistics

	Sample mean	p-value (mean=0)	SE	Standard Dev.	Skew.	Kurtosis	Jarque-Bera	Min.	Max.
				Pre-crisis period 2005 to 2007					
CSAD	0.0122	0.000	0.00015	0.00364	2.0579	11.947	3925.464	0.0037	0.0444
Market	0.0017	0.004	0.00062	0.0060	0.06615	4.368	518.969	-0.0679	0.1033
HML	0.0022	0.001	0.0008	0.0195	-0.4738	1.7296	79.905	-0.0751	0.0662
SMB	0.00071	0.002	0.00085	0.0029	0.2915	1.7155	67.442	-0.0833	0.0754
MOM	0.0004	0.390	0.00052	0.0116	0.0172	3.8718	309.222	-0.0595	0.0638
				Global Financial Crisis 2008 to 2009					
CSAD	0.0137	0.000	0.00028	0.00608	3.5864	29.672	18326.98	0.0081	0.0834
Market	-0.0001	0.000	0.00092	0.0110	1.0698	17.594	6845.628	-0.1030	0.2015
HML	-0.0005	0.003	0.0010	0.0217	-1.175	4.672	450.42	-0.1316	0.0580
SMB	-0.0001	0.002	0.00089	0.0177	2.373	18.067	5743.28	-0.0469	0.1585
MOM	-0.0004	0.371	0.00047	0.0093	-0.1884	2.692	121.30	-0.0497	0.0370
				Arab Spring 2010 to 30/6/2013					
CSAD	0.0152	0.000	0.00023	0.0065	8.508	122.308	496860.03	0.0051	0.1252
Market	-0.0006	0.003	0.00039	0.0120	-1.216	8.868	3210.45	-0.0971	0.0604
HML	0.00014	0.749	0.00045	0.0116	-1.7243	12.599	4727.83	-0.09258	0.0408
SMB	-0.0003	0.002	0.00033	0.00864	0.2283	5.7321	916.19	-0.03972	0.0607
MOM	0.00009	0.661	0.00022	0.00572	0.7216	3.8688	471.74	-0.01642	0.0381
				Second Egyptian Revolution 1/7/2013 to 2014					
CSAD	0.0163	0.000	0.00022	0.00416	3.7216	28.585	12579.215	0.0039	0.0546
Market	-0.0012	0.000	0.00053	0.0155	0.6594	11.073	2036.54	-0.0402	0.0822
HML	-0.0026	0.000	0.00075	0.0128	0.62024	7.451	694.188	-0.0516	0.0872
SMB	-0.0007	0.001	0.00046	0.0082	0.9887	6.839	616.749	-0.0227	0.0537
MOM	0.0003	0.349	0.00033	0.00578	-0.0827	2.124	55.222	-0.0241	0.0218
				Economic Reform 2015 to 2016					
CSAD	0.0154	0.000	0.00026	0.0056	6.7994	89.452	159298.03	0.00495	0.0938
Market	-0.0012	0.163	0.0009	0.0206	-7.7815	130.861	377008.56	-0.3332	0.1129
HML	-0.0005	0.006	0.00118	0.0234	-5.758	91.148	138217.27	-0.3198	0.1360
SMB	-0.0013	0.000	0.00573	0.01135	-4.5835	54.655	50292.11	-0.1389	0.0353
MOM	0.0004	0.241	0.00040	0.00795	1.8688	15.421	4123.17	-0.0265	0.0696
				Post-Crisis period 2017 to 2019					
CSAD	0.0110	0.000	0.0003	0.00721	12.258	207.313	1389.926	0.0169	0.0468
Market	0.0003	0.000	0.00038	0.00959	0.37188	6.460	1145.274	-0.0364	0.07243
HML	0.00157	0.005	0.00051	0.0112	-0.2463	0.7751	17.079	-0.0423	0.04217
SMB	-0.0002	0.598	0.0003	0.0068	0.2363	1.6708	61.058	-0.0226	0.0317
MOM	-0.0000	0.984	0.00047	0.01027	11.665	213.98	938262.89	-0.0488	0.1840

Note: *This table presents descriptive statistics on the cross-sectional absolute deviation measure to proxy daily six subsamples of the Egyptian stock market herding. It is estimated using the following expression:* $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}|$. *In addition to summary statistics on the Fama-French-Carhart factors which are constructed using stocks from the Egyptian stock market. These factors are market factor, size factor (SMB), value factor (HML) and momentum factor (MOM).*

Among all the six subsamples and the Fama-French-Carhart factors, the SMB strategy in the second Egyptian Revolution period is the lowest risk with the narrowest range of returns (-0.2% to 0.2%). While the HML strategy in the Economic Reform period is the highest risk with the widest range of returns (-31.9% to 13.6%).

From the descriptive statistics, some indications of the presence of herding can be seen for some subsamples. Figures 8.6 to 8.11 present the CSAD of each of the six subsamples (with subsample average in blue horizontal line). Starting with Figure 8.6, which is considered a rather stable period for the Egyptian market, where neither the market nor the region encountered any major stress or event. Therefore, following Klein (2013) argument, it is not expected to find a significant evidence of herding in this period. The deviation from the average in Figure 8.6 is not that pronounced except for a very clear spike around the beginning of 2006. This spike is the result of several developments that took place in the stock market, such as issuing new derivative products in March 2006, upgrading the capacity of the trading system to accommodate more transactions per day, and activating online trading system, where investors place sell and buy orders directly on the internet. The good stock market performance was also disturbed by major shocks that hit the market in 2006 in neighbouring countries such as the Gulf stock market crash, the Lebanon War, and the escalation of violence in Iraq (EGX, 2006). In 2007, the government tried to enhance the confidence of both local and foreign investors, while the World Bank chose Egypt to be the best country in 2007 in terms of improving investment and business climate. These actions led to a positive impact reporting a strong year-on-year growth rate of more than 50%. However, by the end of 2007 the fear of a global financial crisis started to affect the market negatively (EGX, 2007).

With the start of the major events, Figure 8.7 presents the GFC period ranging 2008 to 2009. 2008 is one of the toughest years for all economies around the world due to the Global Financial Crisis which is categorized as the worst crisis since the Great Depression in the 1920s (Mathiason, 2008). Despite the GFC that took place in 2008, 2009 can be described as being a stable period where the Egyptian economy witnessed recovery from the major effects of the crisis. The Egyptian market achieved one of the highest growth rates compared to similar economies (EGX, 2009). Hence, the figure shows only a spike in 2008, and the rest of the period the deviation from the average is not that high. Therefore, it is not expected to find herding behaviour in this period, since the major events were not effective and followed by a stable period.

Figure 8.8 presents the Arab Spring period range from 2010 to 30 June 2013. After the good recovery in 2009, the Greek debt crisis caused another fall in the market reaching the lowest point in July 2010, but being able to recover again by the end of the year (EGX, 2010). This is shown by the deviation of the CSAD from its mean in Figure 8.8. With the start of the Egyptian revolution in 2011, the economy witnessed both internal and external pressure. The political unrest, which started in January 2011, forced the Capital Market Authority to close the market for almost two months (causing the missing data in Figure 8.8). Similarly, in 2012 the political and economic uncertainty continued, where the whole region faced the Arab Spring revolution, which is shown by some variation from the mean in Figure 8.8. Moreover, there is a spike towards the mid of 2013 due to the currency weakening by 9% which is the largest fall in10 years, as a result of the raise of the protests against President Mohamed Morsi (EGX, 2013).

Figure 8.9 presenting the second Egyptian Revolution ranging from 1 July 2013 to 31 December 2014, as the beginning of the graph shows some spike as the reflection of the political instability in the street protesting against the President. The economy started to recover towards the end of 2013. Yet, the cost of keeping a stable currency throughout all these events resulted in a loss of international reserves of over $20 billion (EGX, 2013). However, without financing from Qatar to Morsi's government, and the assistance from Saudi Arabia, Kuwait, and UAE that came in 2014, Egypt could have run out of foreign exchange reserves (EGX, 2014). Furthermore, in 2014 the new government restructured the subsidy system in order to minimize the budget deficit which affected the economy positively. This led to an increase Egypt's credit ratings, which increased the confidence in the economy and its ability to recover (EGX, 2014). A positive event is shown as a spike since the CSAD calculates the absolute; therefore, positive and negative events are shown as deviation from the mean.

