Macroeconomic Variables, Oil Prices and Seasonality: Three Key Issues Empirically Investigated for Islamic Stock Market Indices

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Abstract

In the world of finance, the emergence of Islamic finance has led to many Islamic financial products and services. Access to professional fund managers who specialize in forming portfolios that fulfil the needs of Muslim investors to trade in investments that do not violate their Islamic principles and rules is now commonly available in both Muslim and non-Muslim countries. Islamic stock market indices (ISMI) have also been established. This thesis consists of three self-contained empirical essays that focus on important financial issues for Muslim investors: (1) the empirical support for orthodox asset pricing models when applied to Islamic stocks; (2) the volatility of Islamic stock market indices and the relevance of oil to this volatility; and (3) seasonality in an Islamic stock market. In addition, each empirical essay compares the findings of ISIM to those of an appropriate counterpart conventional stock market index (CSMI).

The findings firstly demonstrated that ISMI can be exposed to different risk factors from those proposed by previous empirical works on CSMI. Secondly, the statistical results established that ISMI proves to be a safe investment during the oil market turbulences contrary to CSMI. Thirdly, the last empirical essay found out that the emergence of ISMI in the non-Muslim countries can bring about another calendar anomaly or at least change the effect of an existing one such as Friday effect.

The general conclusion to be drawn from the findings of the whole thesis is that there are variations between ISMI and CSMI in the way they react towards the same exogenous variables. This is despite the fact that previous studies failed to find significant differences between them in terms of performance, and merely observed that investors lose nothing by restricting themselves to ISMI.

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Chapter 1: Introduction

1. Background

In the world of finance, the emergence of Islamic finance has led to many Islamic financial products and services. Access to professional fund managers who specialize in forming portfolios that meet the needs of Muslim investors to trade in investments that do not violate their Islamic principles and rules is now commonly available in both Muslim and non-Muslim countries. Islamic stock market indices (ISMI) have also been established. This thesis consists of three self-contained empirical essays that focus on important financial issues for Muslim investors: (1) the empirical support for orthodox asset pricing models when applied to Islamic stocks; (2) the volatility of Islamic stock market indices and the relevance of oil to this volatility; and (3) seasonality in an Islamic stock market. In addition, each empirical essay compares the findings of ISIM to those of an appropriate counterpart conventional stock market index (CSMI).

First of all, the term ‘Islam’ is the name of the religion that was revealed by Allah (God) to the Prophet Mohammed (peace and blessings be upon him). Islam is an Arabic word that linguistically means “submission, humbling oneself, and obeying commands and heeding prohibitions without objection, sincerely worshipping Allah alone, believing what He tells us and having faith in Him”.

The Quran and the Sunnah are two revelations that represent the main sources of Islam upon which all beliefs, principles and rulings are based. The Quran is a holy book that contains only the words of Allah, and the Sunnah is formed from the words, deeds and approvals attributed to the Prophet Mohammed (pbuh). The secondary sources, to which the texts of the main two sources refer, are the scholarly consensus (*Ijmaa’*) or the analogy (*Qiyaas*). These sources, the main and the secondary, together form what is called “*Shari’aah*” - Islamic law.

Islamic rulings can only be generated from these authentic sources. The importance of that is explained by a great Muslim scholar Imam Al-Shaafa’i (may Allaah have mercy upon him), who said: “no one has any right whatsoever to say that something is acceptable (*Halal*) or prohibited (*Haraam*) except on the basis of knowledge, and the basis of knowledge is a text in the Quran, Sunnah, Ijmaa’ or Qiyaas.”

Therefore, the Islamic rulings on finance and investments must be in accord with these sources of Islam. Muslims are expected to submit themselves to the Islamic rulings and obey them. In turn, there are two guaranteed rewards that Allah promises Muslims for obeying the Islamic rulings: one is promised to be given in this life, and the other for the hereafter. These two rewards are not mutually exclusive. In fact, Muslims are encouraged to practice the deeds that can grant them both rewards. Hence, in regard to finance and investment, maximizing profits is not the only objective of the Muslim investor; they seek to please God and be rewarded in the hereafter, in addition to the materialistic profits of trading. This double goal is achieved by investing in Shari'aah-complaint investments.

The major principle in Islam is that all trades and transactions are permissible unless there is evidence from Shari'aah to show that they are forbidden. Muslim scholars have the responsibility to explain the rulings of Islam to laymen in every aspect of the religion, including the field of finance and investment. People with the knowledge of Islamic finance and economics are motivating and encouraging the establishment of Islamic funds and investments. The Islamic funds have been growing rapidly in recent years. Meanwhile, Muslim scholars, in line with practitioners, have greatly contributed to Islamic finance by screening the available investment opportunities in major international stock markets in order to provide Muslim investors and fund managers with an acceptable field of stocks in which to invest. Screening aims to identify Shari'aah-complaint assets (based on the scholars' knowledge of Shari'aah), so people can invest in them and avoid the others.

In response to the rapid proliferation of Islamic financial services, the global investment community has begun to respond to the potential of the Islamic market. Thus, since the establishment of Islamic equity funds in the early 1990s, the Dow Jones Islamic Market index (DJIM) was developed (among others) as a credible equity benchmark in 1999[1] to provide an Islamic investment vehicle with which to examine the performance of the Islamic equity funds. The DJIM in essence is a specialized ethical index that screens out prohibited stocks, as defined by Shari'aah law, and it is monitored by Muslim scholars.

Since the establishment of the official Islamic stock market indices in the West in particular, there has been an increasing need for empirical tests on them. In this thesis, the stock market index that screens stocks for Shari'aah compliance is called the Islamic

[1] This index can be tracked historically back to 31 Dec 1995.

Stock Market Index (ISMI), whereas the other standard stock market that does not have any restricted rules based on beliefs or faiths is called the Conventional Stock Market Index (CSMI). ISMI and CSMI can coexist in one market and one economy, but the subject to be investigated is what differences exist between them in practice.

The initial subject of Islamic finance that has risen and attracted researchers in the literature of finance is the issue of the performance of the Islamic funds in contrast to their counterpart conventional funds. However, this subject of performance has already been empirically investigated by a number of studies (Hakim and Rashidian 2002; Hakim and Rashidian 2004; Hussein 2004; Abdullah, Taufiq et al. 2007). The overall findings indicate that ISMI does not always underperform the broader index, nor do Islamic funds underperform conventional ones. Instead, the general consensus is that investors are losing nothing by restricting themselves to invest only in Shari'aah-complaint stocks

Similar to the Islamic funds, the socially responsible funds screen stocks based on socially responsible values and beliefs. Also, empirical studies investigating these funds argue that socially responsible funds do not necessarily always underperform conventional funds. Instead, these studies seem to infer that investors lose nothing by investing in social responsible funds in contrast to non-ethical funds (Luther, Matatko et al. 1992; Hamilton, Jo et al. 1993; Mallin, Saadouni et al. 1995; Gregory , Matatko et al. 1997; M'Zali and Turcotte 1998; Reyes and Grieb 1998; Bauer, Koedijk et al. 2005).

Forte and Miglietta (2007) investigated whether the Islamic funds can be classified under the socially responsible funds category. In other words, they attempted to explore the similarities and differences of the two types of screened portfolios using quantitative and qualitative measures. Their main conclusion was that Islamic and socially responsible portfolios show evidence of different characteristics.

In light of what has been found in the literature, the hypothesis that remains to be empirically investigated is that the ISMI and CSMI cannot be different in terms of responding to exogenous effects such as macroeconomic variables, oil price changes and seasonality. Therefore, this thesis focuses on examining this hypothesis by conducting three main empirical essays.

These essays are concerned with investigating the effects of three main subjects: macroeconomic variables, oil price changes and Islamic calendar anomaly on ISMI and

CSMI alike. Each empirical essay investigates one topic in a separate chapter. The outline of thesis is presented in the following section.

2. The Outline of the Thesis

2.1 Chapter 2: An investigation of the sensitivity of the Islamic stock market index towards the systematic risk factors using asset pricing models

Although Islamic finance has increasingly become popular in the financial sector, limited empirical studies have been conducted investigating particular aspects of this new financial field, one of which is the empirical investigation of ISMI sensitivity towards systematic risk factors in comparison to CSMI. It is assumed that Islamic portfolios are in nature associated with low default risk, and prospective investors consequently shall not receive default risk premiums. Hence, the employed default-related risk factors should be only significant in explaining the returns on the conventional portfolios.

In this chapter, the empirical essay employs a variant of Fama and MacBeth's (1973) technique to estimate Capital Asset Pricing Model (CAPM), introduced by Sharpe (1964), Lintner (1965) and Black (1972), Arbitrage Pricing Theory (APT), introduced by Ross (1976), and Fama and French Three Factor Model introduced by Fama and French (1993). These asset pricing models are employed to empirically investigate the sensitivity of the conventional and the Islamic portfolios proxied by S&P500 and Dow Jones Islamic Market US (DJIM US) indices towards the systematic risk factors. Monthly data are employed covering the period from 1996 to 2008.

The findings of this chapter explore some differences between the two indices that are worth knowing for investors, portfolio managers and policy makers. The findings confirm that the default-related risk factors are only significant in explaining the returns of the conventional portfolios; hence, Islamic portfolios are empirically considered less risky to default. There are two main contributions offered by this empirical study to the financial literature about Islamic finance. The first contribution is to examine the sensitivity of Islamic portfolios towards the systematic risk factors for the first time. The second is to record the differences between the Islamic and conventional portfolios in terms of sensitivities towards systematic risk factors.

2.2 Chapter 3: A GARCH examination of the oil effects on the Islamic and conventional stock market indices

The relationship between oil prices and economic growth is believed to be an existing fact. However, this relationship varies between countries according to the dependency of each country on oil, and whether the country is an oil consumer or supplier. Recent major events occurring in the world economy as a result of oil price shocks, alongside the emergence of Islamic finance, have been the main motive to explore how the newly emerging Islamic funds fit in the world economy.

Examining the reaction of ISMI towards the boost in the oil market and comparing it to the reaction of CSMI is the aim of this chapter. Furthermore, the state of the oil consuming and producing economies is explored by looking at how stock markets function in each state of economy. Therefore, this chapter empirically examine the link between oil price changes and the expected return and volatility of three stock markets indices; TASI, S&P500, and DJIM US[2]. These three indices were deliberately chosen to be proxies for three different stock markets; two of them represent the conventional markets of oil-producing and consuming countries, and the last represents an Islamic market. WTI spot price (West Texas Intermediate, also known as Texas Light Sweet) is used to represent the oil prices. The main finding is that the oil return surprisingly exerts an insignificant effect on ISMI. However, significant effects are exerted on CSMI.

This study contributes three main things to the literature. The first is to examine the effects of crude oil prices on ISMI for the first time. The second is recording the differences between ISMI and CSMI in terms of the oil price effects. The third is to examine the effect of oil prices on the CSMI of both oil-exporting and importing countries. Due to the limited availability of the ISMI, only one Islamic index is examined in this study.

2.3 Chapter 4: Day-of-the-week effect on the Islamic and conventional stock markets - evidence from GARCH models

Seasonality[3] has increasingly attracted many researchers' attention in the literature of finance due to its potential effect of generating abnormal returns in the equity markets

[2] TASI stands for Tadawul All Share Index, which is the Saudi stock market index; S&P500 is the Standard and Poor's 500, and DJIM US is the Dow Jones Islamic Market Index in the United States.
[3] Seasonality can also be referred to by the term "Seasonal component"

(Mills 1992). It is required that the capital market returns should be characterised in such a way that all subsequent returns represent random departures from the previous one (Dimson 1988). The existence of seasonality is a violation of this requirement.

This chapter focuses on the day-of-the-week effect (DOWE), one of the most common calendar anomalies. In the Islamic calendar[4], Friday is the Muslim holy day (and part of the weekend in some Islamic countries), although it is an open trading day in the Western markets. On Friday, Muslims tend to be occupied with Islamic rituals and social activities. This overlap between religious activities and trade can have a potential impact on ISMI that are functioning on Friday.

The holiness of Friday, in addition to the fact that it is an open trading day, form the basis of this chapter. It is expected that the market on Friday may suffer from less liquidity due to the fact that Muslim investors are expected to be engaged in religious activities rather than trading in the market. Consequently, less liquidity in a market can drive stock prices to decline (Amihud and Mendelson 1991).

This empirical study employs GARCH and GARCH-M models to investigate DOWE in the Dow Jones Islamic Market Index in the US (DJIM US) with its 10 sub-indices, and the popular conventional index the Dow Jones Industrial Average DJIA. The latter is utilised to explore the differences between ISMI and CSMI in terms of the Friday effect. The main finding is that ISMI exhibits different characteristics from its conventional counterpart in terms of seasonality, and that Friday can be a true source of seasonality in ISMI. The main contributions of this chapter to the literature are two. The first contribution is to examine the effects of Friday as a Muslim holy day on ISMI for the first time. The second is recording the differences between ISMI and its counterpart CSMI in terms of DOWE.

2.4 Chapter 5: Summary and conclusion

This final chapter sums up the thesis by summarising the aim of each empirical chapter and its findings then drawing conclusions from the findings presented in the thesis.

[4] More details about Islamic calendar and Friday are presented in section 2.

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Chapter 2. An investigation of the sensitivity of the Islamic stock market index towards the systematic risk factors using asset pricing models

1. Introduction:

A major question in finance is what determines the price of risky assets such as stock prices. A number of competing popular theories answered the question giving different viewpoints about the risk factors that should be rewarded in the stock expected returns. The first one is the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Treynor (1961), Lintner (1965) and Mossin (1966) . It is an equilibrium model that gives the equilibrium relationship between risk and return under certain assumptions. Assuming investors hold the efficient market portfolio, CAPM states that the market portfolio risk is the only systematic risk that should be rewarded in the stock’s expected return. Hence, investors would be compensated only for the market risk, and any unsystematic risk that is specific to individual stock should be cancelled out through diversification. The major challenge for CAPM known in the literature as Roll’s critique (1977) is that the market portfolio is unobservable and hence CAPM cannot be really tested. Furthermore, empirical evidence in the real world failed to support CAPM leading to the introduction of other asset pricing models.

Alternatively, Ross (1976) introduced another asset pricing theory called Arbitrage Pricing Theory (APT). According to APT, in the state of equilibrium the capital market should have no room for arbitrage opportunities. Hence, APT model requires the absence of arbitrage opportunities to reach equilibrium, whereas CAPM depends on observability and efficiency of the market portfolio. APT is more general and less restrictive than CAPM allowing the systematic risk to be represented by more than one factor and that the expected return of a stock can be modeled as a linear function of various systematic risks factors. Although, APT does not require identifying the market portfolio, the systematic risk factors remained unidentified. However, a popular study by Chen, Roll et al. (1986) (hereafter CRR) identified a set of macroeconomic variables to be the systematic risk factors based on a financial theory and empirical evidence. They observed that innovations in macroeconomic variables are rewarded in the stock market.

Focusing more on the firm's specific risk factors rather than macro variables related to the economy as a whole, Fama and French (1993) introduced Fama and French Three-Factor Model (FF) another competing theory that contributed significantly to the asset pricing modelling. Initially, Fama and French (1992) observed that small firms and high book-to-market firms tend to have high return, on average. Then, they found that the factors related to size and book-to-market value (B/M) perform well in explaining stock returns, while the CAPM beta failed to fully explain the stock returns. Subsequent articles by Fama and French (1995; 1996; 1998) confirmed that FF-model does a good job in explaining stock returns.

Later on, He and Ng (1994) investigated whether FF-factors proxy for CRR multifactor model. They found that CCR variables, the term and default risk factors in particular, lose their explanatory power in the presence of size and B/M. On the other hand, Fama and French (1996) argued that size and B/M are proxies for default risk and financial distress. However, Vassalou and Xing (2012) confirmed that size and B/M are intimately related to default risk and that their effects are compensation for the high default risk that small and high B/M stocks exhibit. Overall, it can be seen that risk factors related to default and financial distress are important and significant in pricing risky assets.

In 1990s, the emerge of the Islamic finance has led to the introduction of Islamic portfolios investing in risky assets that are compliant with Islamic rulings. These portfolios have been rapidly expanding and getting popular leading to the establishment of Islamic stock market indices (ISMI), particularly in the western stock markets. An example of ISMI is the Dow Jones Islamic Market Index (DJIM) that tracks the performance of the Shari'aah[5]-compliant stocks. DJIM screens broader indices based on two main criteria; the business activity and financial accounting ratios. Hence, fewer selected stocks pass rules-based screening for Shari'aah compliance. The ratios aim to ensure that dividing each of total debt, the sum of company's cash and interest-bearing securities, and accounts receivables by trailing 12-month average market capitalization does not exceed 33%. This is considered as a debt limitation excluding all the stocks with more than moderate debt resulting in limiting the risk factors in ISMI[6].

[5] Shari'aah is an Arabic term that means Islamic law.

[6] This is taken from an Article published in Dow Jones Islamic Index Newsletter by Michael Gassner, a Vice-President Islamic Financial Engineering at Bank Sarasin & Co. Ltd. He is a member of the Editorial Board of the

The Islamic rulings seem to characterise the Shari'aah-compliant stock with being low risky to default. To justify this, the Islamic accounting restrictions ensure low debt proportion narrowing the range of ratios across the stocks to vary below 33%. Given the fact that default risk can be defined as the firm's failure to meet its financial obligations, hence the low debt proportion means fewer financial obligations which in turn imply lowering the exposure to the default risk. Another justification, based on facts, is that DJIM ejected three major companies (Tyco, Enron and WorldCom), between 2001 and 2002[7], months before they went bankrupt and collapsed. They were removed from the index due to their violations to the Islamic selection criteria.

An ejection from the index means the stock is not anymore in compliance with Islamic rules; in turn, Islamic investors and fund managers will sell off their shares in that particular stock. The Islamic portfolios managed to come out unscathed from the bankruptcy of these three companies saving their ordinary investors millions of dollars. Effectively, stocks listed in ISMI can be characterised with being less risky to default which can indicate that the default related risk factors should be insignificant in explaining their expected return.

Therefore, this chapter estimates CAPM, FF and APT models to test whether the systematic risk factors proposed by major asset pricing models are also important factors for pricing the Shari'aah-compliant stocks. To conduct the tests, equity Islamic portfolios are used, and parallel models are estimated for conventional counterpart portfolios that are unrestricted and free of Islamic screenings for comparison purposes. For APT model, CRR multifactor model is used. The samples to be tested are extracted from two stock market indices operating in the same country and economy, the U.S. The Islamic portfolios are formed by stocks listed in DJIM US (Dow Jones Islamic Market US), a sub-index containing only Shari'aah-compliant US companies, and the stocks in the conventional portfolios are taken from S&P500. The sample data are monthly covering the period from 1996-2008.

This chapter is motivated by the fact that investors restricting themselves to Shari'aah-compliant investments are not supposed to invest in the risk free securities such as the

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'International Journal of Islamic and Middle Eastern Finance and Management' and Advisory Board Member of the 'Dow Jones Islamic Market Index Newsletter.' He publishes and speaks frequently on Islamic finance issues.

[7] According to R. Siddiqui, Global Director of the DJII- Dow Jones Islamic Indexes http://tyo.ca/islambank.community/modules.php?op=modload&name=News&file=article&sid=1418. Also,http://www.islamic-banking.com/resources/7/NewHorizon%20Previouse%20Issues/NewHorizon_JanMar09.pdf.

bonds and treasury bills because they are not Shari'aah-compliant. This shows that although Shari'aah-compliant stocks are low risky to default, holders of Islamic portfolios remain exposed to risk that is higher than for other investors who can lower their risk exposure by investing in the risk-free assets. Therefore, it is interesting to empirically investigate whether holders of Islamic portfolios will be compensated for this risk exposure by the employed risk premiums. Failure to be compensated by the employed risk premiums does not rule out the possibility that Islamic investors are compensated for this risk, but instead other unknown factors to be identified may perform better in explaining the returns on Islamic portfolios.

The following section presents an overview of this chapter, including brief information on DJIM US. The third section defines and gives details about the asset pricing models. The fourth section reviews the literature, and then sections 5 and 6 explain the data and the econometric methodology (respectively). Section 7 presents the actual empirical results expressed in figures and tables, the analysis and discussion of the results. The final section concludes the study, summarising its results and the findings interpretations.

2. An overview:

This section aims to provide general information related to this study. It contains two subsections, the first one briefly talk about the background information on Islamic finance and Islamic funds. The second provides brief information on DJIM and its establishment. The last explains the motive of this empirical study.

2.1 Background Information:

In the new global financial structure, Islamic finance has become an important aspect concerning many financialists and researchers. The basic distinction of Islamic (Shari'aah) law in finance is the prohibition of charging interest and engaging in interest-based investments. The conventional interest-based investments have been dominating the world trades; hence, Muslim investors have had fewer investment opportunities than the conventional investors. The Islamic rules, other than interest-based trading activities, have also further restricted and minimized the investments opportunities including the restricted trades in the stock markets for Muslim investors.

In recent years, however, Muslim scholars agreed on conditional investments in equity markets, and since then Islamic funds have emerged fulfilling the necessary conditions to provide the Muslim investors with an acceptable field of stocks to invest in. There were 297 Islamic equity funds in 2007, with assets of $17.33 billion, compared to 29 firms with assets of $800 million in 1996, according to a presentation given by Al-Rifai (2003)[8]. Gulf Cooperation Council (GCC) investors investing in GCC markets were responsible for this sharp rise, according to Mark Smyth, Failaka's Managing Director. Of the three hundred existent Islamic equity funds, 125 are based in Asia and 120 in the GCC. 75 of the funds in the GCC are in Saudi Arabia.

As a result, Islamic funds and finance have become increasingly important part of the world of finance. The importance of the Islamic financial market is considerable, with an estimated $1.2 trillion[9] of private liquidity in the GCC, to say nothing of potential funds in other Islamic areas such as Turkey, Malaysia, Indonesia, Brunei, and in expatriate Muslim communities in South Africa, North America and Europe.

In response to the rapid proliferation of Islamic financial services, the global investment community has begun to respond to the potential of the Islamic market. Thus, since the establishment of these Islamic equity funds in the early 1990s, the Dow Jones Islamic Market index (DJIM), among others, was developed as a credible equity benchmark in 1999[10] to provide an Islamic investment vehicle with which to examine the performance of the Islamic equity funds. The DJIM in essence is a specialized ethical index that screens out prohibited stocks, as defined by Shari'aah law, and monitored by Muslim scholars. If the DJIM index removed a certain company, all the Islamic portfolios would have to follow by selling off all of their shares in that company. Hence, having restrictions on the stock screening process based on Shari'aah law is theoretically expected to affect the Islamic portfolios, but in ways that are still only vaguely defined.

2.2 The Dow Jones Islamic Market Index:

DJIM is a subset of the Dow Jones Global Indices (DJGI) family, which includes stocks from 47 countries. It is an Islamic equity benchmark index. Besides, the Dow Jones Islamic Market family itself includes global, regional, national, industrial and market-

[8] A presentation delivered in Islamic Equity Fund Workshop 2003 called *An overview of Islamic finance and the growth of Islamic funds* by Tariq Al-Rifai.
[9] According to the International Real State Finance Summit 2008 (*Access to the GCC, Islamic direct equity and finance*) http://www.islamicrealestate.com/rationale.html
[10] This index can be tracked historically back to 31 Dec 1995.

cap-based indexes. One of the listed major indices in the family of DJIM is the U.S Indices. The U.S Islamic indexes include DJIM US, DJIM US Large-Cap Index, DJIM US Mid-Cap, and DJIM US Small-Cap.

DJIM excludes any stock whose company's primary business is impermissible according to Shari`aah law. The DJIM intends to measure the equity that passes the screens for Shari'aah compliance. The index is maintained based on a strict and published methodology. An independent Shari'aah Supervisory Board counsels Dow Jones Indexes on matters related to the compliance of index-eligible companies. The components of DJIM are selected by filtering the index based on two main criteria. The first criterion screens for business activities, the second for financial ratios. The aim of these screens is to remove from the index any stock that is not considered to be a Shari'aah-compliant investment. Non-Shari'aah-compliant business activities include alcohol, tobacco, pork-related products, conventional financial services (banking, insurance etc.), weapons and defence, and entertainment (hotels, casinos/gambling, cinema, pornography, music etc.). After excluding companies with unacceptable primary business activities, the remaining stocks are evaluated based on the condition that all of the following ratios must not exceed 33%:

• Total debt divided by trailing 12-month average market capitalization.

• The sum of a company's cash and interest-bearing securities divided by trailing 12-month average market capitalization.

• Accounts receivables divided by trailing 12-month average market capitalization.

The composition of DJIM is reviewed quarterly, with changes being implemented on the third Friday in March, June, September and December. Market data from the end of January, April, July and October are used as the basis for the revision process. Changes to the index are implemented after the official closing values have been established. All adjustments are made before the start of the next quarterly cycle.

In addition to the quarterly and annual composition reviews, the Dow Jones Islamic Market Index is reviewed on an ongoing basis. A change in the index is necessary should an extraordinary event such as a delisting, bankruptcy, merger or takeover affect an index component. In these cases, the event is taken into account as soon as it becomes effective. In exceptional cases, the usual one-week announcement period may be shortened.

DJIM US is the index that is used in this study. It tracks stocks traded in the U.S. that pass rules-based screens for compliance with Islamic investment guidelines.

3. The asset pricing models: CAPM, APT and Fama and French Three-Factor Model:

Trading financial assets are different from trading any other ordinary commodities. For example, stock prices are not fixed even in the very short-run and hence cannot be determined by the well of its owners. The prices in the stock market tend to move up and down in a way that can be explained by external forces. The uncertainty in the expected change in prices is considered risk, and external forces responsible for the change will be the risk factors. What risk factors can determine the price of risky assets has been a major question concerning researchers in the field of financial economics. A number of competing theories of asset pricing then emerged to answer this fundamental question.

Before the arrival of the first asset pricing model, Markowitz (1952) developed the Modern Portfolio Theory (MPT)[11] laying the foundation for building asset pricing models. MPT, commonly referred to as the mean-variance analysis, introduced two assumptions:

1- Investors are risk-averse individuals and mean-variance optimisers.

2- The market is perfect and frictionless where there are no market imperfections such as taxes, transaction costs, information costs or restrictions on short selling.

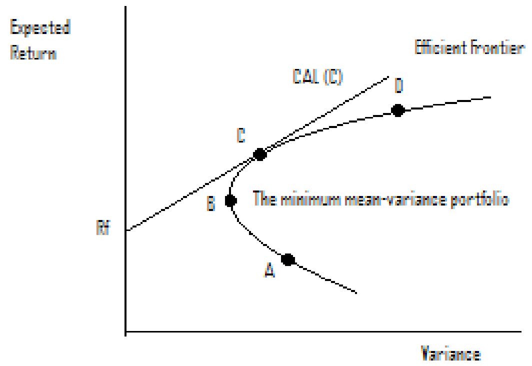
Hence, investors select the mean-variance efficient portfolio of risky assets in the sense that the portfolio 1) minimises the variance of its return, given expected return and 2) maximises the expected return for a given variance (level of risk). When investors can lend and borrow at the risk-free rate, they will rationally lower their risk exposure by investing a proportion of their wealth in the risk-free asset whereas the rest invested in the efficient portfolio of risky-assets. The expected return of any such investment portfolio is hence linear in the variance of its returns. As shown in Figure below, the set

[11] MPT is considered to be one of the cornerstones of the financial theory that has been mentioned in the reward of two Nobel Prize in economics offered to James Tobin in 1981 and Harry Markowitz in 1990

of investments portfolios that combines the risky and risk-free assets can be represented by deriving the Capital Allocation Line (CAL). This straight line involves the risk-free asset with Portfolio C which is the mean-variance efficient portfolio (called the tangency portfolio) that maximises the reward-to-risk ratio (known as Sharpe ratio). Thus, the expected return of any portfolio lies in CAL can be given by

$$E(R_i) = R_f + \sigma_i\left[E(R_C) - R_f\right]/\sigma_C \qquad (1)$$

Where $E(R_i)$ is the expected return of portfolio i, R_f is the risk-free rate of return, $\sigma_i$is the portfolio i standard deviation (total risk), $E(R_C)$ is the expected return on the tangency portfolio, and σ_C is the portfolio C's standard deviation. Sharpe ratio to be maximised is given by the term on the right $\sigma_i\left[E(R_C) - R_f\right]/\sigma_C$.



In Figure above, the preferred location of an investor's investment portfolio would depend on their level of risk-aversion. The more risk-averse the investor the higher the proportion they would invest in the risk-free asset. Any location between the risk-free asset and the tangency portfolio would mean that the risk-averse investor split their wealth between the two. Any location beyond and above the tangency portfolio means that the investor is not risk-averse, so they borrowed more money at the risk-free rate and invested more in the tangency portfolio. Thus, the tangency portfolio (the mean-variance efficient portfolio) is an essential requirement to implement the risk-expected return relation. According to MPT, the tangency portfolio can be constructed if accurate estimation of expected return, variance, and covariance of every asset could be obtained. Practically, however, constructing such portfolio from observed historical returns on large number of assets seems impossible. Instead, a theoretical model was necessarily required to provide the best estimates by identifying the tangency portfolio from sound theoretical assumptions.

3.1 Capital Asset Pricing Model (CAPM):

CAPM, the first coherent model providing the equilibrium risk-expected return relation, was developed by Sharpe (1964), Treynor (1962), Lintner (1965) and Mossin (1966). This model was a major development in the modern capital market theory for which William Sharp was awarded a Nobel Prize in 1990[12]. It identifies the tangency portfolio as the market portfolio which can be easier proxied by a stock market index.

CAPM adds three assumptions to those introduced by MPT:

1- investors can borrow and lend unlimited amount of money at the risk-free
2- Investors gave the same single period investment horizon.
3- All investors and fund managers are price takers and have homogenous beliefs sharing the same views about expected returns and risk “the variance” so they all will choose the tangency portfolio because it maximises the Sharpe ratio.

Besides, equilibrium in capital markets requires that demand for risky assets equal its supply, whereas supply for risky assets is summarised in the market portfolio the one that comprises all assets. As far as the two fund separation theorem is concerned, investors hold efficient portfolios so that all investors hold risky assets in the same proportions dictated by the tangency portfolio due to the assumption of homogenous beliefs. For demand to equal supply in capital markets, the market portfolio must be constructed with identical proportions of the tangency portfolio. This implies that the tangency portfolio must be the market portfolio.

CAPM’s main contribution is that any individual stock has two component of risk; unsystematic risk that is specific to each individual stock which can be diversified away; and systematic risk that is associated with the market as a whole and cannot be diversified. As investors hold many assets in well-diversified portfolios the unsystematic risk vanishes through diversifications. What remains is the systematic risk that investors should be compensated for. According to CAPM, the mathematical presentation of the equilibrium risk-expected return relation is given by

$$E(R_i) = R_f + \beta\big(E(R_m) - R_f\big)$$

[12] Sharp (1964) shared the Nobel Prize with Lintner (1965).

$E(R_i)$ is the asset's expected return (the cost of equity), R_f is the risk free rate of return, β_i (beta) is the sensitivity of the stock's expected return towards the market risk which equals $\frac{\sigma(R_i,R_m)}{\sigma^2(R_m)}$, $E(R_m)$ is the market portfolio's expected return, and $\left(E(R_m) - R_f\right)$ is the market risk premium that equals the market portfolio's excess expected return over the risk free rate.

CAPM simply explains that the stock expected return should equate the risk free rate plus the coefficient β multiplied by the market risk premium. Therefore, the expected return on a particular investment is determined based on its contribution to the market portfolio's risk. According to CAPM, its market beta is the only systematic risk factor represented by the covariance between the asset's return and the market portfolio's return (Sharpe 1964). The beta hence is used in the asset pricing models as the slope on the market risk premium that should be positive and significantly different from zero.

Although the assumptions seem to be unrealistic in practice, CAPM has become popular and useful as a tool for capital budgeting and obtaining the required rate of return to evaluate corporate investment projects. For a company to evaluate a new proposed project, it can use the required rate of return obtained by CAPM to calculate the project's present value (PV) by discounting all its future cash flows using the following formula:

$$PV = \frac{D_1}{(1+R_i)} + \frac{D_2}{(1+R_i)^2} + \cdots + \frac{D_n}{(1+R_i)^n} \qquad (2)$$

Where PV is the present value of an asset. D is the dividend representing the cash flows that the asset holder receives. R_i is the opportunity cost of capital that is needed to discount the cash flows. If beta is known, the unknown R_i can be obtained by CAPM where this rate of return is going to be the minimum return that the project should earn. Also, CAPM can be used in regulated utilities pricing where it helps to determine the extent to which the public utilities can change the prices of goods and services.

The ability of CAPM to accurately predicted the required rate of return attracted the attention of many financial economists. A large number of empirical studies, investigating the validity of CAPM, examined the extent to which the expected return predicted by CAPM fit the data (Friend and Blume 1970; Black, Jensen et al. 1972; Blume and Friend 1973; Blume and Husick 1973; Fama and MacBeth 1973; Stambaugh 1982) among many others. Using a test similar to the one developed by Fama and

MacBeth (1973) the CAPM validity was also examined in an Asian stock market, Yan-Leung and Ka-Tai (1992) empirically test CAPM in the Hong Kong stock market for the period from 1980 to 1989. They found the evidence of CAPM is very weak. Ho, Strange et al. (1998/9) re-examined CAPM in the context of the Hong Kong stock market using an extended version of Fama and MacBeth (1973) model which most of the studies are using. They compared their results with those of Yan-Leung and Ka-Tai (1992), and concluded that their evidence is inconsistent with CAPM.

In conclusion, it can be said that the empirical evidence in general is not in favor of CAPM and that CAPM does not agree well with reality when using the real world data. This empirical failure of CAPM does not mean the model is fundamentally incorrect since the testing procedure of the model was criticised for some methodological and technical problems which may lead to incorrect results and conclusions. Roll (1977) criticized previous studies of the CAPM applicability in the real world data and indicated that CAPM can be tested only if the true market portfolio is used, and that previous tests in fact are just testing the mathematical hypothesis that the stock index is mean-variance efficient.

Roll's critique (1977) was actually the main problem challenging CAPM. Roll's critique emphasized that, since the market portfolio is unobservable, the proxy may fail to truly represent the actual market portfolio by omitting some assets that cannot be included in the proxy. This critique implies that CAPM cannot be tested due to the problem of finding the true market portfolio. Another related problem is called "the benchmark error problem" where the proxy sometimes happens to be inefficient while the true market portfolio is efficient or the vice-versa. In addition, the unrealistic assumptions of CAPM represent another criticism and problem.

3.2 Arbitrage Pricing Theory (APT):

APT model, introduced by Ross (1976), is a popular asset pricing model based on the non-existence of arbitrage opportunities. Arbitrage is a central concept to the capital market theory which means the possibility of exploiting the mispricing asset to generate profits without undertaking risk. APT has become widely accepted due to its usefulness of explaining the cross-sectional variation in the stock returns.

Given the impossibility of empirically verifying the CAPM model, APT, a less restrictive in terms of assumptions, came as an alternative model for asset pricing.

Capital market theory explains that equilibrium market prices are rational in a way that they will rule out the riskless arbitrage opportunities. The difference between CAPM and APT is the fact that the latter is more general than CAPM in terms of the description of equilibrium and accepting a variety of different risk factors.

In terms of description of equilibrium, APT relies on the absence of the free arbitrage opportunities, whereas CAPM depends on the observability and efficiency of the market portfolio. In other words, APT is based on the law of one price which states that in efficient market all identical goods must have a one single price; hence, they cannot be sold at different prices. In equilibrium, all available portfolios under consideration that use no wealth and undertake no risk must generate no return on average (Copeland, Weston et al. 2005). But, in the case of CAPM, each asset must be priced so that its risk-adjusted required rate of return falls exactly on a straight line called Security Market Line which relates the expected return to the only systematic risk “beta” (ibid).

In contrary to CAPM, the second difference is in regards to the modelling of different risk factors. APT states that there are other ways to measure the systematic risk other than beta; however, APT does not identify exactly what the other sources of systematic risk are. In APT, arbitrage takes place when trading two identical assets having at least one being mispriced. The arbitrageur can short sell the more expensive, and then buy the cheaper one. According to APT, an asset is considered mispriced when its current price differs from the one predicted by the model. Thus, the value generated by discounting all future cash flows of the asset using the rate estimated by APT should be equal to the current price of the asset.

In fact, APT relates the expected return from an asset to the return from a risk free asset plus the return of a series of risk premia for systematic risk factors. Before introducing the notion of absence of arbitrage, the basis of APT is the assumption that the stock returns can be explained by a multifactor model represented by the following equation(3)

$$R_i = \alpha_i + \beta_{i1}F_1 + \beta_{i2}F_2 + \cdots + \beta_{in}F_n + \varepsilon_i \tag{3}$$

Where R_i is the return on asset *i*, α_i is the constant term, β_{i1} denotes the sensitivities of stock *i* to the relevant risk factor 1, F_1 denotes the realisation of the employed risk factor 1, ε_i denotes the stock return’s surprise.