Figure 8.10 presents the Economic Reform ranging 2015 to 2016. With the expectation of a recovery period after all these events the graph shows several spikes. The deviation from the mean in 2015 is due to the Egyptian market being faced by severe regional and global challenges, impacting the stock market negatively. On the global level, there was a slow economic growth due to China's weak economic performance and the currency war between China and the US. On the regional level, the recurring tensions between several countries in the MENA region led to reduced economic growth rates of the whole region (EGX, 2015). The instability of the economic conditions continued in 2016, where there was a decline in tourism sector revenues due to the political instability, fall in the Suez Canal revenues, and fall in the foreign investments and exports. This led to a severe pressure on the Egyptian pound and resulted to the emergence of the currency black market. Consequently, the government allowed the currency to float freely in 2016, and adopted a number of fiscal and monetary reform programs. Furthermore, in order to increase international reserves, the government encouraged exports and tried to reduce imports. This is considered a major decision that was taken by the government in November 2016 and is shown by the highest spike in Figure 8.10. Nevertheless, the Egyptian market was able to absorb all these challenges and become one of the top of the emerging markets in 2016 having one of the highest records of growth (EGX, 2016).

Lastly, Figure 8.11 presenting the Post-crisis period ranging 2017 to 2019, the graph is rather stable, where the deviation from the mean is not that much. During this period, Egypt tried to maintain a strong capacity building programs among markets in order to attract new segments of investors and enhance liquidity levels. These ongoing efforts made the Egyptian stock market to actively participate in local, regional and global sustainability initiatives (EGX, 2017). Moreover, in 2018 Egypt became head of the African Securities and Exchanges Association – Sustainability Working Group that aims to prepare a Roadmap report towards the sustainability of the African Capital markets through collaboration with sustainability initiatives at Regional and Global levels (EGX, 2018). In 2019, economic growth started to improve, driven by an expansion in the gas extractives, tourism, manufacturing, and construction, along with improvements in the private investment and net exports (World Bank, 2019). Analysts describe this period as being mostly dominated by a decline in the value of the currency, and the trade war between the US and China (EGX downtrend in 2018, 2019). Although analysts perceive this period negatively, there were a lot of positive events. These include thriving investment in the economy, which may have offset the negative effects of the floatation of the Egyptian pound. The herding outcome will provide evidence of which events were stronger, positive, negative, or equal.

From the CSAD figures against their average, it can be concluded that the periods GFC, Arab Spring, second Egyptian revolution, and Economic Reform are the most deviated from the mean indicating the presence of herding. Furthermore, looking at the scatter plot of the CSAD and market returns also gives indications of herding.

Figure 8.12 to 8.17 show the scatter plots of the CSAD and market returns of the six subsamples. The concavity is clear in the GFC, the Arab Spring, the second Egyptian Revolution, and the Economic Reform. Gabbori *et al*. (2020) argue that this concavity indicates the probability of finding significant non-linearity and herding behaviour in these markets. The CSAD for these subsamples against market returns show the movement of dispersion with the market returns, where dispersion increases with market returns. However, the increase in dispersion increases at a decreasing rate indicating a negative relationship between CSAD and the market returns. As for the pre-crisis and post-crisis period the CSAD is clustered and show no clear concavity.

Figures 8.18 to 8.23 presents the growth of a one dollar for the factor portfolios in each of the six subsamples in order to see how investing in different market conditions is different. First, for the Pre-crisis period, which is considered to be a stable period, Figure 8.18 show that a $1 invested increases throughout the sample but towards the end of 2007 the SMB portfolio began to fall. This can be attributed to the start of the Global Financial Crisis where the market started to get affected by the end of 2008, and in which small firms got affected more by the changes in the market.

The drop in the market due to the GFC is shown in Figure 8.19, where the portfolios start to decline in 2008. However, the portfolios start raising again in 2009. This year was a stable period of the Egyptian Economy. Nevertheless, it is not obvious whether or not this stability in the economy has offset the GFC effect, leaving the market with no herding behaviour during this period.

With the rise of the Arab Spring, Figure 8.20 shows a clear decline in the portfolios. However, the HML investment starting with $1 at the beginning of the period ends back at $1 by the end of the period. On the other hand, the SMB and the market portfolios see their $1 investment at the beginning end with almost $0.5 by the end of the period. Investing during the second Egyptian Revolution is shown in Figure 8.21. Although this is a period of stress, the SMB shows an increase by the end of the period, while the HML shows a decline in investments by the end of the period.

The most interesting period of all subsamples is the Economic Reform shown in Figure 8.22. Almost all the factor portfolios show a decline in investment value during this period. As mentioned above, this period was expected to be the after events recovery. Unfortunately, economic instability, regional, and global tensions led to a sluggish economy. This may be due to the fact that, having been through several years of turmoil, the economy did not have time to fully recover and remained sensitive to external and internal shocks.

Finally, the post-crisis period where the recovery and stability the economy have been striving for is shown in Figure 8.23. The Figure shows similar investing results as the pre-crisis period, where the HML at the beginning of the period is almost the same as at the end of the period. While $1 invested in the SMB portfolio at the beginning of the period is almost doubled to $2 by the end of the period.

Overall, the descriptive statistics highlight the existence of different market patterns in the GFC, the Arab Spring, the second Egyptian Revolution, and the Economic Reform periods and the figures have clear indications of the probability of finding herding behaviour in these subsamples. The next section aims to provide more formal tests on the existence of herding in the six subsamples.