With the absence of arbitrage opportunities, equation (4) represents the statement of APT telling how in equilibrium the expected return on asset will be.

$$E(R_i) = \gamma_0 + \gamma_1 \hat{\beta}_{i1} + \gamma_2 \hat{\beta}_{i2} + \cdots + \gamma_n \hat{\beta}_{in} \tag{4}$$

APT model follows from few basic assumptions as postulated by Ross (1976). The first is that asset returns are generated by a two factor model or a k-factor model in general. The difference between the realised return and the expected return of an asset equals the sum of the risk exposure (betas) multiplied by the realisation for the risk factors plus the asset-specific error term. The asset returns are hence generated by a linear function multifactor model. The second assumption is that arbitrage opportunities cannot exist because the financial markets are expected to be competitive where it is impossible for investors to generate a positive expected return on any combination of two assets unless they undertake additional risk. The last assumption is that there are a large enough number of securities, much larger than the number of the factors, to make it possible to form portfolios that capable of diversifying the firm-specific risk of individual assets.

In the light of the APT assumptions, it seems that APT is free of restrictive postulates on preferences or probability distribution, and it provides a careful foundation for the trade-off between risk and expected return in the capital markets. Unlike CAPM, APT does not assume that investors select portfolio based on the mean-variance analysis. APT also postulates that equilibrium prices will adjust to rule out any arbitrage opportunity. In addition, APT does not require identifying the market portfolio which is the main weakness of CAPM.

What remains is identifying the systematic risk factors for APT. Therefore, CRR came up with a set of macroeconomic innovations as the risk factors deriving the US stock market, and applied APT. They estimated APT using 7 risk factors derived from a number of macroeconomic variables. The risk factors were selected primarily based on economic intuition; industrial production, inflation, term structure, risk premium, market return, consumption and oil prices covering the period from 1953 to 1983. Based on their empirical results, except consumption and oil prices, all the risk factors are found important in explaining the cross-section average returns. They conclude that these five specified factors provide a reasonable specification of the sources of systematic risk in the economy. Similarly, Chan et al. (1985), CCH hereafter, also looked at pricing relative to these macroeconomic variables using CRR significant risk factors over a different period, 1958 to 1977. These two studies are the major ones on the US market that found most of the macroeconomic variations are rewarded in the US stock market.

Copeland, Weston et al. (2005), concluded that APT is more robust than CAPM for several reasons 1) APT makes no assumptions about empirical distribution of asset returns or about the individuals' utility functions, 2) In equilibrium, APT relates the required rate of return to more than a risk factor, 3) APT does not require identifying the market portfolio, and 4) APT can be easily extended to a multiperiod model. Furthermore, Chen (1983) provided strong evidence about the fact that APT is more reasonable model for explaining the cross-sectional variance in asset returns. The evidence was that the APT loading factors were able to explain a significant portion of the of the CAPM residual variance; whereas, CAPM failed to explain the APT residuals. Other proponent of APT are Chen, Roll et al. (1986), Fama and French (1992) and Groenewold and Fraser (1997).

However, the strengths of APT come with weakness. Although, APT can be generalised to any number of risk factors, yet it is difficult to identify which risk factors are the right ones to be included in the model. Having no theoretical guidance for any particular set of factors makes it difficult to decide which factor model is more appropriate for a particular data. Moreover, the relationship between return and certain risk factors can change over time, and failing to account for that may result in generating estimated factors loadings which are biased and inconsistent. Another problem is the fact that having more risk factors included in the model means the model will have more betas which might cause more statistical noise. APT also suffers from another problem which is the requirement of more data in order to reach the stage of eliminating the firm specific-risk.

3.3 Fama and French Three-Factor (FF) Model:

FF model is a popular asset pricing model initiated by Fama and French (1993) in response to the failure of CAPM. It is a model that augments CAPM by including a size related factor and a B/M related factor. FF model is a prominent asset pricing model that has received a lot of attention in finance.

Although, CAPM marks the birth of asset pricing (Fama and French 2004), since 1970s empirical studies have shown contradicting results. The challenge began with observing anomalies in the expected returns such as size effect that is not captured by CAPM beta. Banz (1981) indicates that CAPM is misspecified so that smaller firms, on average, tend to have higher risk-adjusted return than larger firms, referred to as size effect. Another challenging result is the relation between high debt-equity ratio (a measure of leverage) and average return(Bhandari 1988). Furthermore, stocks with high B/M ratios tend to have also high average returns that are not captured by their beta (Stattman 1980; Rosenberg, Reid et al. 1985). In addition, Chan, Hamao et al. (1991)confirmed that B/M has a significant positive impact on the expected returns of the Japanese stocks whereas previous studies examined the U.S market. Both size and B/M become well known anomalies within the CAPM literature.

With referencing these related empirical findings, Fama and French (1992) then finds that for the period 1963-1990 the univariate relations between the U.S. average stock return and size, earning-to-price ratio E/P, leverage and BE/ME are strong, whereas the CAPM beta failed to fully explain the variation in the average returns. However, size and B/M absorb the roles of leverage and E/P and capture much of the cross-section of average stock returns. Hence, Fama and French state that stock risks are multidimensional, one of which can be proxied by size and the other by B/M, so that the market portfolio is apparently not the only risk factor that is capable of explaining returns on average.

Fama and French (1992) relate the last two factors to economic fundamentals, as they are found related to systematic patterns in relative profitability and growth. Fama and French then explain that profitability and growth could well be the source of common risk factors in returns. They document that high B/M firms (low stock price relative to its book value) tend to be persistently distressed, whereas the opposite is observed with low B/M firms (high stock price relative to its book value) which tend to be associated with sustained profitability. The size factor is found related to profitability, where small stocks tend to be less profitable than large stocks. Therefore, Fama and French decide to use size- and B/M- related factors to explain the systematic comovements in the stock returns.

In extension to their previous tests, Fama and French (1993) expand the set of variables to be explained (the dependent variables) by adding corporate and government bonds to the tests on top of the common stocks. They also expand the set of variables to explain the dependent variables by including the term structure variables that are likely to play role in bonds returns. For the test, they constructed mimicking portfolios representing the proposed risk factors to explain the variation in the examined dependent variables. Their aim is to explore whether the bonds related factors are significant in explain the common stock returns, and vice versa. And, if they are significant, then it means the markets are integrated.

Their results show that the bonds related factors capture variation in the common stock returns; however, their explanatory power disappears when the stock related factors are included in the model. The same is for the bonds; stock related factors also capture variations in the bonds returns only when used alone. In addition, each factor also captures the variation in its respective security. Their finding shows that there is overlap between the return processes for bonds and stocks.

Overall, Fama and French’s paper identified five common risk factors in the returns on stocks and bonds. Three of which are stock market factors; an overall market factor, and two factors related to size and B/M. The two remaining bond market factors are related to maturity and default risks. The constructed Fama and French model for the stock market with three factors contributed significantly to the asset pricing models, and since then it has become popular and well known in the field of finance and named “Fama and French Three-Factor model” (FF model).

The FF model is expressed by regressing the monthly stock returns on the return to a market portfolio and mimicking portfolios for size and B/M. The model is given by the following:

$$R_{it} - R_{ft} = \propto + \beta\left(R_{mt} - R_{ft}\right) + \gamma_1 SMB_t + \gamma_2 HML_t + \varepsilon_t$$

Where R_{it} is the return on a stock *i* at time t, R_{ft} is the risk free rate of return at time t, SMB_t is the return on the size factor at time t, HML_t is the return on B/M factor at time t, and ε_t is the error term. Unlike CAPM, FF-model is not an equilibrium model.

The SMB (Small-minus-Big) is a zero-investment portfolio which is long on small MV (market value) stocks and short on big MV stocks. HML (High-minus-Low) is a zero-investment portfolio that is long on high B/M stocks and short on low B/M stocks. Although SMB and HML are zero investment portfolios, they earn positive returns. Their results confirm that the overall market factor and factors related to size and B/M perform well in explaining the cross-section of average stock returns.

Fama and French (1996) argue that SMB and HML proxy for financial distress, because if distress risk is cross-sectionally correlated, workers with specialised human capital in distressed firms will avoid investing in other stocks subject to default risk. They also questioned whether loadings on economic factors such as those of CRR, including default factors[13], can explain the roles of size and B/M.

Although, Fama and French (1995; 1996; 1998) confirmed that FF-model performs well in explaining stock returns, FF-model remains only motivated by empirical experience and evidence while not economically satisfying. In fact, there is no theory underlies the model or clear economic interpretation to explain why size and B/M should be systematic risks. Despite all of that, the model received broader attention in the field which has been a great motivate for many other researchers to further investigate FF model and its risk factors.

4. Literature Review:

It is generally believed that investors seek only to maximise their profits, thus the higher the return the more preferred the investment. However, some investors appeared to have parallel preferences beside the profit maximisation, such as the unwillingness to violate the Shari'aah law or the well known social responsibility (SR). Adding such restrictions to the preferences limit the available investments for the investors. Theoretically, these restrictions can lead the screened portfolios to suffer from lack of diversification compared to the unrestricted portfolios, forcing the screened portfolios to underperform the unscreened portfolios. Hence, since the rise of accepting the responsibility alongside profit maximisation, researchers have begun to conduct empirical studies to evaluate the performance of screened ethical funds in contrast to the conventional funds.

4.1 The performance of the social responsible funds and indices:

Luther et al. (1992) compared the performance of the UK ethical funds relative to their benchmarks FT All-Share Index and Morgan Stanley Capital International Perspective World Index (MISCIP). Their results provide weak evidence of outperformance of the

[13] CRR and Fama-French use the TERM variable as the unexpected change in interest rate (the monthly long-term government bond return minus the one-month Treasury bill. CRR uses Risk Premium (URP) as the unanticipated changes in risk premium (monthly return on Low-grade bonds rated Baa minus the monthly return on long term government bonds), whereas Fama-French use Default Factor (DEF) as proxy for default risk (the return on a market portfolio of long-term corporate bonds minus the long-term government bond return).

UK ethical funds relative to the market indices. They also explained that ethical funds tend to invest in small companies with low dividend yields; therefore, the appropriate benchmarks should be considered and used.

While the previous study compared the ethical funds to the market indices which are the benchmarks, Mallin, Saadouni et al. (1995) analysed the issue of comparing the performance of ethical funds and their counterparts non-ethical funds. This was the first study to compare between the ethical and non-ethical funds performance, overcoming the problem of benchmark, using risk-adjusted measures such as Jensen, Sharp and Treynor ratios. Hence, they assessed the returns of 29 ethical funds and 29 non-ethical funds, all based in the UK. The sample was matched according to fund size and the date from 1986-1993. Finally, the results showed that non-ethical funds tend to underperform the ethical funds.

Gregory , Matatko et al. (1997) argued that Mallin, Saadouni et al. (1995) did not control for the established size bias in the ethical portfolios. Therefore, they conducted a similar matched-pair approach, and employed a size-adjusted measure of performance to reassess Mallin, Saadouni et al.'s (1995) results. Then, they used cross-sectional regression in order to broadly investigate a larger number of trusts than those utilised by matched-pair approach. They demonstrated that unit trust fund size and its ethical status are insignificant in terms of explaining the unit trust performance. Also, they concluded that both ethical and non-ethical funds underperform FTASI benchmark, while there is no evidence of significant difference in the returns earned by two types of funds.

Moving from the UK ethical funds to their peers in the US, similar results were found. Hamilton et al. (1993) compared the performance of a sample of 32 American socially responsible mutual (ethical) funds to that of 170 conventional (non-ethical) mutual funds over a ten-year period (1981-1990). They aimed to compare the risk-adjusted expected return of the Socially Responsible Portfolios (SRPs) to the conventional portfolios and determine if they are equal, or if the expected return of SRPs was lower or greater. They called the latter "doing well while doing good". Their findings suggest that investors lose nothing by investing in socially responsible funds, but unfortunately socially responsible investors cannot do well while doing good.

Another study which goes in line with the findings of Hamilton et al. (1993), that the market does not price social responsibility characteristics, was that of Reyes and Grieb

(1998), who extended the work by using co-integration analysis to investigate the temporal behaviour of 15 Social Responsible Funds (SRF) relative to their counterpart conventional funds, as well as Jobson-Korkie (1983) significance tests and using Sharp ratio in order to evaluate the external performance of SRFs in comparison to their counterparts conventional funds. Their empirical evidence suggests that no co-integration is found between the examined funds. Four SRFs outperform their corresponding funds according to Sharp ratio, yet the performance differences between them were not statistically significantly different according to Korkie significance tests.

Using monthly data from 1994 to 1997, M'Zali and Turcotte (1998) aimed to investigate the performance of the Environmentally Responsible Canadian funds (ERC) and Social Responsible Americana funds (SRA) relative to their own market. They compared the performance of 18 SRA and ERC funds with 10 conventional unscreened funds. Sharpe and Treynor measures were used to examine the funds' performance. The empirical evidence shows that the market index outperforms the majority of the ethical funds. However, underperformance of the market index is observed only with four of the ethical funds.

Recently, on the international level, Bauer et al. (2005) built upon previous studies on evaluating the performance of ethical mutual funds represented by a sample of international mutual funds, 32 from UK, 55 from US, and 16 from Germany, comprising 103 mutual funds covering the time period 1990-2001. Carhart multifactor model (that controls for size, book-to-market and stock price momentum) was used to compare ethical and conventional mutual funds. No evidence was found of significant differences in risk-adjusted return between the two types of mutual funds.

To sum up, the empirical results in general are neither unanimous nor convergent with regard to the differences in the performance between the screened ethical and unscreened non-ethical funds. However, it seems that investors are not statistically worse-off investing in the ethical funds in comparison to the conventional funds.

4.2 The performance of the Islamic funds and indices:

The other screened funds similar to the ethical funds are the Islamic mutual funds which adhere to the Islamic principles. Despite its increasing popularity and the recent established ISMI in the late-90s to serve as a benchmark, the area of Islamic investment literature is still limited and in need of more investigation and studies.

Hakim and Rashidian (2002) observed the effects of the selection restrictions imposed on Dow Jones Islamic Market index (DJIM) in comparison to the unrestricted counterpart stock index Wilshire 5000 (W5000) in order to answer the following questions: firstly, how the selection restrictions affect the performance of ISMI; secondly, whether they make the DJIM less diversified than its counterpart CSMI; thirdly, to what extent ISMI's risk and return is affected by the limitation of the diversification; and fourthly, what is the long-term relationship existent between the two indices? Hakim and Rashidian used co-integration techniques to conduct this study over the time period 1999-2002. They concluded that selection restrictions do not make the investors worse off investing in DJIM in regards to performance and diversification. Their findings also suggest that no co-integration or long-term relationship is observed between the DJIM and the Wilshire 5000 Index, or the three-month Treasury bill, which means that changes in the DJIM are not caused by either the Wilshire 5000 Index or the three-month Treasury bill. However, these filtering criteria have led ISMI to have unique risk-return characteristics unaffected by the broad equity market.

Similar to the concept of previous studies, Hakim and Rashidian (2004), using weekly data from January 200 to August 2004, examined the correlation between Dow Jones Islamic Index DJI and Dow Jones World DJW Index as well as Dow Jones Sustainability World DJS Index. They also investigated the effects of the Islamic restrictions on the DJI's performance. Capital Asset Pricing Model (CAPM) was the method used to examine the extent to which a Shari'aah-compliant index represented by DJI is correlated with DJW Index and Dow Jones Sustainability World Index (DJS). The empirical results show that the DJIM did comparatively well in contrast to the DJW, yet it was outperformed by DJS. The main conclusion is that investors lose nothing by restricting themselves to invest only in Shari'aah-complaint stocks. Finally, they suggested that ISMI components should be revaluated, and hence the index ought to track not only Shari'aah-complaint, but market-competitive stocks as well.

Testing the hypothesis that restricted ISMI underperforms its unrestricted counterparts was also visited by Hussein (2004). Using CAPM, and Sharp, Treynor and Jensen ratios throughout the period from 1996 to 2003, he examined whether there is a significant difference in return earned by investing in FTSE Global Islamic Index (FTSE GII) rather than FTSE All-World Index (FTSE AWI). He divided his sample into two periods, bullish and bearish periods. Although the FTSE GII underperforms FTSEAWI during bear market period, during bull market period FTSE GII generated statistically significant abnormal return. In examining the entire period, the performances of the two indices were the same. Simply, the results reject the hypothesis that FTSE GII has inferior performance compared with their unscreened counterpart FTSE AWI. The inferences of this study show that the differences between the two types of indices can be exploited by fund managers to allocate their portfolios the right stocks in the right time.

Abdullah et al. (2007) aimed to investigate the difference between the performance of Malaysian Islamic and conventional mutual funds for the period from 1995 to 2001. Standard methods were utilised to achieve their objectives, such as Sharpe and adjusted-Sharpe index, Jensen Alpha, Timing and selectivity ability. Their findings demonstrate that Islamic funds outperformed the conventional funds during downwards economic trends, while through upward economic trends the Islamic funds underperformed the conventional ones. While both funds failed to achieve at least 50% market diversification levels, conventional funds had slightly better diversification levels than Islamic ones. Finally, the study's findings suggest that Islamic mutual funds can be used as a hedge portfolio during adverse economic situations.

Having socially responsible and Islamic investments investigated separately, it is interesting to see whether the Islamic portfolios can be classified under the socially responsible mutual funds category exhibiting the same characteristics or not. Forte and Miglietta (2007) were the first to investigate this issue regarding the similarities and differences of the two types of screened portfolios using quantitative and qualitative measures. The quantitative measure is co-integration analysis, while investment strategies and fund management issues are the tools of the qualitative measures. FTSE4 Good and FTSE Islamic were chosen to be the proxies for the social responsible and Islamic portfolios, respectively, covering the period 2000 to 2007. The main conclusion is that Islamic and social responsible portfolios show evidence of different characteristics.

In the light of all of the studies mentioned above, it can be understood that socially responsible, Islamic, and conventional funds are three different types of funds exhibiting different characteristics. However, investors, fulfilling their beliefs, are expected to lose nothing by investing in the ethical or Islamic funds.

4.3 Stock returns, risk factors and the asset pricing models:

At the awake of the failure of CAPM to fully explain the variations in stock returns, empirical studies observed anomalies in the stock returns that are not captured by CAPM, mainly the size effect (Banz, 1981) and B/M effect (Stattman; 1980, Rosenberg, Reid et al.; 1985). Along with the introduction of APT as an alternative multifactor model to CAPM, CRR and CCH identified set of systematic risk factors derived from macroeconomic variables that can capture the systematic variation in the stock returns of the U.S market that CAPM failed to capture. CCH test whether the multifactor model capture the firm size anomaly for the period, 1958 to 1977 in the U.S market as well. They conclude that the multifactor model explains the firm size effect, where higher average returns of smaller firms are justified by the additional risks borne in an efficient market.