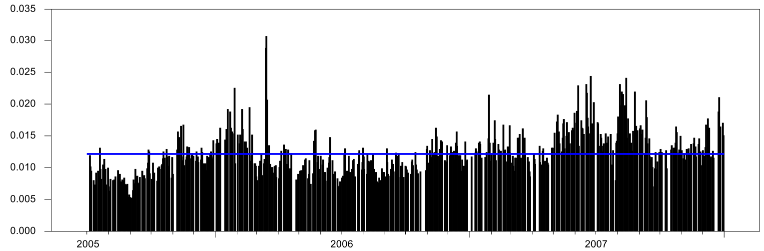

Figure 8.6: Pre-crisis CSAD against sub-sample average CSAD

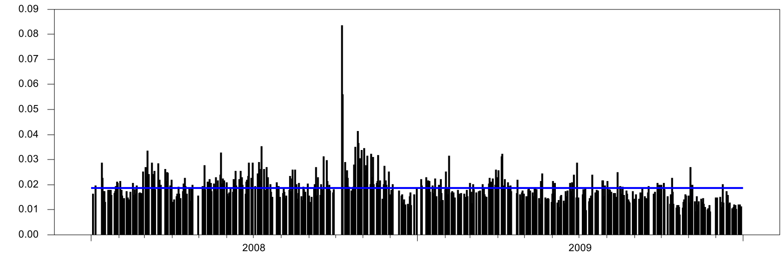

Figure 8.7: GFC CSAD against sub-sample average CSAD

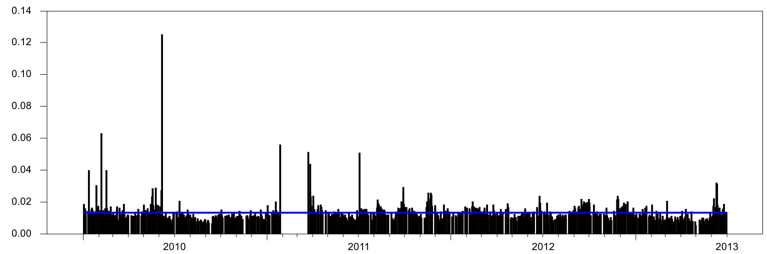

Figure 8.8: Arab Spring CSAD against sub-sample average CSAD

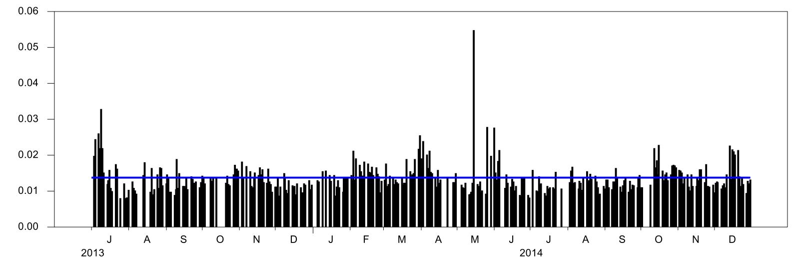

Figure 8.9: The Second Egyptian Revolution CSAD against sub-sample average CSAD

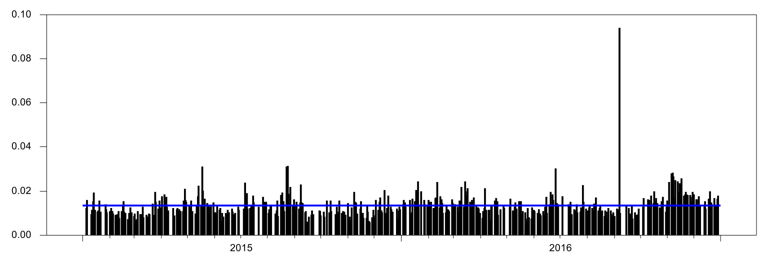

Figure 8.10: Economic Reform CSAD against subsample average CSAD

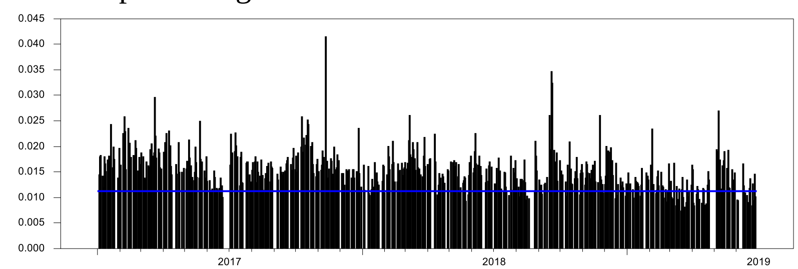

Figure 8.11: Post-crisis CSAD against subsample average CSAD

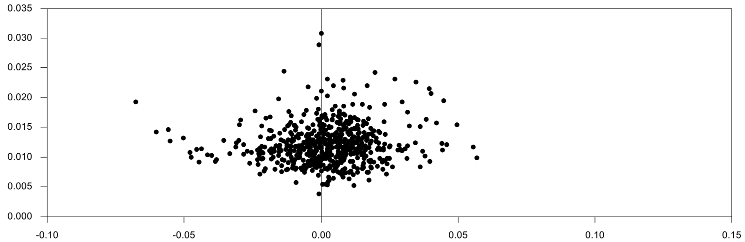

Figure 8.12: Pre-crisis Scatter Plot CSAD against market returns

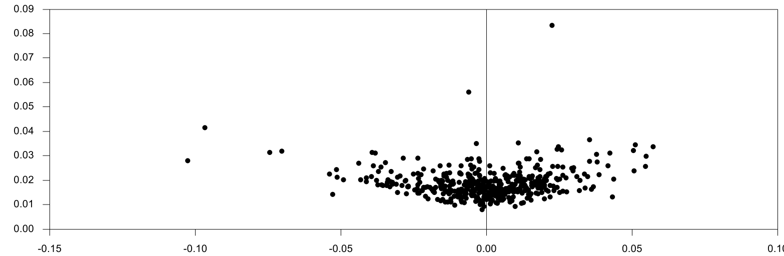

Figure 8.13: GFC Scatter Plot CSAD against market returns

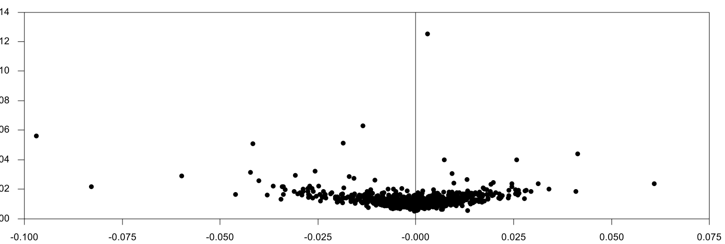

Figure 8.14: Arab Spring Scatter Plot CSAD against market returns

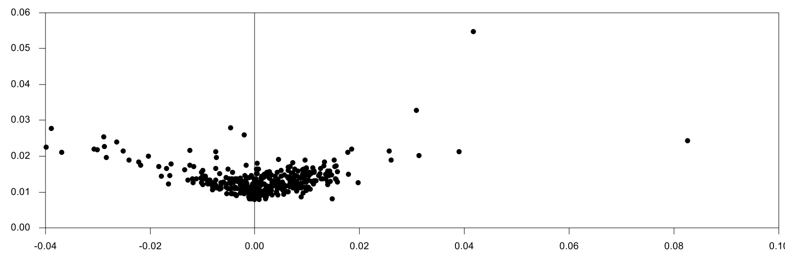

Figure 8.15: The second Egyptian Revolution Scatter Plot CSAD against market returns

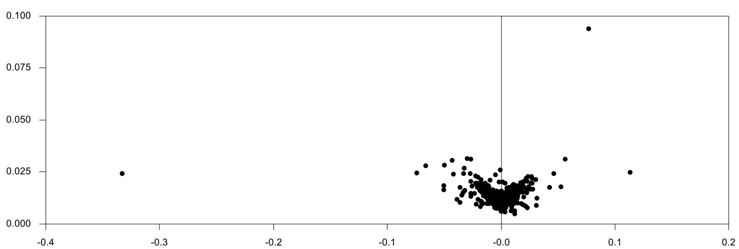

Figure 8.16: Economic Reform Scatter Plot CSAD against market returns

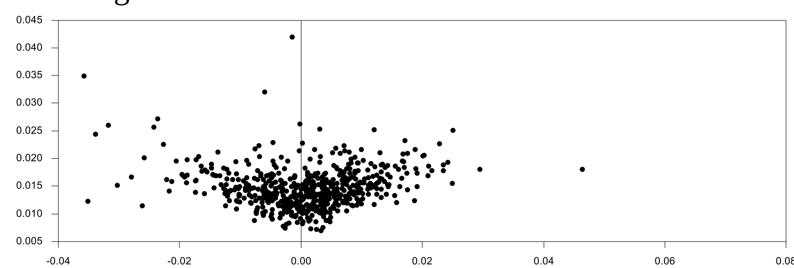

Figure 8.17: Post-crisis Scatter Plot CSAD against market returns

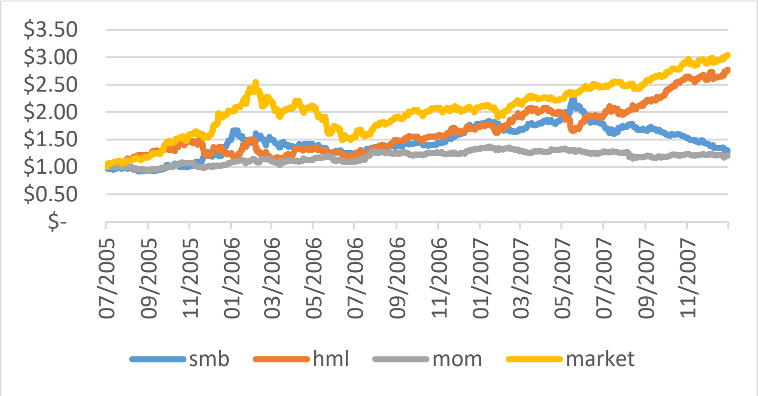

Figure 8.18: Growth of $1 invested in the Pre-crisis factor portfolios (1/7/2005 – 31/12/2007)

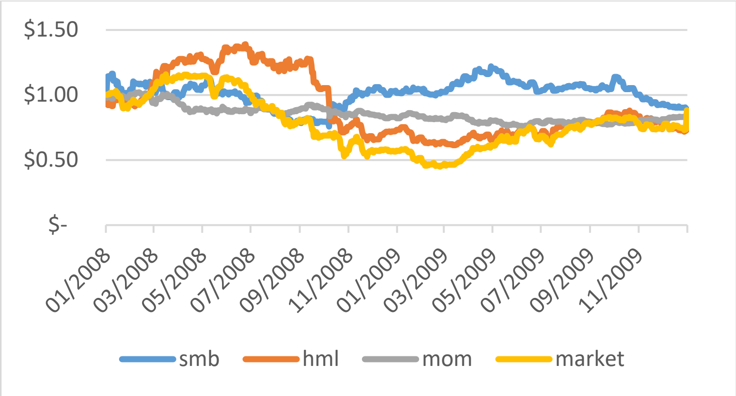

Figure 8.19: Growth of $1 invested in the GFC factor portfolios (2008 – 2009)

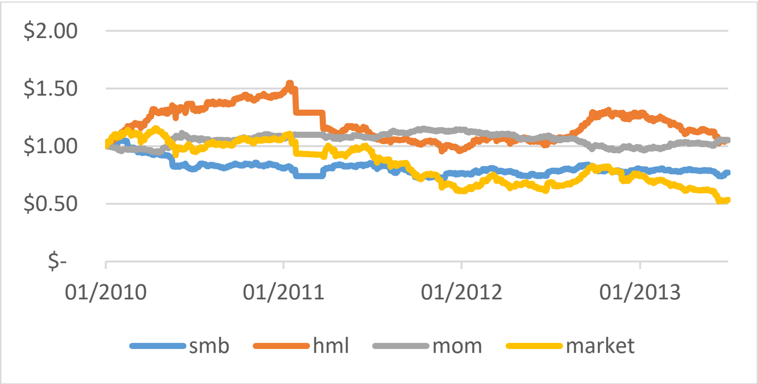

Figure 8.20: Growth of $1 invested in the Arab Spring factor portfolios (2010 – 30/6/2013)

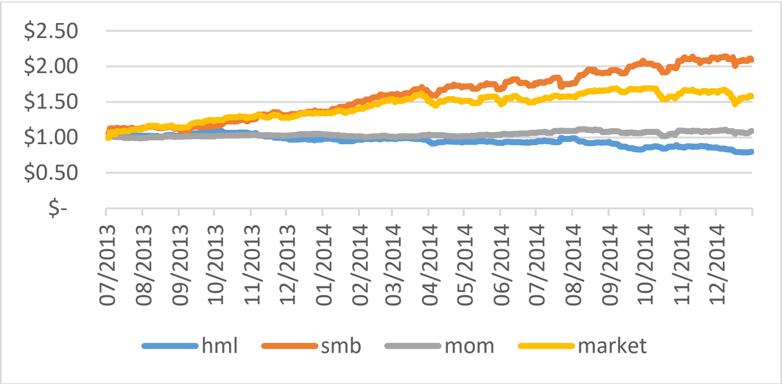

Figure 8.21: Growth of $1 invested in the second Egyptian Revolution factor portfolios (1/7/2013 – 2014)

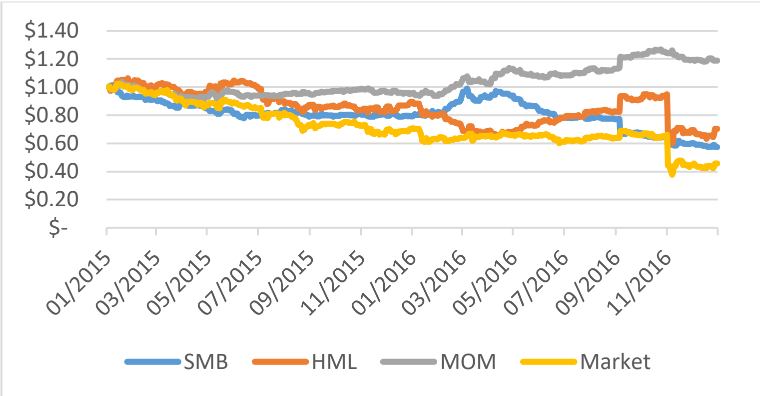

Figure 8.22: Growth of $1 invested in the Economic Reform factor portfolios (2015 - 2016)

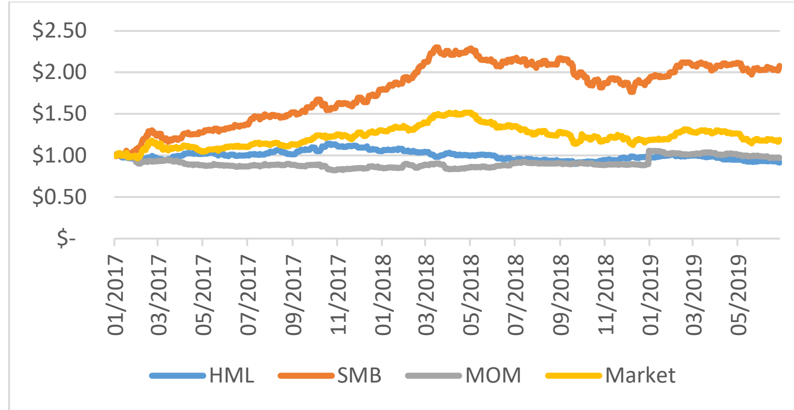

Figure 8.23: Growth of $1 invested in the Post-crisis factor portfolios (2017 - 2019)

8.5.2 Divided Sample Herding Outcome

The results of the previous section provide some indications of the existence of herding in the Egyptian stock market during the six periods discussed earlier. However, in order to provide more formal evidence about the existence of herding in the Egyptian market subsamples, this section aims to regress CSAD on market absolute returns and squared returns to identify whether there is significant evidence on the existence of herding, and whether herding is due to fundamental or non-fundamental factors.

Table 8.5 provides the outcome of total, intentional, and unintentional herding for the six subsamples. The pre-crisis periods show no sign of herding neither total, nor intentional or unintentional. This is expected since this period was calm and stable, consistently with Figure 8.6 and 8.12, and the summary statistics discussed in the previous section.

The Global Financial Crisis (GFC) period shows no sign of total herding, unintentional, or intentional herding as the nonlinear parameter is insignificant. This contradicts the expectations drawn from the descriptive statistics and the graphs in the previous section. However, focusing on the selected period, the GFC in 2008 had a major effect on all the world economies. Yet, as mentioned earlier, Egypt was the least sensitive to this crisis. Furthermore, the sample includes 2009 as well, which was considered a stable period for the economy.

The Arab Spring period has evidence of total herding where the linear parameter β_1 of absolute return is positive (coefficient = 0.295) and significant, while the non-linear parameter β_2 associated with the squared market return is negative (coefficient = -0.658) and significant. With the rise of the Arab Spring in the region, and soon the Egyptian revolution, the instability in the economy began to gather momentum. This result is consistent with Balcilar *et al.* (2013) who examined herding under various market conditions and found herding behaviour in all the GCC countries under the crash regime. In addition to having a significant and positive β_1 (coefficient = 0.194), the coefficient β_2 associated with the squared market returns is also significant and negative (coefficient = -1.61), indicating the presence of unintentional herding. This shows that even when the shrinkage in dispersion accounts for the risk factors in the CSAD measure, there is still evidence of negative non-linearity between cross-sectional absolute deviation and squared returns. Hence, the shrinkage of dispersion in this subsample is more likely linked to the herding behaviour of investors rather than to investors' similar styles or reactions to the same information disclosure.

The second Egyptian Revolution period herding outcome shows evidence of total herding. The absolute return coefficient, β_1, is significant and positive (coefficient =0.416), while β_2 is significant and negative (coefficient = -1.95). This period started with the protests against President Morsi up until he left. It also includes the attempt to stabilize the economy following several adverse events. Unfortunately, the size of debts and the severe loss of reserves were barely covered with the assistance of neighbouring countries (EGX, 2013). This instability is clearly seen in Figure 8.9, and the market has the second highest volatility of 1.5% (Table 8.4) compared to other subsamples. Furthermore, the second Egyptian Revolution shows evidence of both unintentional and intentional herding the nonlinear coefficients are significant and negative (-3.41 and -1.95 respectively). This indicates that herding during this period is linked to both herding behaviour of investors as well as investors' similar reactions to the same information.