Similar to CRR, Hamao (1988) investigated the applicability of the relationship between macroeconomic variables and stock excess return in the context of the Japanese stock market. The empirical evidences are consistent with those of CRR, except for industrial production, which is not priced by the Japanese market. In contrast, Poon and Taylor (1991) reconsidered the results of CRR on the US stocks in order to check these results applicability on the UK stocks. They investigated a sample of 788 companies from January 1965 to December 1984. Their results are inconsistent to the results of the US stocks. They showed that the employed risk factors do not affect the UK market in the way they affect the US market. They concluded that it is either that UK is influenced by different risk factors or the methodology they copied from Chen, Roll et al. (1986) is unable to disclose the relevant risk factors on the UK market.

Shanken and Weinstein (2006) recently re-examined the applicability of the set of macroeconomic variables introduced by Chen et al. (1986) using post-ranking returns, an alternative procedure for estimating the betas, they found that industrial production is the only significant variable, which contrasts with the finding of Hamao (1988). Shanken and Weinstein concluded that this small change in the approach produced an almost totally different result, and yet they wondered whether their result would be consistent with any further investigation conclusion.

A turning point in the asset pricing model followed the results of Fama and French (1992; 1993). They document that risk factors related to size and B/M explain systematic variation in the stock return. But, they wondered whether loadings on economic factors such as those of CRR can explain the roles of size and B/M. He and Ng (1994) investigate whether FF factors, size and B/M, are proxying for CRR risk factors or are measures of stock's risk exposure to relative distress. They find that size absorb the effects of risks associated with the term structure and default risk factors. Their findings conclude that size and B/M are related to relative distress.

From a series of articles on asset pricing models, Fama and French (1992, 1993, 1995 and 1996) argue that SMB and HML are state variables that describe changes in the investment opportunity set. If this is the case, they should be related to fundamental risk in the economy such as the economic growth.

To find economic interpretation for why SMB and HML explain cross-section average returns, Liew and Vassalou (2000) firstly document that SMB and HML portfolio returns contain significant information about future growth in GDP, so that they can predict future economic growth. They hence propose that a risk-based explanation is likely and plausible for FF-model. Secondly and Based on empirical evidence, Vassalou (2003) provide an economic interpretation for the ability of HML and SMB to explain the cross-section returns. She confirms that much of the information in size and BE/ME related factors, that are priced in stock returns, is in fact news related to future GDP growth. Thus, when news related to future GDP growth is included in FF-model, size and BE/ME lose most of their ability to explain returns.

Fama and French (1996) also argue that SMB and HML factors proxy for financial distress. (Dichev 1998) investigates whether a firm's distress risk factors can justify the size and B/M effects using the probability of bankruptcy as a proxy for firm distress. The bankruptcy risk measures are derived using Altman (1968) and Ohlson (1980) models. Hence, the aim is to empirically investigate the relation between risk of bankruptcy, derived from existing literature, and systematic risk which is proxied by subsequent realized stock returns. The results indicate that bankruptcy risk is not rewarded by higher return, and that distress factor related to bankruptcy cannot be explained by FF-factors, size and B/M.

Dichev's results exhibit inconsistency with the view that firm's with high B/M tend to earn high return as a premium for distress risk. A similar conclusion is reached by Griffin and Lemmon (2002). By using Ohlson's measure of the probability of bankruptcy as proxy for distress risk factor, they observe that a group of firms with high B/M tend to earn low returns whereas more low B/M firms earn high returns. Overall, Dichev (1998) and Griffin and Lemmon (2002) show that distress factor related to bankruptcy cannot be explained by Fama-and-French factors, size and B/M.

In contrast, Vassalou and Xing (2004) explain that Altman (1968) and Ohlson (1980) accounting models use the firm's financial statement reporting its past performance to estimate the default risk of equities. The models, hence, use backward-looking information, whereas prices should reflect investor's expectation about a firm's future performance. Alternatively, Vassalou and Xing suggest using Merton's (1974) (1974) option pricing model to accurately estimate the default risk that contains forward-looking information about the likelihood that a firm defaults in the future. In addition, Merton's model takes into account the fact that because of asset's volatility firms with similar leverage exhibit different default probability.

Thus, Vassalou and Xing (2004) investigate the effect of default risk on equity returns using Merton's model to estimate the default risk of equities, and find different results. They viewed that size and B/M as default risks and systematic providing another risk-based interpretation for FF-factors effects. For example, small firms earn higher returns than big firms only if their default risk is high, and value stocks earn higher returns than growth stocks only if they have high default risk. In line with this finding, Hahn and Lee (2001) find that changes in default and term spreads[14] capture most of the systematic risks proxied by size and B/M factors, so that higher average returns on small stocks and value stocks are compensation for higher default risk.

Since the systematic risk factors are rewarded in the stock returns as compensation for higher default risk, their effect can be expected to loss explanatory power in the context of portfolios containing stocks with low default risk. Thus, this study contributes to the existence literature by examining the effect of the systematic risk factors on stocks with low default risk represented by the Shari'aah-compliant stocks. Second contribution is to compare the performance of the asset pricing models between the Islamic and the conventional portfolios to find out the impact of the Islamic financial rules on the relationship between stock returns and systematic risk factors.

[14] They define default spread as the spread between yield to maturity on a Baa corporate bond index and 10-year Treasury constant maturity rate, and the term spread as the spread between 10-year and one-year Treasury constant maturity rates. They are commonly used proxies for the market's expectation about credit market conditions and future interest rates.

5. Data

This study requires collecting a number of Shari'aah-compliant stocks and conventional stocks in order to create artificial portfolios. These portfolios are formed to estimate asset pricing models CAPM, FF and APT. This is done by using the companies listed in DJIM US and S&P500 representing the Islamic and conventional markets respectively which, in turn, requires obtaining the list of constituent of each index. Accordingly, the times series data of the stocks are collected for the period from 1996 to 2008.

S&P500's constituent list were easily found in Data-stream and S&P500's website. DJIM US's constituent list were provided by the Dow Jones support team. The constituent lists were collected in order to get the companies listed in each index, and then form the Islamic and conventional portfolios accordingly. The DJIM US was designed in a way that tracks stocks traded in the US that pass regulatory screening for compliance with Islamic investment guidelines. The stocks are reviewed every three months to exclude those that have become incompatible with Islamic investment guidelines. On the other hand, S&P500 is a conventional US equities market index that does not subject companies to any Islamic considerations for inclusion in the index.

DJIM US quarterly excludes, whenever necessary, companies that violate Shari'aah. This simply means that one snap-shot of list of constituents is not enough, especially for ISMI, because it is possible that many of these companies are ejected from the index in the next panel review (reviews are held every three months). Thus, the required task here is to make sure that all of the Islamic constructed portfolios contain only the stocks that represent Shari'aah-compliant portfolios throughout the whole period. Practically, it is almost impossible to obtain the listed companies for every quarter throughout the whole examined period. Instead, the best possible method is to randomly take four one-time snapshots of the constituent list at different points of time throughout the whole period from 1996 to 2009. Hence, the four one-time snapshots were taken in 1996, 1999, 2004 and 2009. The number of the companies listed in the index in each of these years was around 600. However, after excluding the companies that dropped out of the index at any one of the four one-time snapshots, the remaining stocks were 138. These 138 stocks are believed to be the only ones that managed to remain compatible with Shari'aah investment rules during the period. Hence, it is presumed that fund managers and investors were allowed (Islamically) to invest in these stocks from 1996 until 2008.

When a company is dropped from the index, the fund managers and investors follow by selling off all the shares in that particular company.

This study only takes the 138 companies to run this empirical test. A similar procedure had to be applied on S&P500 in order to generate similar results that can be valid for comparison. Four one-time snapshots were taken for S&P500 in 2000, 2004 and 2009, and the fourth one-time snapshot was of the 138 stocks of DJIM US in order to have a complete separation between the conventional stocks and the Shari'aah-compliant ones. After an exclusion process similar to the previous one, the remaining stocks were 202 out of 500.

Two one-time snapshots 2004 and 2009 are the same for both indices, but the other two are different, because the oldest available list of constituent for S&P500 is 2000, whereas DJIM US offers 1996, which is the beginning of the index establishment, and 1999. This should not make any difference to the empirical results, as this filtering method is mainly used to ensure that Islamic portfolios contain only Islamically approved stocks, and hence the same was applied on S&P500 to avoid the problem of manipulated data.

When considering the apparently low number of stocks in the sample data of this study, it is worth mentioning the sample data of other studies. Some studies formed 20 equally weighted portfolios without mentioning the number of stocks (Chan, Chen et al. 1985; Chen, Roll et al. 1986); whereas Clare and Thomas (1994) collected a large number of UK stocks (840), facilitating the formation of 56 portfolios, each of which contained 15 stocks. Yan-Leung and Ka-Tai (1992) used only 90 stocks in their investigation, forming only 10 portfolios. Ho et al. (1998/9) considered the sample of 90 companies to run such an investigation to be a weakness, so they collected a sample of 127 stocks, forming 16 portfolios, in order to overcome this and to enhance the statistical reliability of the tests. In fact, their sample was smaller than that employed in this chapter, which uses 138 and 202 companies for DJIM US and S&P500 (respectively), forming 10 and 23 portfolios for each. In summary, the sample data in this study largely managed to avoid the problems of sample size in order to enhance the statistical liability.

It is logically expected that the financial crisis can influence the empirical results. For robustness testing purposes, the data is split into two sub-samples. The first sub-sample is the pre-crisis period from 2000 till 2005, and the second sub-sample is the crisis period from 2006-2008. Although, the crisis was beginning to emerge in 2007, the year 2006 is used in order to increase the number of observations to reach an acceptable level of 36 months. As a result, the models are estimated using the data of the full-sample, the pre-crisis sub-sample, and the crisis sub-sample.

6. Econometric Methodology

One of the early approaches to applying asset pricing model is to simply regress a cross-section of average asset returns on estimates of assets betas, while the independent variable in this cross-section regression is estimated using a normal time series regression (Fama and French 2004). However, this approach clearly suffers from two main problems. The first is the measurement error problem, when the estimates of beta for individual assets are allowed to explain the average returns. This is due to the inaccuracy of the betas when they are estimated using individual assets. The second problem comes from the existence of a common source of variation influencing the regression residuals, such as industry effects in average returns. This results in creating a positive correlation in these residuals, producing a downward bias in the OLS estimates of the standard error of the cross-section regression slopes. A solution for the first problem would be forming portfolios in order to produce more accurate estimates of beta than the individual assets. Portfolios can reduce the critical error in the variable problem. The use of portfolios rather than individual assets was pioneered by Blume (1970), Friend and Blume (1970) and Black, Jensen et al. (1972).

In regard to the second problem, Fama and MacBeth (1973) proposed a method to solve it. They estimate month-by-month cross-section regression of monthly returns on the estimated betas rather than estimating only a single cross-section regression of average monthly return on betas. This amendment in the methodology was intended to avoid the problem caused by the positive correlation of the residuals in cross-section regressions. Estimates generated from this month-by-month cross-section regression form a time series of slopes and intercepts which can be tested using t-statistics. This approach has become popular, and is a standard method in the literature of finance.

Therefore, the asset pricing models in this chapter are estimated using a variant of the Fama and MacBeth (1973) method. The stocks are sorted into equally weighted portfolios based on their market value (size) at the end of December of each year, and then returns are computed for these portfolios in each month of the following year. The composition of each portfolio changes every year according to the market value of the individual stocks. The first portfolio contains lowest market value (small) stocks up to the last portfolio containing highest market value (big) stocks. Non-random sorting portfolio is to avoid the problem of shrinking the range of betas, as well as to increase the statistical power.

The main aim of this section is to explain the procedure used in estimating the models. There are four main sub-sections which explain the main steps of conducting the methodology used to estimate the models. Step 1 explains the collected time series of returns of the selected stocks and the formation of the portfolios. Step 2 presents the risk factors used in the models, and the way of choosing and deriving them. Step 3 explains in detail the application of the technique used in this study.

6.1 First Step: Generating the returns, and the procedure of the formation of portfolios:

Firstly, the returns of the selected stocks were collected from DataStream, then the excess returns $(R_{it} - R_{ft})$ were generated by subtracting the risk free rate R_{ft} represented by 3Tbill from the securities returns R_{it}.

Secondly, the stocks were ranked based on size using their market value at the end of December of the preceded year, and then the selected stocks were grouped into a number of equally weighted portfolios according to their market value. They are separated into 23 and 10 equally weighted portfolios. The list of components of each portfolio changes every year, according to the new market value of the stocks.

The number of portfolios, 23 and 10, is actually going to be the number of observations in the cross-sectional regression, thus the greater the number of observations, the better the generated results. On the other hand, in order for the portfolios to achieve most of the benefits of diversification, each portfolio should contain 15 stocks (Fama 1981). Due to the limited number of stocks available, it was reasonable for this study to firstly try 23 portfolios, which is the highest possible number of observations offered for the cross-sectional regressions; and secondly to try 10 portfolios for investigating robustness, each of which had the chance to contain around 15 stocks to achieve the greatest possible diversification benefits.

Furthermore, this study estimate the asset pricing models using 10 and 23 equally weighted portfolios comprising 138 stocks for the Islamic portfolios and 202 stocks for the conventional portfolios. The first portfolio, in both the 10 and 23 portfolios cases, always contained the small stocks associated with the lowest market values, whereas the last one always contained the big stocks associated with the highest market values.

The difference in numbers of stocks available in DJIM US and S&P500, 138 and 202, forces the Islamic and conventional portfolios to contain different numbers of stocks. Therefore, for the Islamic portfolios, each portfolio in the case of 10 portfolios contained 14 stocks, the closest possible number to 15, except two portfolios that had 13 each. In the case of 23 portfolios, each one of the 23 contained 6 stocks. For the conventional portfolios in the case of 10 portfolios, each one contained 20 stocks, except two portfolios that had 21. In the case of 23 portfolios, each one of the 23 portfolios contained 9 stocks except 5, which had 8 stocks. This dissimilarity in numbers was negligible, and did not make any difference in the generated results of the Islamic and conventional portfolios. In fact, Ho et al. (1998/9) encountered the same problem, yet it was not criticised for this inequality of stocks number in some portfolios.

6.2 Second Step: Deriving the risk factors:

CAPM and FF models require deriving three risk factors; the market excess return, SML and HML. These factors however are directly taken from Fama and French website where these derived factors are available for academics and researchers. For APT and on the basis of previous empirical studies, this chapter uses CCR risk factors. However, CRR risk factors are not available and need to be derived. The following subsection displays these risk factors and explains how they are derived.

6.2.1 CCR risk factors

A set of macroeconomic variables are firstly required in order to derive the CCR risk factors. Hence, table 1 explains the basic variables used to derive the required macroeconomic surprises, according to the methodology used by Chen, Roll et al. (1986). Throughout the whole study, the data frequency employed is monthly. Then, from the variables displayed in table 1, the APT risk factors are derived. Table 2 presents the risk factors to be used and their descriptions.

Table 1

Variable (symbol)	**Definition**
Inflation (*I*):	The relative, seasonally adjusted log of monthly Consumer Price Index (CPI), obtained from Federal Reserve Bank of St. Louis.
Expected Inflation (*EI*):	University of Michigan Inflation Expectation (UMIE) data.
Three-Months' Treasury Bill Rate (*TB*):	The rate of Three Month Treasury Bill Secondary Market Rate, obtained from Federal Reserve Bank of St. Louis.
Return on Long-term Government Bonds (*LGB*):	The Ten-Year Treasury Constant Maturity Rate, obtained from the Federal Reserve Bank of St. Louis.
Return on Baa Low-grade bonds (*Baa*):	The Moody's Seasoned Baa Corporate Bond Yield, obtained from the Federal Reserve Bank of St. Louis.
Industrial Production (*IP*):	The industrial production and capacity utilization, obtained from Federal Reserve Bank of St. Louis.

Table 2

Risk Factor	**Description**
Monthly growth rate of *IP (MP)*:	The first difference of the log of *IP*. $$\Delta MP_t = \log eIP_t - \log eIP_{t-1}$$
Unanticipated Inflation (*UI*):	The difference between *I* and the *EI*. $$UI_t = I_t - EI_t$$
Change in *EI* (*DEI*):	The difference between the expected inflation on the period (*t+1*), and the expected inflation on period (*t*). $$\Delta EI_t = EI_{t+1} - EI_t$$
Risk Premium (*URP*):	The difference between the monthly return on *Baa* and the monthly return on *LGB*. $$URP_t = Baa_t - LGB_t$$ This variable could affect the value of an asset through the change in discount rate. It can be a direct measure of the degree of risk aversion implicit in pricing (Chen et al. 1986).
Term Structure (*UTS*):	The difference between the monthly return on *LGB* on period (*t*) and monthly return on short-term *TB* on period (*t-1*). $$UTS_t = LGB_t - TB_{t-1}$$

6.3 Third Step: The technique application:

This step goes through three stages to explain the application of FM technique, which is used to estimate the asset pricing models. The first is to estimate the factor beta coefficient of each portfolio using time series regression. The second is to obtain the estimates risk premia associated with each of the risk factors by using the estimated betas as independent variables in cross-sectional regressions against the same portfolios' returns. The third is to form time series of the resulted estimates of risk premia and test whether the sample means of risk premia estimates are significantly different from zero over the period 1996 to 2008.

Firstly, betas of each portfolio for each year are estimated by running the following time series regression for the prior 60 months (5 years)[15]:

$$R_{it} = \alpha_i + \beta_i \eta_t + u_i \tag{2}$$

Where R_{it} is a vector of holding period returns on portfolios, α_i is a constant, β_i is a vector of loading associated with the risk factors, and η_t is a vector of risk factors at time *t*. The portfolios' returns are regressed against the market excess return as to estimate CAPM, and regressed against the market excess return, SMB and HML as to estimate FF model, and regressed against the CCR risk factors as to estimate APT model. The portfolios' returns estimation is then rolled forward one calendar year (12 months) to estimate new betas. Thus, the first time series estimation for betas is from 1996-2000, and the next rolling forwarded time series regressions must be seriatim according to the following periods (97-01, 98-02, 99-03 up to 03-07).

Secondly, estimating the risk premia associated with each of the risk factors using cross-sectional regression:

$$R_{pt} = \gamma_0 + \gamma_1 \hat{\beta}_{1pt} + \cdots + \gamma_1 \hat{\beta}_{ipt} + \eta_{pt} \tag{3}$$

Where *p* = number of portfolios, *i* = number of risk premia and *t* = the specific month.