The Economic Reform period's herding outcome is similar to the second Egyptian Revolution herding outcome. Total, unintentional, and intentional herding are found during the period (the coefficients of the squared return are -0.94, -0.74, -0.209 respectively and all significant). It would have been natural that, after a series of events and two revolutions in the country, the market would recover during these (Economic Reform) years. However, in 2015 there were regional tensions that took place along with weak economic performance in China. Although these events were outside Egypt, the Egyptian market was still affected (EGX, 2015). Moreover, the aftermath of the prior events left the market weak. The government tried to stabilize the market and implemented shock therapy reforms, including currency floatation in 2016 (EGX, 2016). These events made the Economic Reform subsample a period of instability that explains the presence of herding, as can be seen in Figure 8.10, and the highest market volatility of 2.06% (Table 8.4) compared to other subsamples.

Finally, after all these political and economic events, the recovery period is shown in the post-crisis period. Here we find no evidence of total, intentional, or unintentional herding. As mentioned in the previous section, this period had positive and negative events going on, and we argued that the positive and negative events may have offset each other, leading to no herding. Indeed, the decline in the value of the Egyptian currency could well have been offset by the thriving of investments during this period.

Overall, the herding outcome shows that in periods of stability there is no evidence of herding behaviour. In contrast, in periods of stress the presence of herding is clear. Another important point is that the most volatile subsamples showed evidence of total, intentional, as well as unintentional herding. This indicates that as markets experience instability and high volatility, investor's reaction to fundamentals or news tend to become more homogenous.

After analysing the whole market and finding the presence of herding behaviour, along with examining the six subsample periods and noticing the effect of the crisis periods, the next section concludes.

Table 8.5: Divided Sample Herding Outcome

	β_0	p-value	β_1	p-value	β_2	p-value	R^2
Pre-crisis period 2005 to 2007							
Total	0.0127	0.000	-0.118	0.000	3.364	0.000	0.115
NON-FUND	0.0004	0.101	-0.103	0.000	2.993	0.000	0.127
FUND	0.012	0.000	-0.0162	0.0218	0.568	0.000	0.075
Global Financial Crisis 2008 to 2009							
Total	0.0162	0.000	0.1602	0.000	0.313	0.619	0.161
NON-FUND	0.0026	0.000	0.207	0.000	-0.478	0.517	0.166
FUND	0.0187	0.000	-0.002	0.875	-0.0439	0.873	0.0012
Arab Spring 2010 to 30/6/2013							
Total	0.0104	0.000	0.2955	0.000	-0.658	0.000	0.210
NON-FUND	0.0019	0.000	0.194	0.000	-1.616	0.002	0.149
FUND	0.0127	0.000	0.0069	0.610	0.746	0.002	0.0595
Second Egyptian Revolution 1/7/2013 to 2014							
Total	0.0103	0.000	0.416	0.000	-1.957	0.000	0.443
NON-FUND	0.002	0.000	0.4323	0.000	-3.412	0.000	0.387
FUND	0.0103	0.000	0.416	0.000	-1.957	0.000	0.443
Economic Reform 2015 to 2016							
Total	0.0100	0.000	0.357	0.000	-0.944	0.000	0.3992
NON-FUND	0.002	0.000	0.264	0.000	-0.745	0.000	0.297
FUND	0.0126	0.000	0.097	0.000	-0.209	0.000	0.095
Post-Crisis period 2017 to 2019							
Total	0.0127	0.000	0.2779	0.000	-0.992	0.5916	0.189
NON-FUND	0.00174	0.000	0.2443	0.000	-0.649	0.728	0.179
FUND	0.0145	0.000	0.0198	0.0065	-0.3629	0.1485	0.028

Note: This table presents the estimates of the model specification in equation (8.2): $CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + e_t$ *for the subsamples. This specification retains total herding where both fundamental and non-fundamental components in the CSAD for the Egyptian stock market herding and provides estimates for linear and non-linear herding parameters* β_1 *and* β_2 *respectively. The estimates of the model specification in Equation (8.4):* $CSAD_{NONFUND,t} = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + e_t$*. This specification runs the regression on non-fundamental CSAD removing the Fama-French-Carhart factors. We replicate the estimation of this regression using fundamental CSAD where we replace non-fundamental CSAD with fundamental CSAD as the dependent variable in equation (8.4). The estimates for linear and non-linear herding parameters* β_1 *and* β_2 *respectively.*

8.6 Conclusion

Generally, the existence of herding behaviour provides a general indication of the market efficiency. Where investors' tendency to imitate the action of others in the economy is what the herding behaviour is about. In this chapter, the presence of herding behaviour is examined in the Egyptian stock market from 1/7/2005 to 27/7/2019 using daily data. Total herding behaviour is tested using cross sectional absolute deviation twice, once using the weighted average returns of all companies used and the other using the EGX30 index returns, in order to see if the market returns are reliable.

Lao and Singh (2011) argue that during periods of market stress that are usually characterized by high volatility flow of information and significant market changes, investors are willing to ignore their own beliefs and knowledge in order to follow the market consensus or in other words herd. To narrow the scope of the sample, it is divided into six subsamples, Pre-crisis, Global Financial Crisis (GFC), Arab Spring, second Egyptian Revolution, Economic Reform, and Post-crisis. Herding may exist but may be due to fundamental factors or in other words, similar investors' reactions towards the same information. In order to differentiate between herding due to fundamental factors and herding due to non-fundamental factors, the CSAD is regressed on the four Fama-French-Carhart factors.

Generally, the statistics show that the Egyptian market returns as well as the average returns of investing in factor portfolios are typically positive with the exception of the SMB strategy. The outcome of examining herding is summarized in Table 8.6, which shows that total herding, unintentional, and intentional herding presence during the full sample period, along with the six divided sample periods. In pre-crisis and post-crisis periods which are considered stable periods, no evidence of herding is not found. During periods of stress, such as Arab Spring, second Egyptian Revolution and Economic Reform there is evidence of herding behaviour as well as evidence of unintentional herding in the three subsamples, while intentional herding is found in only two of these subsamples, second Egyptian Revolution and Economic Reform. The interesting outcome is finding no evidence of herding during a period that is considered as a volatile period which is the GFC period, however, it is explained by not being affected severely by the GFC as well as having a stable year (2009) in the sample that may have offset any effect that the crisis has done.

Table 8.6: Full and Divided Sample Outcome Summary

	Total	Non-fund	Fund
Full Sample	√	√	*X*
Pre-crisis	*X*	*X*	*X*
GFC	*X*	*X*	*X*
Arab Spring	√	√	*X*
Second Egyptian Revolution	√	√	√
Economic Reform	√	√	√
Post-Crisis	*X*	*X*	*X*

Note: The Table shows the existence of herding in the samples whether total herding, fundamental, non-fundamental herding using weighted returns or EGX index returns.

To conclude, herding is found in volatile periods where unintentional herding exists too. After the 1st Egyptian revolution, investors became more uncertain and continued to herd due to both fundamental and non-fundamental factors, with the raise of the second Egyptian Revolution and the Economic reform that took place.

Chapter 9

Conclusions and Suggestions for Future Research

9.1 Introduction

Emerging markets are generally characterized by high average returns and low correlations of returns with developed markets, providing high yields and diversification potential that attract foreign investors. However, emerging markets are also characterized by large fluctuations of market returns, which casts doubt on the efficiency and accuracy of the valuation of investment opportunities (Pryymachenko, 2003).

One part of emerging markets, the Middle East North African (MENA) region, has grabbed the attention of researchers for several reasons (Öztürk and Volkan, 2015). First, globalization has increased the connectedness between markets by removing trade and investment barriers between the countries. Second, the region has undergone extreme political instabilities and revolts, which makes the region an interesting case to examine the effects of political turmoil on cross-market transmissions. Third, the region includes rich oil-producing countries, which is of interest to investors and policy makers across the world. Given the significance of examining the MENA region, the main aim of this thesis is to investigate the stock market volatility and volatility spillover of the Middle East North African (MENA) region. This would help understanding the behaviour of the MENA markets, particularly the markets' interdependence within the region. The main reason behind the choice of the MENA region, is that the region is still witnessing wars, political turmoil, and economic instability. It is also one of the most diverse and interesting mixture of political and economic configurations.

The phenomenon of volatility has always been of great interest for many researchers, since it supports the investigation of the efficiency of the stock market, and helps investors and financial analysts understand the uncertainty of the returns on their investment caused by the variability in speculative market prices and the instability of business performance (Alexander, 1999). Understanding and measuring the interactions among markets are of great relevance to financial market participants in many different areas. The knowledge of spillover, conditional variance and covariance can be utilized in many decisions such as forming a portfolio, hedging, pricing derivatives or other assets, risk management, and the preparation of regulatory policy of financial markets (Stoica and Diaconasu, 2013). The analysis of the volatility spillover in the MENA region contributes to the existing literature and broaden the notion about the transmission mechanism among the markets not only within one particular market, but also among all the selected markets of the region.

Furthermore, after analysing the behaviour of the MENA markets and the transmission between them and having a clear understanding of the market behaviour in this area, this thesis also sheds light on investors' behaviour in these markets by taking the Egyptian stock market as an example as it is the market that witnessed significant events during the sample period. Moreover, Egypt is one of the largest developing markets in the region, and is one that has witnessed the greatest number of events, including the Global Financial Crisis, two revolutions and the floatation of the currency. In order to highlight the significance of the investor behaviour, this thesis tests for the presence of herding behaviour, which refers to market swings in finance that arise from investors' correlated decisions, while ignoring their own information and following others. The existence of herding can lead to deviation of equity prices from their fair and excess volatility in the market and thus it can contribute to explaining the excess volatility that the Egyptian stock market witnessed during the sample period.

9.2 Research Objectives

Given the research aims and objectives highlighted in Chapter 1, this section revisits the objectives of this thesis and addresses how they were accomplished.

Objective 1: Provide a comprehensive literature review concerning the different models of volatility in the MENA region.

The importance of this objective arises from discussing the main theoretical propositions upon which this thesis is based, as the literature review acts as a foundation for knowledge progress. Since one of this thesis aims is to model volatility of the MENA region, a background is given about importance of volatility along with analysing the different measures that emerged in the literature to measure volatility that vary between simple model to more complicated models. Chapter 2 accomplishes this task by highlighting the importance of examining volatility and that it is a major input in several decisions. However, reviewing the literature shows that there is a significance lack in examining volatility in the MENA region.

Examining volatility of stock market returns is of interest to investors, analysts, brokers, dealers and regulators (Glantz and Kissell, 2014). Policy makers rely on market estimates of volatility as a barometer of the vulnerability of financial markets. Investors and financial analysts are concerned about the uncertainty of the returns on their investment assets, caused by the variability in speculative market prices (and market risk) and the instability of business performance (Alexander, 1999).

While most researchers agree that volatility is predictable in many asset markets, they dissent on how this volatility predictability should be modelled (Bollerslev *et al*., 1992). Based on the literature review, it is apparent that the ARCH/GARCH models are the most commonly used (Bellini *et al.*, 2014).

Objective 2: Investigate the volatility spillover among the MENA region markets and highlight the important spillovers among the markets.

One of the key decisions that uses volatility as an input is examining volatility spillover that test the volatility transmission between markets. Many researchers are also motivated to test volatility spillover which help understand how information is transmitted across markets, their independence during different market conditions. By examining the volatility spillover, this reflects the externalities of economic activity or processes that affect those who are not directly involved, exploring and exhibiting the linkages between markets. One of the main factors that makes the spillover effect analysis contentious issue of research is the globalization and the tight connection of financial markets (Thessaloniki, 2014). Chapter 3 provides the theoretical background of the concept of spillover, highlights its significance, along with shedding the light of the most commonly used methods of investigating spillover.

In light of the previous studies, investigating spillover of the MENA region is significant due to the different events that took place, and the behaviour of its markets that shows dependency.

In order to investigate this volatility spillover, first the volatility of the markets needs to be estimated. The results show that the GJR-GARCH is the best model that capture volatility in the MENA region markets. Bahrain, Jordan, Kuwait, Oman and UAE are affected by negative shocks producing higher volatility in the future than positive shocks of the same magnitude. Meanwhile, Egypt, Saudi Arabia and Turkey are affected more by positive shocks producing higher volatility in the future than negative shocks of the same magnitude.

After estimating the volatility for all the selected MENA markets, the volatility spillover is then investigated by the most commonly used index, the Diebold and Yilmaz (2012) index. Chapter 6 provides the results of the volatility spillover of the eight MENA markets (Bahrain, Egypt, Jordan, Kuwait, Oman, Saudi Arabia, Turkey, and UAE). Generally, the spillover outcome shows a strong transmission between the eight MENA region countries, where the total spillover index for the represented sample of the MENA region is 57.5%. Turkey reports the lowest ‘contribution to others’ by 21.8%, while Oman has the highest ‘contribution to others’ by 125.7%; which means that Oman is a much stronger transmitter than Turkey is. On the other hand, the lowest ‘contribution from others’ is Egypt by 22.6%, while the highest ‘contribution from others’ is the UAE by 76.6%; which means the UAE is a stronger receiver than Egypt. Egypt reports the highest spillover to own market at 77.44%. This can be due to the effect of the Arab Spring transmitting risk to own market.

Overall, Egypt is considered neither a receiver nor a giver, unlike Kuwait and Bahrain that can be considered both receivers and givers. Saudi Arabia and Turkey are like Egypt, receiver and giver of themselves more than other markets. Moreover, the results show that the UAE, Jordan, and Oman are receivers from other markets.

Objective 3: Test spillover over three subsamples that reflect different market conditions to analyse how spillover behaves in different circumstances.

Due to the significance of investigating volatility spillover, and the numerous interpretations that can be drawn from its results, and motivated by the several events that took place in the MENA region during the sample period, a narrowed analysis of subsamples is made. From the full sample results, it can be concluded that the Global Financial Crisis and the Arab Spring are the most influential events that took place, from the Spillover plot (Figure 6.34) which shows that there are peaks and fluctuations around the two major events (GFC and Arab Spring) that took place within the sample period. To investigate the impact of these different events on volatility spillover, we divide our sample into three categories, 'pre-crisis' 2003 to 2007, 'during the events' 2008 to 2013, and 'post-events' 2014 to 2018 and analyse volatility spillover for each.

The results of the subsamples provide an insight of the behaviour of the markets, along with seeing the transmission between and within the market during different market conditions. From the spillover index results, the pre-crisis period has a spillover index of 36.8%, on the other hand during the events that took place the spillover index reached 75.9%. However, post-event period spillover index decreased more than pre-crisis period showing 29%.

Pinpointing each country individually, Jordan can be seen as a country that is influenced by other markets throughout the three subsamples. Bahrain is a transmitter of spillover before and during the events by 76.2% and 65.1% respectively, mainly to Jordan, Saudi

Arabia, and the UAE. However, Bahrain is not a receiver, neither before nor after the events, but becomes a receiver during the events by 76% from Jordan, Kuwait, Oman, Saudi Arabia, and the UAE. Having a relation with Saudi Arabia up until the end of the events can be due the kingdom's largest oilfield that Bahrain found in 2018.

Egypt's spillover results are very close to the full sample results; it is an independent country that is neither receiver nor transmitter. However, during the events Egypt becomes a receiver from Jordan, Kuwait, Oman, and Saudi Arabia, and a transmitter to Turkey.

Likewise, Kuwait is not a receiver nor a transmitter pre-crisis and post-events. However, during the events it becomes a receiver from Jordan, Oman, and Saudi Arabia, and a transmitter to almost all markets. Turkey becomes a transmitter to Jordan and Saudi Arabia post-events, and a receiver from Egypt, Jordan, Kuwait, Oman and Saudi Arabia during the events. UAE is a receiver and transmitter of spillover pre-crisis and during the events, but not in post-events. Saudi Arabia is a receiver from Bahrain by 23.19% pre-crisis, while during the events it can be seen as a receiver and transmitter from almost all countries.