[15] This duration is common in the literature (Chen et al. Chen, N.-F., R. Roll, et al. (1986). "Economic Forces and the Stock Market." Journal of Business **59**(3): 383-403.; Chan et al. Chan, K. C., N.-f. Chen, et al. (1985). "An exploratory investigation of the firm size effect." Journal of Financial Economics **14**(3): 451-471.; He and Ng, He, J. and L. K. Ng (1994). "Economic forces, fundamental variables, and equity returns." Journal of Business **67**(4): 599.; Shanken and Weinstein, Shanken, J. and M. I. Weinstein (2006). "Economic forces and the stock market revisited." Journal of Empirical Finance **13**(2): 129-144..

A. The resulting estimates of betas yielded by the 60 months' time series regression are then used as the independent variables in the following 12 month in a cross-sectional regression. For example, betas estimated from 1996 to 2000 serve as the independent variables in 12 cross-sectional regressions in 2001, as shown in Equation 3, with one regression for each of the next 12 months of 2001. So, for each cross-sectional regression, we have 10 or 23 portfolios-returns observations for the month, being the dependent variables and the risk factors' betas of each portfolio, being the independent variables against its portfolio return.

B. This procedure was then repeated for every year from 2001 to 2008 using the preceding five calendar years data for each one for estimating betas. The twelve cross-sectional regressions were subsequently run for the following year, starting immediately with the first month.

C. Repeating this procedure for each year yields a time series for each risk factor of estimates of its associated risk premia.

Thirdly, testing the time series of the risk premia associated with each risk factor was actually the main risk premia that the study wanted to test and investigate. It is also the final step where the time series means of the risk premia estimates are tested using a t-test for significant difference from zero.

$$t\text{-statistic:} \quad t_{\gamma} = \frac{\hat{\gamma}}{\sigma_{\hat{\gamma}}/\sqrt{n}}$$

Where γ is the mean value of the *i*th estimated risk premium, $\sigma_{\hat{\gamma}}$ is the standard deviation of γ_i, and n is the number of observations.

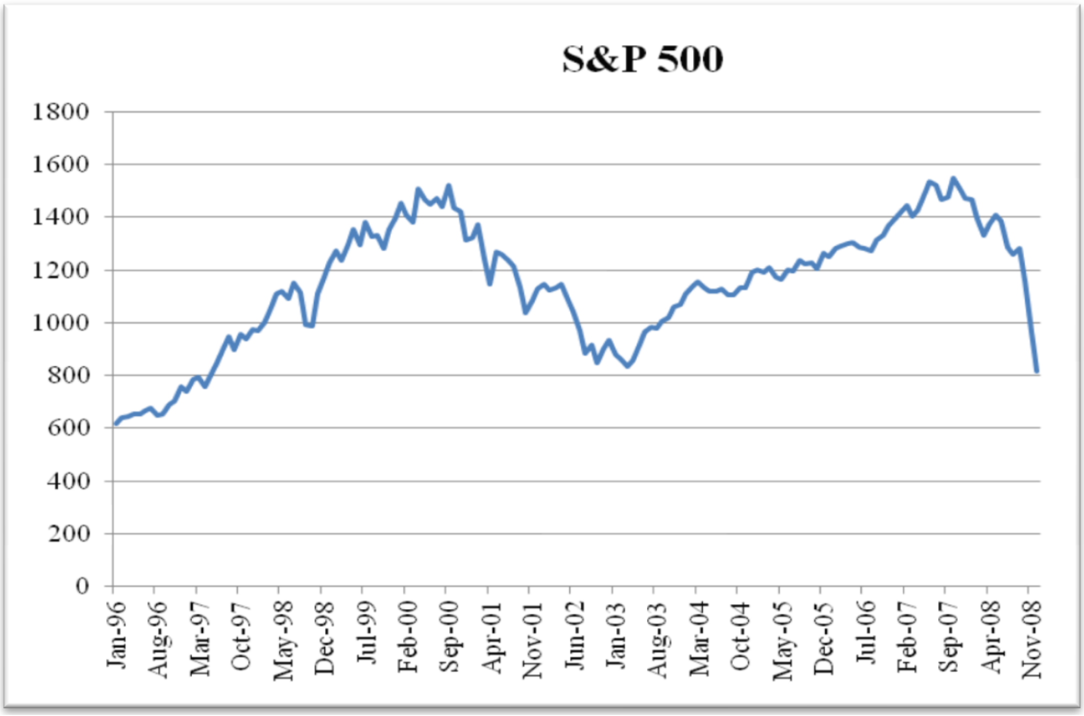
7. Actual Results, Analysis and Discussion

Two sub-sections are presented here. The first subsection generally overviews the historical prices of DJIM US and S&P500 presented in figures 1 and 2, and it also explores the correlation statistics between the variables which are presented in table 3. The second subsections displayed the empirical results of estimating the asset pricing models in tables 4 to 7 along with relevant analysis and discussion.

7.1 Figures and correlation matrix:

Figures 1 and 2 show the graphs of the index prices of DJIM US and S&P500, respectively. It is clear from the illustrated graphs that the directions of the price fluctuations seem to have a very similar pattern. The prices of the two indices seem to be constantly increasing from 1996 till 2000, then they show a decline trend till the end of 2003. Since then, the two indices had been doing well and increasing before the financial crisis occurred where both indices plummeted again. However, the financial crisis seems to be more severe in S&P500. In figure 1, the index reached down its lowest level since the last 10 years by November 2008. From the beginning of 2007 till November 2008, S&P500 index dropped more than 45% falling from about 1500 to 800 points.

Figure 1: S&P500



Contrarily as shown in figure 2, DJIM US shows upward trends from 2003 similar to that of S&P500, but with much less severe decline in 2008 than in S&P500. In comparison to 45% decline in the conventional stocks, the financial crisis is much less severe on the Islamic compliant stocks which dropped by about 36% falling from around 2500 points in 2007 to just above 1500 points in 2008. However, the bottom it reached is still not the lowest in the last 10 years, not even the last 5 years. Overall, as shown in figures 1 and 2, the sharp decline in 2008 demonstrates that the period of the financial crisis is an important phase and can significantly influence the estimation results.

Figure 2: DJIM US Index

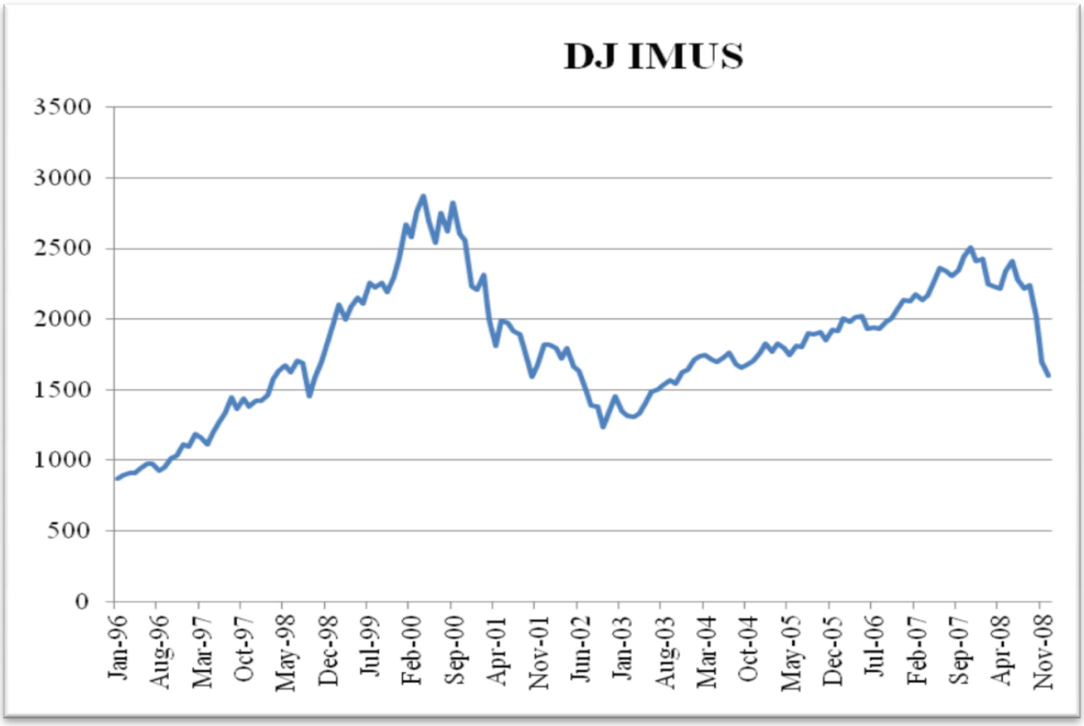


Table 3 displays the correlation matrix for the state variables computed for the period from January 1996 to December 2008. Correlation is a single number that describes the degree of the relationship between two variables. It seems that no correlations between the variables are strong enough to warrant any variable being substituted for another. The correlation between FF factors and the macroeconomic factors are low. The highest correlation among FF factors is between SMB and HML at the order of -0.31. For the economic factors, the correlation between URP and UTS and between DEI and UI are from the highest ones. This is probably because both URP and UTS contain the Long-term Government Bond (LGB) series, and both DEI and UI contain the Expected Inflation (EI) series. Lower unanticipated risk premia tend to be correlated with higher growth rates in industrial production, and this is a negative correlation between MP and URP. In previous similar studies in the 1980s and 1990s, the usual correlation between the two variables was positive, and sometimes negligible in contrast to the other variables' correlation. However, in this study, MP and URP correlation has a value similar in strength to some other variables in this correlation matrix. Overall, this should not be a problem as these reported correlation results are in fact lower than what Chen et al. (1986) and Chan et al. (1985) reported in their correlation matrix results.

Table 3 Correlation matrix of the employed risk factors

	Rm-Rf	***SMB***	***HML***	***MP***	***DEI***	***UI***	***URP***
Rm-Rf							
SMB	0.2538						
HML	-0.1839	-0.3109					
MP	-0.0003	-0.0653	-0.0692				
DIE	0.2057	0.0927	-0.0138	0.1236			
UI	0.2293	0.1565	0.0683	0.1445	0.3756		
URP	-0.2552	0.0622	-0.0142	-0.3947	-0.3077	-0.1167	
UTS	-0.0365	0.1524	-0.0392	-0.0082	-0.0321	0.0656	0.3900

Note: Rm-Rf is the excess return on the market portfolio taken from Fama and French website; SMB= small-minus-big is a risk factor related to size taken from Fama and French website, HML= high-minus-low is a factor related book-to-market value taken from Fama and French website, MP = monthly growth rate in industrial production; DEI = change in expected inflation; UI = unanticipated inflation; URP = unanticipated change in the risk premium (Baa and under return - long-term government bond return); UTS = unanticipated change in the term structure (long-term government bond return - Treasury-bill rate); Roil = Oil growth rate. b

7.2 Asset pricing models results:

The literature showed that the systematic risk factors capture elements of financial distress and default risk. Thus, the significant effects of the risk factors on the stocks are actually compensations for the high default risk that the risky stocks tend to exhibit. On one hand, Islamic portfolios tend to be less risky to default mainly because they invest in firms with less than moderate debt. If this is true, then one can assume that an Islamic portfolio holder shall not require compensation for high default risk. Hence, the default related risk factors should be insignificant in explaining the returns. On the other hand, investors restricting themselves to Islamic compliant securities portfolios are exposed to more risk than other investors mainly because they do not invest in the risk-free assets. Therefore, one can assume that the risk factors would only remain significant in the context of the Islamic portfolios if they are able to capture element of risks other than default and financial distress.

The empirical tests, investigating these issues, employ the data from January 2001 until December 2008, preceded by the 60 months of data (January 1996 to December 2000) utilised to estimate betas of the risk factors. The estimation period is then split into two sub-samples, one before the financial crisis, and the other during the crisis. The risk is greater during the crisis than before, and that during bearish market investors do not expect to receive premiums for bearing higher risk. In addition, during this crisis, interest rates dropped down to its lowest level and banks were reluctant to lend out money. Investors, hence, are not compensated by higher return for the higher risk, plus are not attracted by higher rate of return in the risk free assets.

Tables 4 to 7 below present the empirical results of estimating the asset pricing models. Each table contains 3 panels; A, B and C. Panel A presents the results of the full-sample from 2001-2008, panel B presents the results for the pre-crisis sub-sample 2001-2005, and panel C presents the results of the crisis sub-sample from 2006-2008.

Table 4 presents the results of the empirical estimation using 23 Islamic portfolios. For the full-sample data, panel A presents the empirical of estimating of CAPM, FF, APT and FF augmented by APT. It seems that there is no risk factor that is significant in explaining the average cross-sectional returns in the full-period sample. The results imply that returns on Islamic portfolios are not compensated by any of the employed risk premiums. This comes with no surprise as the Islamic portfolios contain only stocks associated with low default risk, and avoid investing in financial firms and banks.

Although it is understood that stock prices should be responsive to the external forces; however, the usual relationship between the prices and the risk factors may significantly change during crisis and extraordinary events. The recent financial crisis is an example that can temporarily influence the relationship between stock prices and external forces by affecting the economy in general and the stock markets in particular. Therefore, this chapter empirically estimates the asset pricing models after excluding the data during the crisis in order to avoid the influence of the financial crisis on the results.

However, the results of the pre-crisis data, shown in panel B, confirm the findings of the full-sample estimation where no risk factor is able to explain the average cross sectional returns. In fact, this finding is not surprising, but instead supporting the perception that the employed risk factors should be insignificant in explaining the returns on Islamic screened portfolios as they contain only stocks with low default risk.

Furthermore, the data during the financial crisis are also investigated and the results are displayed in panel C. Interestingly, when estimating APT model, MP captures some information related to the stocks returns during the financial crisis where the slope on its risk premium is positively significant at the 90% level of confidence. Other risk factors are still insignificant. After including FF factors, MP remains significant, whereas other risks premiums remain unrelated to the returns on the Islamic portfolios. This can possibly mean that during the crisis the Islamic portfolios become sensitive to the risk premium of the growth rate of the industrial production due to its relation to the future output growth and the economic recovery. Meanwhile, the result of significant positive effect of MP is in line of that of Shanken and Weinstein (2006) who finds that only MP is positively significant in the US stock returns.

In general, it is clear that the risk factors related to the economy as a whole are of more importance in the context of the Islamic portfolio than the firm's specific risk factors or the market portfolio. This can be attributed to the fact that FF factors capture financial distress from which Islamic portfolios do not tend to suffer. In addition, the presence of the other insignificance risk factors does not alter the significance level of MP as shown in Panel C.

Table 4: 23 Islamic Portfolios

	Const	*M-Beta*	*SMB*	*HML*	*MP*	*DEI*	*UI*	*URP*	*UTS*
Panel A: Full-sample 2001-2008									
CAPM	-0.0281	0.4213		--	--	--	--	--	--
	(-4.9587)	(0.6968)							
FF	-0.0310	0.5940	0.2704	0.2487	--	--	--	--	--
	(-4.3453)	(0.7942)	(0.7733)	(0.7329)					
APT	-0.0245	--	--	--	0.0004	0.0004	0.0000	0.0003	-0.0012
	(-3.7396)				(0.3951)	(0.8047)	(-0.0622)	(0.3238)	(-0.6349)
All	-0.0276	0.1863	0.0188	0.0498	0.0008	0.0005	0.0004	0.0002	-0.0001
	(-3.9441)	(0.2138)	(0.0483)	(0.1140)	(0.6321)	(0.9884)	(0.4737)	(0.1896)	(-0.0571)
Panel B: Sub-sample 2001-2005									
CAPM	-0.0232	1.1409		--	--	--	--	--	--
	(-2.9500)	(1.5000)							
FF	-0.0277	1.3655	0.6548	0.2384	--	--	--	--	--
	(-2.6549)	(1.3469)	(1.4923)	(0.4929)					
APT	-0.0177	--	--	--	-0.0015	0.0005	-0.0001	0.0011	0.0001
	(-2.1743)				(-1.4329)	(1.0520)	(-0.2010)	(1.1032)	(0.0776)
All	-0.0259	1.2583	0.2307	0.1074	-0.0014	0.0007	0.0003	0.0007	0.0001
	(-2.6141)	(1.1480)	(0.4517)	(0.1724)	(-1.0219)	(1.2665)	(0.3980)	(0.7290)	(0.0450)
Panel C: Sub-sample 2006-2008									
CAPM	-0.0361	-0.7779		--	--	--	--	--	--
	(-4.8889)	(-0.7960)							
FF	-0.0365	-0.6919	-0.3703	0.2658	--	--	--	--	--
	(-4.6630)	(-0.6641)	(-0.6493)	(0.6337)					
APT	-0.0360	--	--	--	0.0035	0.0002	0.0001	-0.0010	-0.0035
	(-3.2837)				(1.8115) c	(0.2109)	(0.0354)	(-0.5083)	(-0.8096)
All	-0.0303	-1.6004	-0.3343	-0.0464	0.0043	0.0003	0.0007	-0.0008	-0.0004
	(-3.4570)	(-1.1386)	(-0.5561)	(-0.0866)	(1.9781) c	(0.2437)	(0.3259)	(-0.4048)	(-0.1031)

Note: The results shown in the table are generated from two stage-regressions, the first is a time series regression to generate the betas of the risk factors to be used as independent variables in a cross-sectional regression as the second stage in the process of the methodology. The results from the cross-sectional regression form a time series of risk premium for each risk factor which is the risk premium to be tested using t-statistic. The table exhibits the mean of the time series of each risk premia and below it the critical value of the t-statistic put between brackets; The letters (a), (b) and (c) are the level of significance of 1%, 5% and 10%, respectively. Panel A presents the results of the full-sample, panel B presents the pre-financial-crisis sub-sample, and panel C presents the financial crisis sub-sample.
The symbols in the heading row are Const= constant and the slope of the following risk premiums: M-Beta= CAPM beta which is the excess return on the market portfolio; SMB= small-minus-big portfolio; HML= high-minus-low portfolio, MP= monthly industrial production growth rate; DEI= change in expected inflation; UI= unanticipated inflation; URP= unanticipated change in the risk premium; UTS= unanticipated change in the term structure. The symbols in the heading column are CAPM= the capital asset pricing model, FF= Fama and French three-factor model, APT= arbitrage pricing theory and All= the model that incorporate all the risk factors in the empirical estimation (FF model augmented by APT risk factors).

To investigate robustness, table 5 presents the empirical results using 10 portfolios that are formed in order to increase the number of components in each portfolio for diversification benefits. Interestingly, the CAPM market beta becomes positively significant at the 90% level of confidence in the full-sample. But, beta seems to be more significant before the occurrence of the financial crisis, where its significance is at the 95% level of confidence in the pre-crisis sub-sample. The reduction in the significance in the full-sample can be due to the financial crisis where CAPM market beta appears to be insignificant during the crisis period. This underpins the fact that Islamic portfolios are more exposed to the macroeconomic risk factors rather than firm's specific factors such as size and B/M.