Overall, the results are expected for the countries that experienced the events to have the highest spillover during the crisis subsample. However, some results are not expected, such as Saudi Arabia being a receiver and transmitter to almost all countries during the events which can be due to several events that occurred either the campaigns or strikes led by Saudi Arabia against Yemen, or the political unrests in nearby countries like Egypt. Also, Egypt not being a receiver or a transmitter except during the events behaves more like an independent market. In general, whether the countries are receivers or transmitters or neither before and after the events, they all become both receivers and transmitters during the events, indicating that during volatile periods transmission increases within the region. Therefore, these few years are very critical for the MENA region with a lot of spillover transmissions.

Objective 4: Re-evaluate the results of the DY framework and assess whether their conclusions differ when the statistical significance of the estimates are taken into consideration.

Although the implemented Diebold and Yilmaz (2012) index is the most commonly used method, one of the main criticisms for this framework is that it does not identify whether or not the spillover from one market to another is significantly different from zero. In order to determine the significance of the estimates of the spillover index, the standard errors of the index and its sampling distribution are required. However, there are no simple statistical methods for the standard errors of the volatility spillover indexes.

The feasible solution used in this thesis to solve this drawback, is implementing a bootstrapping technique to find the significance of the estimates of the index. Chapter 3 discusses the bootstrapping phenomenon and compare between different methods of bootstrapping providing when to use each method. The chapter also highlights the most applicable method for this thesis which is the stationary bootstrapping. Stationary bootstrapping works well with dependent data (Choi and Shin, 2018), is used with almost all cases of dynamic models, and handles heteroscedasticity (Politis and Romano, 1994).

To see the impact of formally testing spillover indexes, we reconsidered the Diebold and Yilmaz (2012) study of the volatility spillover across US Stocks, Bonds, Commodities, and Foreign exchange market from January 1999 to January 2010.

Chapter 7 provides the statistical significance results of Diebold and Yilmaz spillover statistics that turned out not to be all significant, leading to different interpretations. The conflicting outcomes of the significance of estimates highlight the importance of testing the significance of the DY Index.

The results show insignificant spillover from commodities market to stock market (Index=0.35%, p-value=0.318) being one of the small figures across the markets. The spillover from the FX market to the stock market (Index=3.61%, p-value=0.14) is also insignificant, despite being relatively large. The commodities do not receive from stocks (Index=0.47%, p-value=0.248) or FX (Index=2.14%, p-value=0.07). The results conclude that the commodities market is the least susceptible to volatility transmission from others. The spillover from commodities market to the FX market is statistically insignificant (Index=1.55%, p-value=0.133).

Overall, Bonds receive from all three markets, FX receives from Stocks and Bonds, Commodities from Bonds only, and Stocks from Bonds only. In terms of giving, the Bonds market is again the most important, giving to all three markets, followed by stocks which give to Bonds and FX. Both Commodities and FX give to Bonds only.

Objective 5: Reconsider the results of the volatility spillover of the MENA region, and analyse whether the interpretations drawn differ when the statistical significance of the estimated spillover indexes are taken into consideration.

Taking into consideration the significance of the volatility spillover outcome in Chapter 6 and by highlighting the importance of finding the significance of the estimates, the thesis reanalyses the volatility spillover of the MENA region and finding the significance of its estimates. The results of bootstrapping the volatility spillover of the MENA region in Chapter 7 confirms some of the outcome of the index, while finding some of the results statistically insignificant.

Overall, the total spillover index 57.5% is significant for the whole region, implying that the spillover in the region exists. However, there are some estimates that were statistically insignificant between individual markets invalidating the dependency between some markets. Jordan, Kuwait, and Oman are the most influential markets reporting the highest significant spillover estimates, as well as having bidirectional relation between these three markets. On the other hand, Saudi Arabia, Turkey and UAE are the least influential and the most affected by other markets, however there are no bidirectional spillover between the three markets. Both Egypt and Bahrain can be considered to be low transmitters and low receivers

Without this formal testing it would not have been possible to draw out these interpretations. These results are inconsistent with the expectations derived from observing the strong ties between the selected countries due to the aforementioned reasons and the richness of the sample period that includes several political, economic and financial events. Thus, these results warrant further analysis to identify the reasons behind the deviations between the results and the observations. The significance level makes the spillover percentages easier to interpret, which gives the analysts or policy makers greater confidence in using these results to draw conclusions and recommendations. Another contribution from testing the significance is classifying the markets, the markets can be classified by the number of markets it transmits to and receivers from.

The split samples are reanalysed in order to validate the drawn interpretations. The 'pre-crisis' subsample contains fewer significant spillovers than the full sample, indicating that the spillover is possibly attributed to the volatile period included in the full sample. One of the interesting results is that all the spillover 'to' and 'from' Egypt and Turkey are statistically insignificant. Kuwait and Saudi Arabia do not transmit to any of the other markets, unlike in the full sample, where both transmit to and receive from other countries. During the 'pre-crisis' subsample, Bahrain, Jordan, Oman, and the UAE are the only markets transmitting and receiving risk in the region. While other markets are relatively isolated during this period. Overall, the behaviour of the MENA region markets is mostly calm and have minimal spillover.

In the 'crisis' subsample the crisis has clearly increased spillover. From interpreting the results' significance of the stationary bootstrapping, it is clear that the crises have increased the spillover between markets in the MENA region (when compared to the pre-crisis period). The total spillover index moved up from 36.8% to 75.9%, obtaining more significant relations during the crisis period rather than pre-crisis period.

Finally, the 'post-crisis' subsample the transmissions are accentuated by crises. The results are markedly different from the 'crisis' and pre-crisis subsamples. Most of the transmissions are clearly due to the volatility periods driven by economic crises and social unrest. Overall, by finding the statistical significance of the estimates of the divided samples, our study gives a more accurate insight of the spillover within the region and how economic and social instabilities affect volatility spillover.

Objective 6: Test the presence of herding behaviour in the Egyptian stock market.

In light of the previous analysis of the MENA region, and the findings that show that there is a transmission between and within the markets, there remains one important issue relating the investor behaviour. Therefore, further analysis of testing the presence of herding behaviour in the Egyptian stock market is implemented. Herding behaviour in a financial market may result from transactional and informational flows. This behaviour refers to market swings that arise from investors' correlated decisions, while ignoring their own information and following others.

Chapter 4 discusses different methods of measuring herding, and highlights the most commonly used method, namely the cross sectional absolute deviation CSAD. The scope of this thesis is narrowed in this analysis to the Egyptian stock market, since it's one of the largest developing countries (World Bank, 2020) and the market that experienced the most events (such as the Global Financial Crisis, the Egyptian Revolution, and the floatation of the Egyptian currency) throughout the sample period.

The results of Chapter 8 show that there are signs of herding behaviour in the Egyptian stock market during the full sample period. The herd behaviour is common between investors and is considered a main reason behind periods of high volatility and market instability, which can be linked to the volatility results in Chapter 6. Moreover, economists suggest that herding may lead to destabilizing prices and lead to bubble-like episodes in financial markets (Spyrou, 2013).

Objective 7: Test whether herding in Egypt is due to fundamental risk factors or due to non-fundamental factors.

Prior research does not seem to have accounted for the possibility that investor herding in Egypt is intentional or unintentional. This means that sometimes market investors could make similar investment decisions as a response to fundamental market information. Therefore, differentiating between intentional and unintentional herding is needed in order to avoid wrong interpretations about the investors and market. Unintentional herding is the result of the imitation on investors of others' actions, while with intentional herding investors don't imitate but base their reactions and decisions on public information and similar problems (Bikhchandani and Sharma, 2000).