However, CAPM beta's significance disappears when FF factors are included in the model, whereas FF factors are not significant though. The disappear of the significance of the risk factors during the crisis can be attributed to the crisis influence on the relationship between stock prices and other forces where investors become more concerned about the economy as a whole. The change in the usual relationship can also be due to the sharp decline in the prices of many assets in the economy as well as in the consumers' confidence in the economy.

During the financial crisis, as the market beta fails to capture information in the stock returns, MP exerts significant impact only in the augmented model at the 90% level of confidence. The results confirm the significant presence of MP during the financial crisis in the context of the 23 portfolios. Thus, it could be said the risk factor related to the industrial production is not diversifiable. However, the significance of MP should be interpreted with cautious because the number of observations of the dependent variable in the cross section regression is 10 whereas the number of independent variables is 8. This can result in producing misleading and biased results, but the MP remains significant even when this problem is avoided such as when the 23 portfolios are used in table 4.

Overall, the risk factors that are related to financial distress and default risks are not priced in the returns of the Islamic screened portfolios. Besides, the employed risk factors failed to capture any other element of risk in Islamic portfolios such as the higher risk exposure when the Islamic portfolio are restricted from investing in the risk-free assets.

Table 5: 10 Islamic Portfolios

	Const	*M-Beta*	*SMB*	*HML*	*MP*	*DEI*	*UI*	*URP*	*UTS*
Panel A: Full-sample 2001-2008									
CAPM	-0.0434	2.3564		--	--	--	--	--	--
	(-3.7483)	(1.7059) c							
FF	-0.0325	0.6899	0.7215	-0.4602		--	--	--	--
	(-2.3928)	(0.3928)	(1.3239)	(-0.6837)					
APT	-0.0232	--	--	--	-0.0003	0.0002	0.0008	0.0017	-0.0038
	(-2.9949)				(-0.1580)	(0.1850)	(0.6531)	(1.1409)	(-0.7673)
All	-0.0359	2.0882	1.3928	-2.1224	-0.0031	-0.0016	0.0017	0.0066	0.0045
	(-1.5150)	(0.6514)	(1.4038)	(-1.0290)	(-0.4414)	(-0.6045)	(0.7403)	(1.5872)	(0.5533)
Panel B: Sub-sample 2001-2005									
CAPM	-0.0465	4.1204		--	--	--	--	--	--
	(-3.1779)	(2.3696) b							
FF	-0.0325	1.9867	1.1403	-0.2851	--	--	--	--	--
	(-1.8845)	(1.0094)	(1.5081)	(-0.2931)					
APT	-0.0126	--	--	--	-0.0024	0.0009	-0.0013	0.0005	-0.0009
	(-1.1914)				(-0.9751)	(0.8180)	(-1.3762)	(0.3381)	(-0.2238)
All	-0.0145	3.0010	1.5955	-3.5079	-0.0116	-0.0017	-0.0015	0.0048	-0.0008
	(-0.4539)	(0.6495)	(1.0493)	(-1.0985)	(-1.1193)	(-0.4237)	(-0.7262)	(1.3378)	(-0.0920)
Panel C: Sub-sample 2006-2008									
CAPM	-0.0383	-0.5836		--	--	--	--	--	--
	(-1.9945)	(-0.2631)							
FF	-0.0324	-1.4715	0.0235	-0.7519		--	--	--	--
	(-1.4540)	(-0.4391)	(0.0326)	(-0.9571)					
APT	-0.0407	--	--	--	0.0032	-0.0010	0.0042	0.0038	-0.0085
	(-4.0258)				(1.1054)	(-0.5513)	(1.5987)	(1.1540)	(-0.7549)
All	-0.0716	0.5670	1.0548	0.1868	0.0112	-0.0015	0.0072	0.0095	0.0134
	(-2.1236)	(0.1500)	(1.3369)	(0.1356)	(1.7951) c	(-0.5714)	(1.3994)	(1.0210)	(0.8234)

Note: The results shown in the table are generated from two stage-regressions, the first is a time series regression to generate the betas of the risk factors to be used as independent variables in a cross-sectional regression as the second stage in the process of the methodology. The results from the cross-sectional regression form a time series of risk premium for each risk factor which is the risk premium to be tested using t-statistic. The table exhibits the mean of the time series of each risk premia and below it the critical value of the t-statistic put between brackets; The letters (a), (b) and (c) are the level of significance of 1%, 5% and 10%, respectively. Panel A presents the results of the full-sample, panel B presents the pre-financial-crisis sub-sample, and panel C presents the financial crisis sub-sample.
The symbols in the heading row are Const= constant and the slope of the following risk premiums: M-Beta= CAPM beta which is the excess return on the market portfolio; SMB= small-minus-big portfolio; HML= high-minus-low portfolio, MP= monthly industrial production growth rate; DEI= change in expected inflation; UI= unanticipated inflation; URP= unanticipated change in the risk premium; UTS= unanticipated change in the term structure. The symbols in the heading column are CAPM= the capital asset pricing model, FF= Fama and French three-factor model, APT= arbitrage pricing theory and All= the model that incorporate all the risk factors in the empirical estimation (FF model augmented by APT risk factors).

Table 6 presents the empirical results of the 23 conventional portfolios. In the full period as shown in panel A, no risk factor is significant in explaining the return of the conventional portfolios. This finding is strange and contradicting the general perception about the asset pricing theories. But, this is not the case when taking into account the possible influence of the financial crisis which may possibly be the reason behind the failure of the risk factors to explain the portfolios returns. Splitting the data into two sub-samples to exclude the crisis period, however, confirms that.

In the pre-crisis period, 2001-2005, as shown in panel B, SMB exerts significant positive effect on the average cross-sectional returns at the 95% level of confidence in the context of FF model. This can show that SMB was present as a significant risk factor in the conventional stocks before the occurrence of the financial crisis. This indicates that the higher size-related risk that stocks exhibit in the conventional portfolios receive risk premium as a compensation. Meanwhile, when estimating APT model, UTS as a default-related risk factor also significantly exerts negative effect on the stock returns at 95% level of confidence. Chen, Roll et al. (1986) explained the negative risk premium of UTS as an indication for the fact that the stocks whose returns are negatively related to the long-term interest rates over the short-term rates are more valuable. Thus, investing in such stocks can protect investors against the possibility of the decline in the long-term real rates of interest. Moreover, when FF model is augmented by the APT risk factors, SMB's significance disappears whereas UTS remains significant at the same level of confidence with the same sign. This can show that the default risk captured in returns by SMB can be accounted for by UTS. Therefore, UTS, as a default risk factor, is stronger in terms of its presence than SMB in explaining the average cross sectional returns in the conventional portfolios

In the subsample of the financial crisis period 2006-2008 as shown in panel C, the default related risk factors loss their significance. During this period, as the stock prices are falling sharply while central banks cut interest rates as a consequence of the crisis, neither SMB nor UTS is able to explain the average cross-sectional stocks return. The default related risk factors failure to explain the stock returns is observed only during the crisis. Hence, a plausible interpretation for this failure can be given by the fact that returns on equity portfolios are not compensated for taking any higher risk during the crisis. Instead, during the crisis period, DEI has however become more important factor to which the stocks have become more sensitive. DEI exerts negative significant effect on the stock returns during the crisis at the 90% level of confidence. This negative risk premium can possibly indicates that investors consider the equity assets as hedging instruments against the sharp decline in the assets that are more fixed in nominal rates (Chen, Roll et al. 1986). Increase in the expected inflation indicates a decline in the real rates which in turn implies lowering the purchasing power. The significant effect of DEI during the crisis can possibly indicate that investors tends to buy the cheap stocks that experienced sharp decline in their market value in order to protect themselves against the higher expected inflation described by DEI. Overall, it is clear that the portfolios returns exhibited different characteristics towards the employed risk factors in each sample period, where the financial crisis has a clear influence on the relationship between the conventional portfolio returns and the risk factors.

Table 6: 23 Conventional Portfolios

	Const	*M-Beta*	*SMB*	*HML*	*MP*	*DEI*	*UI*	*URP*	*UTS*
	Panel A: Full-sample 2001-2008								
CAPM	-0.0254	-0.4537		--	--	--	--	--	--
	(-4.1618)	(-1.0891)							
FF	-0.0299	-0.0388	0.6048	0.2178		--	--	--	--
	(-4.3487)	(-0.0850)	(1.3762)	(0.6790)					
APT	-0.0284	--	--	--	0.0006	-0.0006	0.0000	-0.0005	-0.0030
	(-4.6313)				(0.4545)	(-1.0852)	(0.0097)	(-0.4754)	(-1.3970)
All	-0.0269	-0.1975	0.9162	-0.1981	0.0008	-0.0007	0.0000	-0.0005	-0.0015
	(-3.0835)	(-0.4030)	(1.2053)	(-0.4474)	(0.6099)	(-1.1235)	(-0.0178)	(-0.4427)	(-0.5149)
	Panel B: Sub-sample 2001-2005								
CAPM	-0.0120	-0.6179		--	--	--	--	--	--
	(-1.6074)	(-1.2236)							
FF	-0.0176	-0.1872	1.2703	0.5138		--	--	--	--
	(-1.9805)	(-0.3445)	(2.0647) b	(1.2198)					
APT	-0.0159	--	--	--	-0.0010	0.0004	0.0005	0.0014	-0.0047
	(-2.1544)				(-0.8931)	(0.8799)	(0.5094)	(1.2556)	(-2.3874) b
All	-0.0092	-0.3994	1.7495	-0.2816	-0.0012	0.0004	-0.0001	0.0010	-0.0048
	(-0.8040)	(-0.5796)	(1.4961)	(-0.4286)	(-1.0457)	(0.7198)	(-0.1240)	(0.9059)	(-2.1253) b
	Panel C: Sub-sample 2006-2008								
CAPM	-0.0477	-0.1801		--	--	--	--	--	--
	(-5.0380)	(-0.2459)							
FF	-0.0504	0.2085	-0.5043	-0.2754		--	--	--	--
	(-5.0054)	(0.2534)	(-0.9560)	(-0.5675)					
APT	-0.0493	--	--	--	0.0031	-0.0022	-0.0007	-0.0036	-0.0001
	(-4.9308)				(1.1637)	(-1.8811) c	(-0.3944)	(-1.6519)	(-0.0208)
All	-0.0565	0.1390	-0.4728	-0.0590	0.0040	-0.0026	0.0002	-0.0031	0.0039
	(-4.6759)	(0.2201)	(-0.9415)	(-0.1299)	(1.5131)	(-1.9349) c	(0.0695)	(-1.2006)	(0.5594)

Note: The results shown in the table are generated from two stage-regressions, the first is a time series regression to generate the betas of the risk factors to be used as independent variables in a cross-sectional regression as the second stage in the process of the methodology. The results from the cross-sectional regression form a time series of risk premium for each risk factor which is the risk premium to be tested using t-statistic. The table exhibits the mean of the time series of each risk premia and below it the critical value of the t-statistic put between brackets; The letters (a), (b) and (c) are the level of significance of 1%, 5% and 10%, respectively. Panel A presents the results of the full-sample, panel B presents the pre-financial-crisis sub-sample, and panel C presents the financial crisis sub-sample.

The symbols in the heading row are Const= constant and the slope of the following risk premiums: M-Beta= CAPM beta which is the excess return on the market portfolio; SMB= small-minus-big portfolio; HML= high-minus-low portfolio, MP= monthly industrial production growth rate; DEI= change in expected inflation; UI= unanticipated inflation; URP= unanticipated change in the risk premium; UTS= unanticipated change in the term structure. The symbols in the heading column are CAPM= the capital asset pricing model, FF= Fama and French three-factor model, APT= arbitrage pricing theory and All= the model that incorporate all the risk factors in the empirical estimation (FF model augmented by APT risk factors).

Table 7 displays the results of the tests of 10 conventional portfolios in order to investigate robustness. As shown in panel A, CAPM and FF risk factors fail to explain the average cross sectional returns on the conventional portfolios. APT model continues to reveal that DEI is negatively significant at the 95% level of confidence in the full period sample as well as the crisis period, whereas DEI fails to explain portfolios returns on the full-sample when using 23 portfolios for the empirical estimation[1]. Surprisingly, when estimating the FF model augmented by APT risk factors, HML becomes significant at the 90% level of confidence, whereas DEI loses its significance. This is only the model that found HML significant; however, it is not clear why HML should be significant only after including APT risk factors.

For the pre-crisis sub-sample as shown in panel B, although market beta is not significant in CAPM, it becomes positively significant in FF model at the 95% level of confidence, whereas neither SMB nor HML exerts any significant effect on the portfolios returns. When estimating APT model, the risk premium of URP is very significant at the 99% level of confidence, with a positive sign as expected. URP represents the unanticipated change in the risk premia; hence, its positive sign can be justified by the fact that individuals perceive a stock market asset as a hedge item against changes in uncertainty that is caused by the unanticipated change in the aggregate risk premium. Unexpectedly, UI appear to be positively related to the returns on the conventional portfolios at the 90% level of confidence, whereas it is expected to have a negative sign in a way similar to that of DEI. Although these risk factors lose their significance in the augmented model, UTS surprisingly becomes negatively significant at the 90% level of confidence.

For the crisis period as shown in panel C, CAPM and FF risk factors fail to find any significant risk factors in explaining the portfolios returns. When estimating APT model, MP, DEI and UI are found significant at the 95% level of confidence except UI at the 90%. The sign of the significant risk premium is negative for DEI and UI, whereas it is positive for MP. They are the only significant factors in the pre-crisis sub-sample, but their significance totally disappears when the FF risk factors enter the APT model. Although, FF risk factors have not exhibited any significant effect when estimating FF model, yet its inclusion in the augmented model is not without a cost. FF

[1] See table 6 for the 23 portfolio empirical estimation results.

factors inclusion in the APT model seems to have an influence on the APT risk factors particularly MP, DEI and UI.

Other than the positive sign of UI found in the pre-crisis sub-sample estimation of APT (see table 7 panel B), the signs of the remaining macroeconomic significant risk factors are the same in each of the 4 models across the tables 4, 5, 6 and 7. These signs are in line with the findings of Chen, Roll et al. (1986). Overall, as presented in table 7, the empirical estimation of 10 portfolios across the models and samples exhibited inconsistency in the results in a way that it is difficult to reconcile and clearly interpret. This mixing results can be attributed to that fact that the difference between the number of the independent variable and the number of the dependent variable is not big enough in the cross sectional regression .

Table 6: 10 Conventional Portfolios

	Const	*M-Beta*	*SMB*	*HML*	*MP*	*DEI*	*UI*	*URP*	*UTS*
	Panel A: Full-sample 2001-2008								
CAPM	-0.0208	-0.8766		--	--	--	--	--	--
	(-3.0711)	(-1.4794)							
FF	-0.0428	0.8696	0.9142	0.8917		--	--	--	--
	(-4.7103)	(1.2260)	(0.9926)	(1.1639)					
APT	-0.0326	--	--	--	-0.0004	-0.0025	-0.0002	0.0012	0.0025
	(-4.5197)				(-0.1431)	(-2.4571) b	(-0.1627)	(0.8968)	(0.9788)
All	-0.0527	-0.4721	-4.1340	7.5252	-0.0074	-0.0007	0.0038	0.0018	-0.0060
	(-1.8120)	(-0.2626)	(-1.0918)	(1.7059) c	(-0.9298)	(-0.2802)	(0.5929)	(0.3110)	(-0.7535)
	Panel B: Sub-sample 2001-2005								
CAPM	-0.0113	-0.6737		--	--	--	--	--	--
	(-1.2678)	(-0.8266)							
FF	-0.0463	2.1017	1.3991	1.6367		--	--	--	--
	(-3.5038)	(2.1785) b	(1.0013)	(1.4474)					
APT	-0.0217	--	--	--	-0.0044	-0.0004	0.0028	0.0042	-0.0002
	(-2.2829)				(-1.2570)	(-0.5005)	(1.8425) c	(2.7718) a	(-0.0753)
All	-0.0632	0.6912	-6.3963	10.0407	-0.0185	0.0027	0.0069	0.0063	-0.0114
	(-1.4604)	(0.2722)	(-1.0825)	(1.5234)	(-1.5583)	(0.9265)	(1.6214)	(1.0266)	(-1.7127) c
	Panel C: Sub-sample 2006-2008								
CAPM	-0.0367	-1.2149		--	--	--	--	--	--
	(-3.6987)	(-1.4842)							
FF	-0.0369	-1.1841	0.1060	-0.3500		--	--	--	--
	(-3.6060)	(-1.2971)	(0.1341)	(-0.4572)					
APT	-0.0508	--	--	--	0.0063	-0.0061	-0.0053	-0.0037	0.0071
	(-4.8961)				(2.0713) b	(-2.5968) b	(-1.7561) c	(-1.5932)	(1.3873)
All	-0.0352	-2.4110	-0.3634	3.3327	0.0110	-0.0065	-0.0014	-0.0056	0.0029
	(-1.2081)	(-1.0673)	(-0.1619)	(0.7858)	(1.5404)	(-1.3557)	(-0.0867)	(-0.4651)	(0.1574)

Note: The results shown in the table are generated from two stage-regressions, the first is a time series regression to generate the betas of the risk factors to be used as independent variables in a cross-sectional regression as the second stage in the process of the methodology. The results from the cross-sectional regression form a time series of risk premium for each risk factor which is the risk premium to be tested using t-statistic. The table exhibits the mean of the time series of each risk premia and below it the critical value of the t-statistic put between brackets; The letters (a), (b) and (c) are the level of significance of 1%, 5% and 10%, respectively. Panel A presents the results of the full-sample, panel B presents the pre-financial-crisis sub-sample, and panel C presents the financial crisis sub-sample.

The symbols in the heading row are Const= constant and the slope of the following risk premiums: M-Beta= CAPM beta which is the excess return on the market portfolio; SMB= small-minus-big portfolio; HML= high-minus-low portfolio, MP= monthly industrial production growth rate; DEI= change in expected inflation; UI= unanticipated inflation; URP= unanticipated change in the risk premium; UTS= unanticipated change in the term structure. The symbols in the heading column are CAPM= the capital asset pricing model, FF= Fama and French three-factor model, APT= arbitrage pricing theory and All= the model that incorporate all the risk factors in the empirical estimation (FF model augmented by APT risk factors).

8. Conclusion

On one hand, this empirical study assumes that Islamic portfolios are in nature associated with low default risk, and prospective investors consequently shall not receive default risk premiums. Hence, the employed default-related risk factors should be only significant in explaining the returns on the conventional portfolios. The only case where risk factors would be significant in explaining returns on the Islamic portfolios is when they can capture other elements of risk than default and financial distress. Another source of risk in the context of the Islamic portfolios is the higher exposure to risk resulted from giving up the investment opportunity in the risk-free assets in order to be complied with Islamic financial rules.

The findings of this chapter confirm that the default-related risk factors are only significant in explaining the returns of the conventional portfolios; hence, Islamic portfolios are empirically considered less risky to default. The effects of the employed risk factors in the asset pricing models on the Islamic portfolios seem not to be as important as they are in the context of the conventional portfolios. Furthermore, the other source of risk associated with Islamic portfolios is also not captured by the employed risk factors. Having investors restricted to the Islamic portfolios indicates that they are exposed to higher risk; however, the employed risk premiums fail to compensate for that. It is possible that other unknown risk factors are more important and hence are priced in the stocks that are Shari'aah-compliant.

In the context of ISMI, it is expected that stocks with lower Islamic accounting ratios are less risky than the ones that are high and approaching 33%. Stocks with high accounting ratios would be more risky because of two things. First, they have higher debt ratios relative to others. Second, stocks eject form the index as soon as their accounting ratios exceed 33%, and hence stocks with high accounting ratios are closer to ejection than others. The consequence of the ejection is to sell the shares which may result in losing dividends to be distributed later on, or having to sell the shares at low prices. Since the employed risk factors fail to explain the returns on the Islamic portfolios, it would be interesting for future research to investigate the effect of the Islamic accounting ratios by creating related mimicking portfolios in an attempt to capture risks in the Islamic portfolios.

Another finding of this chapter is the significant influence of the financial crisis on the effect of the risk factors. Conventional portfolios during the crisis are more sensitive towards DEI, whereas the Islamic portfolios are more sensitive towards MP. This generally indicates that variables related to the economy as a whole are more important and significant for the stock market during the crisis than other firms' specific risk factors.

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Chapter 3. A GARCH Examination of the Oil Effects on the Islamic and Conventional Stock Market Indices

1. Introduction:

It is interesting and important that for financial economists to observe and study the oil price movements due to their significant role in the economy. For example, an increase in oil prices can be a source of inflationary pressure which can, in turn, predict the future of interest rates and investments. The relationship between oil prices and economic growth is believed to be an existing fact. The positive correlation between oil prices and economic growth is expected to exist particularly in countries that hugely depend on oil revenues where oil has a significant share in GDP. For example, in Saudi Arabia, Russia and Venezuela, ones of the major oil-producing countries, the oil sector contributes to an estimated 45%, 30% and 33% of their respective GDP[17], respectively. A developed country such as the UK where the oil reserves are declining, its GDP is by far accounted for by the service sector such as banking, insurance and other business services. Moreover, the service sector also accounts for about 76% of the GDP of the developed economy of the USA, whereas its imported oil accounts for two-third of its consumption. Although, the U.S. gets some oil from its own reserves[18], but it chooses to import oil from foreign countries in order to conserve its oil for the longest time possible[19]. Hence, it is expected that the relationship between oil and economic growth varies between countries according to the dependency of each country on oil and whether the country is an oil- consumer or supplier.

The first decade of the 21st century witnessed many major events that are believed to have directly or indirectly affected oil prices and the economies around the world[20]. In fact, since 2000 the world oil prices have been substantially higher than those of the 1990s. Besides, some major oil exporting countries are from the GCC (Gulf Cooperation Council) where a large proportion of investors are investing in Islamic funds. Wilson (2009) indicated that GCC are significant sources of capital and are contributing to the development of Islamic finance worldwide. The value of the Islamic

[17] These statistics are provided by EIA reports (Energy Information Administration), except Russian's statistic was according to the Russian government as Juurikkala and Ollus (2006) stated in their research.
[18] Oil Reserves can be classified as the quantity of crude oil that is discovered, commercially recoverable, and still remaining.
[19] The UK and U.S. statistics are provided by the CIA (Central Intelligence Agency) publications.
[20] More details are presented in the following section.

or Shari'aah[21] compliant assets is estimated to be around $951 billion in 2008, according to IFSL Research. And, analysts[22] explained the rapid expansion in the Islamic finance by the oil-related boom in the Middle East. Moreover, Smyth (2006), managing director of Failaka International reports, agrees that the growth in GCC stock markets are the reasons behind the increase in the Islamic funds.

Overall, it can be seen that there is a link between GCC states and Islamic funds. Oil prices boom appears to be influencing the GCC economies. The latter, in turn, influences the Islamic funds around the world. Therefore, only the empirical investigation can tell whether this hypothetical link between Islamic stock market index (ISMI) and oil prices exists in the practice.

These facts make it interesting to shed the light on how the new emerging Islamic funds fit in the world economy by looking at ISMI's react to the boost in the oil market. Equally important and interesting is to revisit the linkage between the conventional stock market index (CSMI) and oil market in recent years that experienced the boost in the oil market. By doing so, this study is set to be a comparison investigation between, ISMI and CSMI. There are two conventional indices used in this study representing an oil- importing and exporting countries' economies. Access to ISMI proxies is limited; hence, one index is believed to be enough

Therefore, this chapter aims to empirically examine the link between oil price changes and the expected return and volatility of three stock markets. This study investigates the ISMI provided by Dow Jones Islamic Market U.S. (DJIM US) which is a sub-index of Dow Jones Islamic Market (DJIM) the first index created for investors seeking investment in compliance with Islamic law which was recently announced to be named "Best Islamic Index Provider". The chapter goes on to investigate its counterpart conventional index Standard & Poor's 500 (S&P500) in the U.S. an importing oil country. The chapter also investigates the effect of the oil returns on Tadawul All Share Index (TASI), the stock market of Saudi Arabia, one of the largest oil-producing countries.

Saudi Arabia is located at the centre of the Muslim world which is considered to be one of the leading countries for Shari'aah compliant assets in the world with $127.9

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[21] Shariaah is the sacred law of Islam derived from two primary sources: Quran (Holy book) and the biography of the holy prophet Muhammed peace and blessing be upon him.

[22] This information is taken from an article published in the Financial Times written by David Oakley, 2008. http://www.ft.com/cms/s/0/541693d2-9f6c-11db-9e2e-0000779e2340.html#axzz1ABg63rwD

billion[23]. Although Saudi Arabia is well known for its adherent of Islam and for its leading role in Islamic finance, its stock exchange market Tadawul All Share Index (TASI) is not fully compliance with Shari'aah and that why this study used DJIM US as a proxy to the ISMI not TASI.

This empirical work is conducted using econometric technique to achieve its aims. GARCH model is going to be the method utilised to analyse the relationship between oil and the selected stock market indices for the period from Sep 2002- April 2009. This methodology is well known for its usefulness of analysing stock markets return and volatility. It allows the researcher to observe the effect of the oil return on the stock market expected return and conditional variance. It also allows testing the relationship between risk and return by including the conditional variance in the mean return equation. Besides, the forecasts of the future expected returns of the three indices are computed before and after the inclusion of the oil variable using forecasting GARCH models. Then, the forecasted expected returns are evaluated based on the Root Mean Squared Errors (RMSE) in order to explore if including the oil return in the forecasting GARCH model can help producing more accurate forecasts.

The outline of this chapter is that the following section shed the light on the background and the motive of this study. Section 3 reviews the literature of the studies that investigated the relationship between oil and stock markets, and then section 4 and 5 explain the data and the econometric methodology, respectively. Section 6 presents the actual empirical results expressed in figures and tables accompanied with interpretations. Section 7 presents the analysis and discussion of the results. The final section 8 concludes the study, summarising its limitations and giving recommendations for further research.

2. Background[24]:

This section explains the recent history and the development of the major events that concerned the oil market and the oil producing and consuming countries during the first decade of the third century. It also demonstrates the link between the oil market and the GCC countries which has led this research to be motivated to investigate the effect of

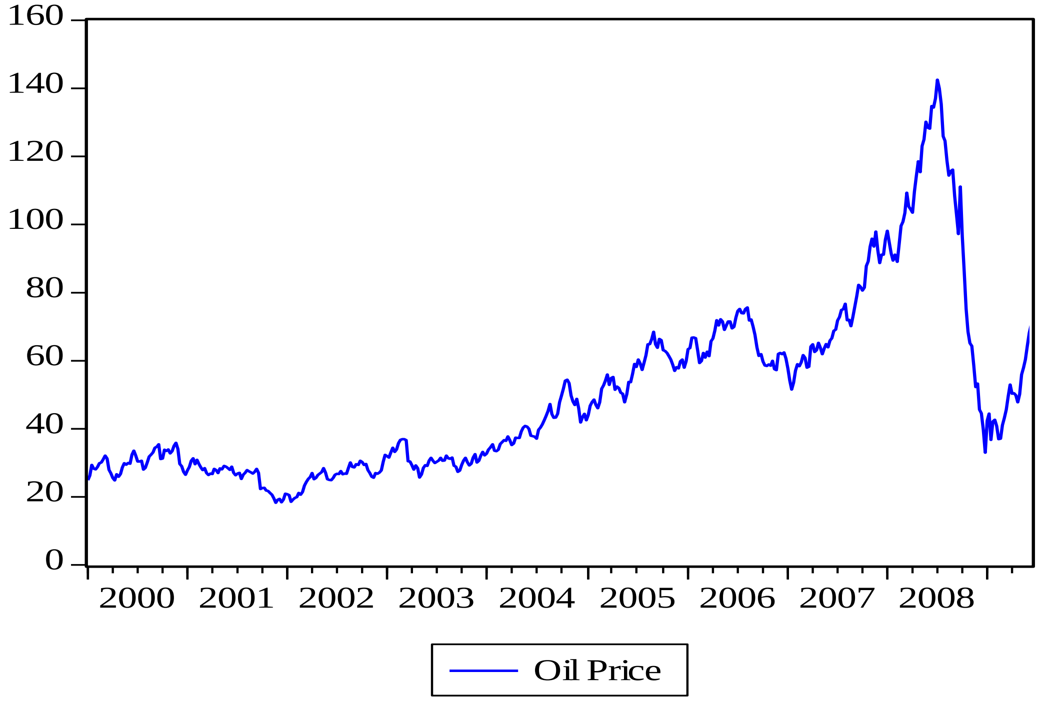
[23] Source: The Banker, Top 500 Islamic Financial Institutions, (November 2009) 4).
[24] All the information in this section is extracted from OPEC's annual reports; 2001 and 2003, unless mentioned otherwise. The reports are available online at OPEC website.

oil prices on ISMI and compare it to its effect on Conventional Stock Market Index CSMI.

At the wake of 9/11 attack, the crude oil prices plummeted resulting in a decrease by 35% in WTI spot prices by the middle of November 2001, reaching a level of around $17 in December, as shown in figure 1. Major oil producing countries represented by OPEC (Organisation of the Petroleum Exporting Countries) delayed their response until 2002 when it actually cut its production by 1.5 mb/d. Several non-OPEC countries, including Russia, joined the production cut of 462,500 b/d. All these practical efforts, offered by OPEC and non-OPEC countries in response to the events, took place for the sake of stabilising the oil market.

However, that was not the end of the event that kept the oil market unsettled. Because the political conflict of 2002-2003 in Venezuela, one of the world’s leading exporters of oil and OPEC member, had also led to a strike in PDVSA, a Venezuelan state-owned petroleum company. The strike resulted in causing PCVSA crude oil production to drop from 3.5 mb/d to less than 1 mb/d (Mares and Altamirano 2007). This production cut raised the risk of a supply shortfall as the strike removed more than 2.5 mb/d from the market. In response, OPEC increased quotas by 1.5 mb/d from 23mb/d to 24.5 mb/d by February, 2003 to cover the interruption of oil supply.

Figure 3: The graph of the crude oil price.



In March 2003, as Venezuelan oil production started to recover, the U.S. and its allies invaded Iraq. In addition to the fact that inventories in U.S. and OECD (Organisation of Economic Co-operation and Development) countries were low, these two events caused an interruption in the oil production in the world forcing OPEC to increases quotas, in June 2003, by 900,000 b/d from 24.5 to 25.4 mb/d in order to meet the growing international demand. This eventually has led to the erosion of the spare oil production capacity which as a result fell from 6 mb/d in 2002 to 2 mb/d in mid-2003 reaching down to less than 1 mb/d by 2004-2005. Less than 1 mb/d was obviously not enough to cover an interruption of oil supply from OPEC producers.

All these events were of the major factors that pushed oil prices up and high. The world witnessed that in the first decade of the 21st century, as shown in figure 1. In fact, the world oil prices since 2000 have been substantially higher than those of the1990s. The prices were well above the estimation of EIA of the long-run equilibrium prices. EIA pointed out the facts that have led to this sharp increase in oil prices exceeding the equilibrium level. It stated that many facts combined together are believed to be the explanation for this phenomenon which are temporary shortage of experienced personnel, equipment, and construction materials in the oil industry; political instability in some major producing region; and recent strong economic growth in major consuming nations.

Apparently, OPEC understands the fact that having the oil prices remain above its equilibrium level for longer period could lower the long-run profits of the oil producer by encouraging more investment in non-OPEC conventional and unconventional supplies and discouraging consumption of liquids worldwide.

Although, having oil prices far above the reasonable level might not be profitable for the producers in the long-run, yet it is true that the sharp rise in oil prices boosts the oil-producing countries' budgets and stimulates their economies especially the GCC countries. They have been, as a result of that, experiencing an economic expansion and increased in liquidity; whereas, the economies of oil-consuming countries are suffering from the rise in costs caused by the rise in oil prices.

Clear examples from the GCC area for the fact that oil price increases boosted some economies and created liquidity can be Saudi Arabia and Qatar. The revenue of the Saudi economy[25], major oil-producing country, in 2008 was three times as much as its revenue in the beginning of the decade reaching SR 1.1 trillion (around $ 293 billion) in 2008 where it was 295 SR billion (more than $ 78 billion) in 2003. Government expenditure on education, workforce training, health, social developments, transportation, telecommunication and agriculture was consequently doubled during the same period. Similar to Saudi, Qatar is also experiencing a surplus and increase in liquidity. In 2007, Qatar, represented by the family's investment vehicle Delta Two, has bought 435 million shares (25% of the total number of shares) in Sainsbury, the UK's third biggest supermarket chain[26]. In addition to other investment such as buying the luxury store Harrods in London in a deal reported to be worth of £1.5 billion pound in 2010[27].

On the other side of the world, particularly in developing Asian countries such as Indonesia and Malaysia, despite the increase in oil prices their economic growth were progressing very well and that growth was mainly driven by strong domestic demand and export growth. The two economies still yet were hit by the global financial crisis as all other countries; however, the Indonesian economy is believed to have successfully

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[25] The information about the Saudi economy is extracted from the ministry of economy and planning reports.

[26] According to BBC website: http://news.bbc.co.uk/1/hi/business/6755497.stm. last access on 18 Jan 2011

[27] According to Bloomberg News http://www.businessweek.com/news/2010-05-08/qatar-s-harrods-purchase-adds-to-emirate-s-british-investments.html last access on 18 Jan 2011.

managed to deal with the global crisis relatively smoothly due to its heavy reliance on domestic consumption[28].

Wilson (2009) expected that the fact that GCC is located at the heart of Muslim world accommodating the two holy mosques for Muslims has made it at the centre of the fast growing Islamic finance industry. He found out that GCC are significant sources of capital and are contributing to the development of Islamic finance worldwide. Islamic finance is a small but a growing fast segment of the global finance industry. According to IFSL Research, the Islamic finance services measured by Shari'aah compliant assets grew up by 25% from 2007 to 2008 reaching around $951 billion.

Analysts said that the fact that Islamic finance experiences a rapid expansion is caused by the oil-related boom in the Middle East and appetite among western institutions to invest in Shari'aah-compliant products.

By the end of 2008, there were around 500 Islamic funds around the world, 137 of them was only issued in 2007. Islamic funds are predicted to easily reach 1000 funds by 2010. In addition to the GCC countries, Malaysia and Indonesia are also of the main sources of Islamic funds nowadays. Moreover, Saudi and Malaysia are considered to be the two largest markets for Islamic asset management in the world[29].

At first glance, it seems that the economies that contain huge oil reserves are doing well because of their dependency on its natural resource in addition to the increase of the oil prices. However, that may not be the case as the oil export proceeds exhibit extreme volatility which, in turn, increases the vulnerability of those particular economies to the oil prices fluctuations. Therefore, the respective governments of these economies are advised to diversify theirs to weaken the linkage between oil and economic growth by finding other sources of income such as renewable energy, real state, tourism and financial services...etc.

In appraising the performance of an economy, a number of measures can be used two of which are the GDP, the most conventional indicator in measuring the size of a particular economy, and the stock market, a leading indicator that reflects investors sentiment – including managers of pension funds and other investment funds and rich individuals –

[28] This information is provided by CIA publications.

[29] This information in this paragraph is according to Islamic funds and Investment reports done by Ernst and Youth.

on the state of their prospective economy as well as their expectation on the future economic prospects.

In fact, the stock markets have been playing an important role in assessing the economic activity of a population, and reflecting the state of the economy. Stock markets can be the first affected sector in an economy when bad or good news are announced. Also, its important role lays in the fact that stock market provides the economy with the stock exchanges that facilitate the following; raising capital for businesses, mobilising savings for investments, company growth, profit sharing, corporate governance, creating opportunities to small investors, government capital-raising for development projects and indicator of the economy.

The stock market can exert significant effects on the other measures of the economy. For example, an increase in stock price causes an increase in wealth which results in increase in consumer spending which is another measure for the economic activity. However, it is generally believed, that stock market theoretically should have no impact on oil crude; instead, it is the oil price changes that should perhaps lead to changes in the uncertainty of the stock markets which may end up affecting the whole economy. Higher oil prices translate into higher transportation, production and heating costs which finally can, in turn, be a drag on corporate earnings.

3. Literature Review:

3.1 Oil prices and economic output:

Since it is believed that there is a link between oil prices and economic output, investigating the relationship between oil return and stock market return and volatility has become an appealing topic for researchers in finance and economics. The existence of inverse relationships between oil prices and economic activity was examined by Hamilton (1983; 1996), one of the first authors that estimate the impact of oil price increases on real income in the U.S economy after the first oil price shock in 1973. Hamilton demonstrated that historic correlation between oil price increases and economic recession is not a statistical coincidence for the period 1948-1980. He found out that increase in oil prices reduced the output growth of the US economy. In sum, Hamilton showed that most of the U.S. recessions were preceded by oil price increases suggesting that oil price increases are of the main causes of recessions. Burbidge and Harrison (1984) examined the economies of the U.S, Japan, Germany, UK, and Canada using monthly data for the period from January 1961 to June 1982. They generally found a causal relationship from oil price shocks to economic variables, although the results are ambiguous for some countries.