In order to differentiate between intentional and unintentional herding, the Fama-French-Carhart risk factors are used as a representative of the fundamental factors. Since these factors are not readily available for the Egyptian stock market, they are constructed by the author. By subtracting the Fama-French-Carhart investment styles/risk factors from the CSAD, the actual herding behaviour is represented in the market from the relation between squared market returns with the remaining dispersion. The outcome of this differentiation (Chapter 8) indicates the presence of unintentional herding in the Egyptian stock market for the full sample, while there is no sign of intentional herding.

Objective 8: Test whether intentional or unintentional herding differ across different market conditions.

In normal conditions investors would have enough time to collect the required information, think rationally, analyse the market and make decisions. In distress periods, however, investors are more biased towards others' opinions and would rather follow other investors' actions. Hence, market distress decreases the time for proper information gathering, leading investors to follow rumours and herd (Mertzanis and Allam, 2018). In light of the previous analysis and results, and in order to provide more formal evidence about the existence of herding in the Egyptian market, the sample is divided into six subsamples that reflect the different market conditions that it experienced. The first subsample is the pre-crisis period which covers the period from 2005 to 2007 which is considered a stable period. The second subsample is the Global Financial Crisis (GFC) period which covers the period from 2008 to 2009. The third subsample is the Arab Spring period which represents the period from early 2010 to 30 June 2013. The end of this subsample is significant since the date of 30 June 2013 is a turning point for Egypt where the start of the second crisis begins. Therefore, the fourth subsample is the second Egyptian revolution which covers the period from 1 July 2013 to end of 2014. The fifth subsample is the economic reform which represents the period from beginning of 2015 to the end of 2016 where the government carried out a number of reform policies in an attempt to boost the economy such as the floatation of the Egyptian Pound. Finally, the sixth subsample is the post-crisis period which represents the period from the early of 2017 to the mid of 2019, where no major events took place, the economy is recovering and nearly stable.

The outcome of testing the presence of herding behaviour in the six subsamples are provided in Chapter 8. Generally, herding was not found in stable period such as the pre-crisis and post-crisis periods, while found in volatile periods. Total herding is found in the Arab Spring, Second Egyptian Revolution, and the Economic reform subsamples. These three subsamples show the presence of herding due to non-fundamental factors, while the during the second Egyptian revolution and Economic reform subsamples both show herding due to fundamental factors as well. Indicating that investors became more uncertain and continued to herd after the first Egyptian revolution.

9.3 Limitations of Research

As with any study, time, financial, and physical constraints cause the present thesis to be subject to several limitations. This thesis tests several models of volatility to determine which model best fits the sample of the eight countries representing the MENA region. It would have been interesting to include all countries within the region. However, due to limited availability of the data this was not possible. Besides, some countries, such as Iraq, Syria, Libya and Algeria have excessively small financial markets.

Investigating the volatility spillover within the region is challenging. Specifically, although previous research normally uses the DY index to measure volatility spillover, the index suffers from a number of limitations. One of the limitations of the DY index is that it does not distinguish between the potential asymmetry in spillover that originates due to bad or good news. This limitation is overcome by the use of realized semi-variance proposed by Barndorff-Nielsen *et al.* (2010) which measures the variation of the change in the asset price and reflects the direction of the change. Specifically, negative realized semi-variance and positive realized semi-variance measure volatility coming from negative and positive changes in prices (negative and positive returns), respectively. However, this requires high frequency data which is not available for all countries in the sample.

Although this thesis focuses mainly on examining volatility and volatility spillover in the eight selected markets of the MENA region, when testing the existence of herding to determine whether it is one of the reasons behind the observed in the market, this thesis narrows its analysis to the Egyptian stock market only. This can be attributed to the data limitation that constrains testing the existence of herding in other markets.

One final limitation relates to the current Covid-19 pandemic. Although this is a major crisis, by the time the crisis started in early 2020, most of the empirical work carried out in this thesis was completed.

9.4 Recommendation for Future Research

This thesis investigates volatility spillover in the MENA region, and employs the bootstrap method to test the statistical significance of the estimated spillover indexes. We show the existence of spillover between some of the MENA countries, but this depends on the pairs of countries in question and the type of event in question. Since the volatility spillover exists within the region, and the sample period involves several events, further analysis of the region is needed to capture the relation between these countries.

It is significant to stress on the implications of the findings for investors, regulators, policymakers and other interested groups. Since the findings provide more accurate information to aid global as well as local investors in achieving an efficient mean-variance frontier and to supply policymakers on which to formulate appropriate risk management strategies. Furthermore, policymakers reply on volatility analysis to learn about market expectations and uncertainty about policy, as well as understand policy tools and objectives of the analysed market. Chai *et al*. (2020) argue that their study's finding has important implications for investors and policymakers in the G20 stock markets that they examined. Indicating that they clustered into three categories and there are spillover effects in stock market co-movements of each cluster, and the dominant source of volatility spillovers can be identified from multiple markets.

First, the analysis may employ other factors such as exchange rate, oil prices, or other macroeconomic variables in order to see if these variables are the reason behind the spillover between these countries. Including a macro-economic variable such as economic growth can give an implication on how it plays a role in understanding the region, the importance of public policies which helps in portfolios diversification, especially during pandemics. Silva *et al.* (2019) study examine the spillover effect of Chinese growth on South America, their results show that expanding exports from traditional sectors of the South American economies is not enough for earnings to increase with China's growth. They emphasized the importance of public policies to diversify South America's portfolio of exports to China, such as incentives for exporting by non-traditional sectors.

Second, the analysis may extend the sample period to recent years in order to examine the effect of the pandemic of Covid-19 effect on the region and how these countries affected one another. Third, taking into account the Sustainable Development Goals (SDGs) set by the United Nations, the MENA region needs to implement economic, social, or environmental policies in order to face the coming challenges such as climate change, demographic change, political instability, urbanization, global protectionism and digitalization (Ghoneim and Vaitilingam, 2020). Hence, the region is expected to be more integrated in the coming years, which makes it interesting to analyse the effect of implementing these goals and their spillover results in the coming years. Fourth, in light of the SDGs, the analysis may extend previous studies that examine the volatility spillover from/to MENA region and other developing countries and finding the significance of the estimates by bootstrapping the index, since the development of the countries may play an important role in the development of the region.

Moreover, with Egypt setting the Vision 2030, the strategic plan to achieve sustainable development and balanced regional development, is actually an explanation of how Egypt would contribute to serve the UN agenda of SDGs. However, the success or failure of this strategic plan depends at least partially on the Egyptian market being subject to volatility spillover from other markets within the region, especially the Gulf markets. A forecast of volatility spillover from the most influential Gulf markets would therefore help policy makers in Egypt to fine tune future social and economic policies in order to reduce potential adverse effects within these markets.

One of the important determinants of economic development is the existence of an effective financial system, which varies between different stock markets across countries. Therefore, investigating volatility spillover for the MENA region which include different markets, hence, including different financial market characteristics such as market capitalisation, and list firms' ownership would enrich the analysis of the region's volatility spillover. Considering the capacity and effort measures of stock market capitalization, which consider country's characteristics that can be diagnostic tool to assess the gap between the actual level of stock market capitalization and the capacity of countries (Bayraktar, 2014).

In this context, the integration for the region has a clear vision and Egypt has a major role in this development and integration. Therefore, further analysis for the Egyptian investor behaviour is needed in coming years to include the vision 2030 implementation stages. For example, a useful study would be based on experimental data collected from individual and institutional investors in Egypt. Another example, is to test the presence of herding in the Egyptian stock market in bull and bear market conditions, since the market has been experiencing several ups and downs.

Relating herding behaviour to trading volume would also be an interesting venue for future research. This will give a more precise interpretation of the behaviour of the market. A more concentrated analysis can be further implemented by analysing the sectors of the market, by dividing the firms into sectors and testing the existence of herding behaviour industry-wide or market-wide. More specifically seeing the effect of the sectors in the economy for example the Healthcare sector which with no doubt is very interesting to examine during these years with the raise of the Global pandemic (Covid-19).

Another further research may include differences in herding between institutional or individual investors. Little previous studies have focused on formally investigating the herding behaviour of each of these investors separately (Li *et al*, 2017). Hence, these are two different types of investors with different characteristics therefore, the herding behaviour may be different for each.

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