Despite the presence of the statistical significant negative relationship between oil price increases and recessions, the collapse of oil prices in 1986 failed to generate economic boom in oil consuming economies. This failure motivated a number of researchers to assume the asymmetric relationship. Thus, Mork (1989) rechecked if Hamilton's results remain accurate even after the oil market collapse in 1980s. The empirical results confirmed the negative relationship between oil price and output growth for an extended period from 1948-1988, and the negative correlation was even stronger than it appeared in Hamilton's study. However, Mark concluded the presence of the asymmetric effect when he observed that the economic output growth was slowed down even after the decline in oil prices in 1980s.

Hooker (1996) confirmed Hamilton's results but refuted the linear relationship between oil prices and output as well as the asymmetric effects because Hooker actually could not confirm that only oil price increases have a negative impact on economic output, while the oil price decreases do not affect the economic output.

Moreover, Ferderer (1996) showed that both oil price changes and oil price volatility have a negative impact on output growth. The oil price changes effects occur in a year time; whereas, the oil price volatility has both an immediate and late effects. The late effect occurs in 11 months time. Hamilton (2003), examining data from 1949-2001, showed some results indicating that oil prices increases occurring after a long period of stable prices have a bigger impact than the increases that occur to correct previous decreases. Also, his results showed that oil price increases matter significantly more than oil price decreases.

3.2 Oil prices and stock markets:

It is vital to investigate the oil prices impact on the stock market. The important side of it lays in the fact that it is to the advantage of investors, fund managers and policy makers to understand the relations between the two markets. Theoretically, the oil market can possibly exert significant effects on the stock market. Oil prices changes cause production costs to vary, and thus oil price shocks empirically affect real output and expected earnings resulting in a change in aggregate stock prices. This theoretical fact has been empirically proved by previous studies. In fact, a body of literature exists shedding the light on the linkage between oil prices and stock returns.

Jones and Kaul (1996), investigating U.S. 1947 to 1991, Canada 1960-1991, United Kingdom 1962-1991 and Japan 1970-1991 stock markets, concluded that oil price hikes had significant effect on each stock market of the four countries where it is most dramatic in Japan and much weaker in Canada. In each country –except the UK- both current and lagged oil prices affect stock returns negatively. Also, their regression analysis conclude that oil shocks generate volatility in the post-war period in the context of the UK and Japanese stock markets, whereas US and Canadian stock markets are rational in a way that oil shocks can be justified by their impact on real cash flows.

Roger et al.(1996), using VAR framework to investigate the relationship between daily oil futures returns and U.S. stock returns, suggested that oil future contracts can be good investments to be included in stock portfolios for diversification benefits. Because they found out that those oil futures returns are not correlated with stock market returns, even contemporaneously, except in the case of oil company returns. Oil future returns appeared to be significantly Granger-causing returns of oil companies stocks. The study, using daily data covering the period from October 1979 to March 1990, generated the same results applying a simple bivariate correlation method and more sophisticated multivariate vector autoregressive approach. The oil and stock market volatilities relationships were investigated and similar results to the oil and stock market returns were concluded, yet the volatility results are not as clear as the returns ones.

Hammoudeh and Aleisa (2004) examined the linkage between NYMEX oil futures prices, the prices quoted for delivery at specific quantity, time and place on the NYMEX, and Saudi stock market as well as the other GCC using daily data covering the period from 1994 to 2001. Utilising co-integration, causality and error correction techniques, and the main conclusion is that only Saudi stock market returns have predictive power for oil futures prices, and they can be predicted by oil prices as well.

Maghyereh (2004) has found out that oil returns had no impact on 22 emerging markets using a generalized VAR approach. However, later on Maghyereh and Al-Kandari (2007) attempted to explore the possibility of finding nonlinear relationship between oil prices and stock markets in GCC countries. They concluded that there is a nonlinear relationship between oil prices and stock market indices in GCC countries.

The literature on the relationship between oil and stock market so far is simply saying that the oil returns can have to some extent an influence on the stock market returns. However, Ross (1989) has also shown that the rate of information flow actually affect volatility in asset returns as well. Malik and Hammoudeh (2007: p.360) state that: "Since information flow and the time used in processing that information varies with the individual markets, one should expect different volatility patterns across markets". They contributed the volatility spillovers to cross-market hedging and change in shared information. They find that relationship between stock market and oil market can exist between second moments. Therefore, the question to be answered here is regarding whether the stock market returns and its conditional variance are sensitive to oil price shocks and volatility. In other words, can oil market shocks and volatility explain the mean stock market expected return and conditional volatility, and which sign the oil volatility will carry if it can explain the expected return.

Furthermore, the accuracy of measuring oil market volatility is also important to see whether it can help explain the mean stock market return. The autoregressive conditional Heteroscdasticity (ARCH) model originally developed by Engle (1982), and later generalized by Bollerslev (1986), is by far the most popular method for modelling volatility of high frequency financial time series data. Multivariate generalized autoregressive conditional Heteroscdasticity (GARCH) models have been popular in estimating the volatility spillover effects among different markets.

A negative sensitivity from the US stock market returns toward the oil returns volatility is a conclusion drawn by Sadorsky (1999). His empirical study, using US monthly data from January 1947 to April 1996, examined the links between the fuel oil prices and stock prices utilizing unrestricted VAR model that also included short-term interest rate and industrial production. It was evident that oil price and a univariate GARCH measure of oil price volatility both play important role in explaining stock returns. However, oil price gained a stronger significance in affecting stock returns after 1986 due to the increase in the oil market turbulence.

Hammoudeh and Aleisa (2002), utilising monthly data from 1991 to 2000, employed the two-step univariate GARCH models. In the context of Bahrain, Indonesia, Mexico, and Venezuela markets, the results indicated that mean spillovers from oil markets to stock markets. These results did not come as a surprise since some of these countries are major oil exporters and their economies are heavily dependent on oil. Hammoudeh and

Aleisa suggested that further researches can test whether the relationship between oil and stock markets returns exist in the second moments.

In response to that suggestion, Malik and Hammoudeh (2007) examined the volatility and shock transmission mechanism among US equity, global crude oil market, and equity markets of Saudi Arabia, Kuwait, and Bahrain, by applying a multivariate GARCH model on the daily data from 14 February 1994 to 25 December 2001. They found significant volatility transmission between the conditional variances of US equity and the global crude oil markets. The conclusion was that, in the Gulf markets, a significant volatility spillover from the equity market to the oil market was only found in the case of Saudi Arabia, whereas the other equity markets are the recipient of volatility from the oil market.

Malik and Ewing (2009), using weekly returns covering the period from 1 January 1992 to 30 April 2008, employed a bivariate GARCH models to simultaneously estimate the mean and conditional variance between oil prices and five different US sector indexes; financial, industrial, consumer services, health care and technology. It was statistically evident that shocks and volatility are transmitted between oil prices and some of the examined market sectors.

3.3 Islamic and conventional markets and oil:

To sum up the presented literature above, the empirical evidences are reasonably consistent about the fact that there is volatility transmission between oil prices and conventional US and some emerging stock markets. But, it would be also interesting to see whether this applies to ISMI due to the fact that GCC, including some major oil exporter countries, is a significant source of capitals to the Islamic funds. The studies using GARCH models that looked at Islamic markets so far are only investigating the risk-return relationship. They have not yet touched upon the effects of oil volatility on the Islamic markets.

Hassan (2002), utilizing a GARCH model, examined the time-varying risk return relationship for the Dow Jones Islamic Index (DJIM) over the 1996-2000 period. The empirical evidence showed that there is a significant positive relationship between conditional volatility and DJIM equity index returns.

However, another study conducted by Mohd and Majid (2006), using GARCH-M model, compared the risks and returns of ISMI and CSMI volatilities in the context of Malaysia market. The conditional standard deviation measured by GARCH, representing the conditional volatility in this study, did not have any effect on the stock returns during the period of analysis. There is no evidence of significant time varying risk premium for both conventional and Islamic stock returns.

Mohd and Majid (2007), in an extension of their previous work, attempted to explore the extent to which the conditional volatilities of both ISMI and CSMI are related to the conditional volatility of monetary policy variables in the context of Malaysian market using monthly data covering the period from the January 1992 to December 2000. The monetary policy variables employed were the narrow money supply (M1), the broad money supply (M2), interest rates (TBR), exchange rate (MYR), and Industrial Production Index (IPI). The Federal Funds Rate (FFR) was used as a measure of volatility in the US monetary policy in order to capture the international influence on both ISMI and CSMI. The findings indicated that ISMI is not sensitive to the interest rate, but the sensitivity to interest rate was evident in the case of CSMI.

However, the only study that can be somehow related to the relationship between ISMI and oil prices is the one that investigates the social responsible index. It is an index that is similar to the Islamic one in terms of having certain restrictions based on beliefs. Sariannidis et al. (2009) examined the impact of crude oil prices on both social responsible stock and conventional indices using GARCH model. They aimed to record the differences in the effects of oil prices among several macroeconomic variables towards the Dow Jones Sustainability (DJSI US) and Dow Jones Wilshire 5000 (DJ W5000) indices using monthly data covering the period from January 2000 to January 2008. The first index includes companies that integrate Corporate Social Responsibility (CSR) standards in their operations while the other stock index represents all U.S. equity securities. They found out that the return of crude oil prices negatively affect the U.S. stock market returns. However, DJSI US reacts with a month delay in changes of oil return.

This study contributes three main things to the literature. First contribution is to examine the effects of crude oil prices on ISMI for the first time. Second one is recording the differences between ISMI and CSMI in terms of the oil price effects. Third contribution is to examine the effect of oil prices on CSMI of an oil-exporting and an oil-importing country. And, due to the limitation of the availability of ISMI, only one Islamic index is examined in this study.

4. Data:

This chapter examines the relationship between oil prices and three stock markets indices; TASI, S&P500, and DJ IMUS. These three indices are deliberately chosen to be proxies for three different stock markets; two of which represent the conventional markets of oil-producing and consuming countries and the last one represent an Islamic market, respectively. Also, WTI spot price (West Texas Intermediate, also known as Texas Light Sweet) is used to represent the oil prices. WTI spot prices, widely used by researchers, are the one quoted for immediate delivery of crude oil in the Cushing Oklahoma, the trading centre. WTI crude oil price has also been used as a benchmark for pricing crude oil exports to the U.S. since 1994 by Saudi Aramco, the state-owned national oil company of Saudi Arabia which is the largest oil corporation in the world.

The financial time series are usually stationary in the first difference. Unit root tests, presented in Table 1, confirm that by rejecting the null hypothesis of unit root after the first difference indicating that all the series in this study are I(1). Hence, the time series data used are all in the form of returns. The return is generated using the first difference of the log of the prices.

In Table 1, the term Exogenous indicates the deterministic of the model which only includes constant with no trend. The lag length is the number of lags used in the unit root test determined by AIC. The numbers of lags are chosen to be 2, 0, 0 and 8 for TASI, S&P500, DJIM US, and Oil, respectively.

Table 7: Results of unit root tests

Null Hypothesis: the series has a unit root

Exogenous: Constant.

Lag Length: 2, 0, 0 and 8 respectively (determined based on AIC, Maximum Lag=16)

Period: 03/09/2002- 16/06/2009

	TASI	S&P500	DJIM US	Oil
ADF test statistic	-9.2545***	-20.2094***	-19,9472***	-4.2257***
	Test critical values			
1% level	-3.4488	-3.4486	-3.4486	-3.4491
5% level	-2.8696	-2.8695	-2.8695	-2.8697
10% level	-2.5711	-2.5711	-2.5711	-2.5712

ADF is Augmented Dickey-Fuller a test for a unit root in a time series sample. ADF is to test the null hypothesis that the series has a unit root. The test is conducted separately for TASI, S&P500, DJIM US and Oil to ensure that all the series are stationary. All the series are in the first difference the form of return. The null hypothesis is rejected if the ADF test statistic is more negative than the test critical values. Rejection means the series has not a unit root and therefore it is stationary. The signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

The data in this chapter covers the period from 3 Sep 2002 to 16 June 2009 utilising the weekly format data of the selected samples to overcome problems of dates matching[30]. The weekly record is on every Tuesday of the week for the stock markets and every Friday for the oil market. This interval is particularly chosen for reasons. Firstly, it is a crucial time for the oil markets in which different events took place one after another affecting the oil market. OPEC started taking actions by cutting its production in 2002 after the 9/11 attack due to the decline in prices. Other events subsequently followed. In addition, it coincided with the start of online-trading in TASI, in Sep 2002, which made the market popular among many investors.

The weekly data is useful due to a number of facts one of which is that weekend days in TASI, for example, are Thursday and Friday, while the oil market has its weekend on Saturday and Sunday. Besides, some of the days' prices that are recorded in the oil market are not found recorded in the stock indices for some unknown reasons. Moreover, the use of weekly returns eliminates or significantly reduces any potential biases that may arise such as the bid-ask effect, non trading days (Malik and Ewing 2009).

[30] Matching dates refers to the fact that the trading days in each market are not always matching each other. Some days happen to be trading days in one market while they are not in the other.

5. The methodology:

In this empirical study, GARCH model is firstly employed to investigate the relationship between the selected stock market indices and the oil prices. Then, forecasting GARCH model is performed in order to explore the contribution of the oil variable to the conditional mean and the conditional variance of the data by looking at what market index is better forecasted and explained by the oil variable using the standard measure of forecast RMSE.

5.1 Review of volatility modelling:

Volatility is a key variable, a measure of uncertainty that plays a crucial role in many areas of finance. And, there have been two approaches of modelling volatility for financial assets returns. One is unconditional approach where the time-varying stock returns volatility is assumed to be constant over time. This assumption was pursued despite the fact that the stock prices follow a random walk. Therefore, normal distribution was the first to be considered to model the unconditional volatility for the financial time series with the assumption that returns are independently identically distributed (IID) random variables. However, empirical findings have been rejecting this assumption and finding that financial data exhibits volatility clustering where large (small) changes tend to be followed by large (small) changes of either sign. In other words, volatility exhibit strong correlation, hence non-randomness of changes is observed in financial assets returns.

The constant variance assumption to measure volatility is considered to be inappropriate (Nelson 1991). This is for the fact that economic and financial time series tends to have large volatility periods that are followed by small volatility periods. In other words, the economic and financial time series exhibit non-normality and time dependence. Therefore, the second approach was to be the conditional variance which was first proposed in the seminal paper by Engle (1982). He introduced the class of Autoregressive Conditional Heteroscdasticity (ARCH) model that allows the variance of the disturbance to vary over time by using past error terms squared to model the conditional variance of the series. Later on, Bollerslev (1986) generalised ARCH (GARCH) which allows the conditional variance to be a function of previous period of squared error terms as well as the lag of the conditional variance.

ARCH and GARCH are by far the most popular method for modelling volatility of high frequency financial time series; thus, they are used in this empirical study. And so the concentration in the remaining will be on the second approach.

The introduction of ARCH and GARCH was followed by numerous studies proposing some modification of the approach to modelling conditional volatility in order to better capture the stylized characteristic of the data. ARCH and GARCH, which treat Heteroscdasticity as a variance to be modelled, have been doing very well since then in describing the financial data. Furthermore, the formation of the simple GARCH (1, 1) can do better than other lag length type of models in estimating the conditional volatility for the financial data (Bollerslev, Chou et al. 1992).

Due to the fact that financial data exhibit volatility clustering , Mandelbrot (1963) and Fama (1965), investigating the validity of normal distribution for financial assets returns, rebut the normality hypothesis for a simple reason that the financial returns distributions tend to have fatter tails than the compatible normal distribution. In other words, financial data exhibit leptokurtosis; and hence normal distribution cannot accurately predict the distribution of financial assets returns as they tend to be more peaked around the centre with fatter tails than be predicted by the normal distribution (José and José 2007). Hence, adopting the right conditional distribution to model the fat-tailed property is one solution to avoid spurious results (Bollerslev, Chou et al. 1992).

Different types of distributions have been used to characterise the data such as the generalised error distribution GED (Box and Tiao 1962), student's t distribution[31] (Blattberg and Gonedes 1974), mixtures of normal distributions (Ali and Giaccotto 1982), discrete mixtures of normal distributions (Kon 1984), generalized beta of the second kind (Bookstaber and McDonald 1987), Tukey's *g* and *h* distributions (Badrinath and Chatterjee 1991) , and the Laplace and double Weibull (Mittnik and Rachev 1993).

From all these different distribution regimes, using t-distribution was suggested by Bollerslev (1987). The t and GED was used by Hsieh (1988). In the case of large and positive excess kurtosis, the solution is to use t-distribution (Baillie and Bollerslev 1989). Hamilton and Susmel (1994), using U.S. weekly stock returns, found that the latent innovations are better described by t-distribution rather than normal distribution.

[31] Student's t-distribution can also be simply called "t-distribution".

This finding is in line to some extent with those of Wilhelmsson (2006) who estimated the forecasting performance of the GARCH(1, 1) model on S&P500 index Future returns with nine different error distributions. Wilhelmsson firstly found that allowing for a leptokurtic error distribution leads to a significant improvement in variance forecasts compare to normal error distribution, and concluded that GARCH model estimated with t-distribution is the best performing model.

5.2 GARCH Application:

The aim of this chapter is to investigate the impact of oil returns on the mean and volatility returns of ISMI and CSMI, and to investigate the effect of risk on the expected returns by using GARCH models. Several empirical studies indicate that the simple GARCH (1, 1) model satisfactorily fits the stock returns as well as other economic time series (Taylor 1986; Bollerslev 1987; Akgiray 1989; Bollerslev, Chou et al. 1992; Liljeblom and Stenius 1997).

Equally important is the issue of which density distributions can be used for the examined samples. Most financial asset returns are believed to be not normally distributed (Fama 1963; Mandelbrot 1963). Jondeau, Poon et al (2007) said that non-normality is strongly featured in two statistical phenomena: the first is that extreme events occur more than it is predicted by a normal distribution which result in having excess kurtosis or fat tails (Fama 1963; Mandelbrot 1963; Blattberg and Gonedes 1974; Kon 1984). The second is that crashes also occur more than booms which result in producing negative skewness or asymmetry in the distribution (Fama 1965; Arditti 1971; Simkowitz and Beedles 1978; Singleton and Wingender 1986).

To settle this issue, the figures 2 and 3 below are produced to show a distribution analysis of the data employed in this study and the residuals. The residuals are obtained by running a simple linear regression of the return of each employed variable against a constant and the first lag of the respective return. The data in Figure 2 are the returns of all the three indices and the oil, whereas Figure 3 displayed the residuals of the all four variables.

And, it can be clearly seen from the graphs in the figures that the t-distribution better suits the data which is shown by the bold line whereas the normal distribution is shown by the dashed line. In addition, the descriptive statistics shown in table 2 in the following section 4 revealed that J-B test rejects the normality of the residuals, and they are leptokurtosis with small negative skewness.

Figure 4: Normal distribution vs. t-distribution for the returns

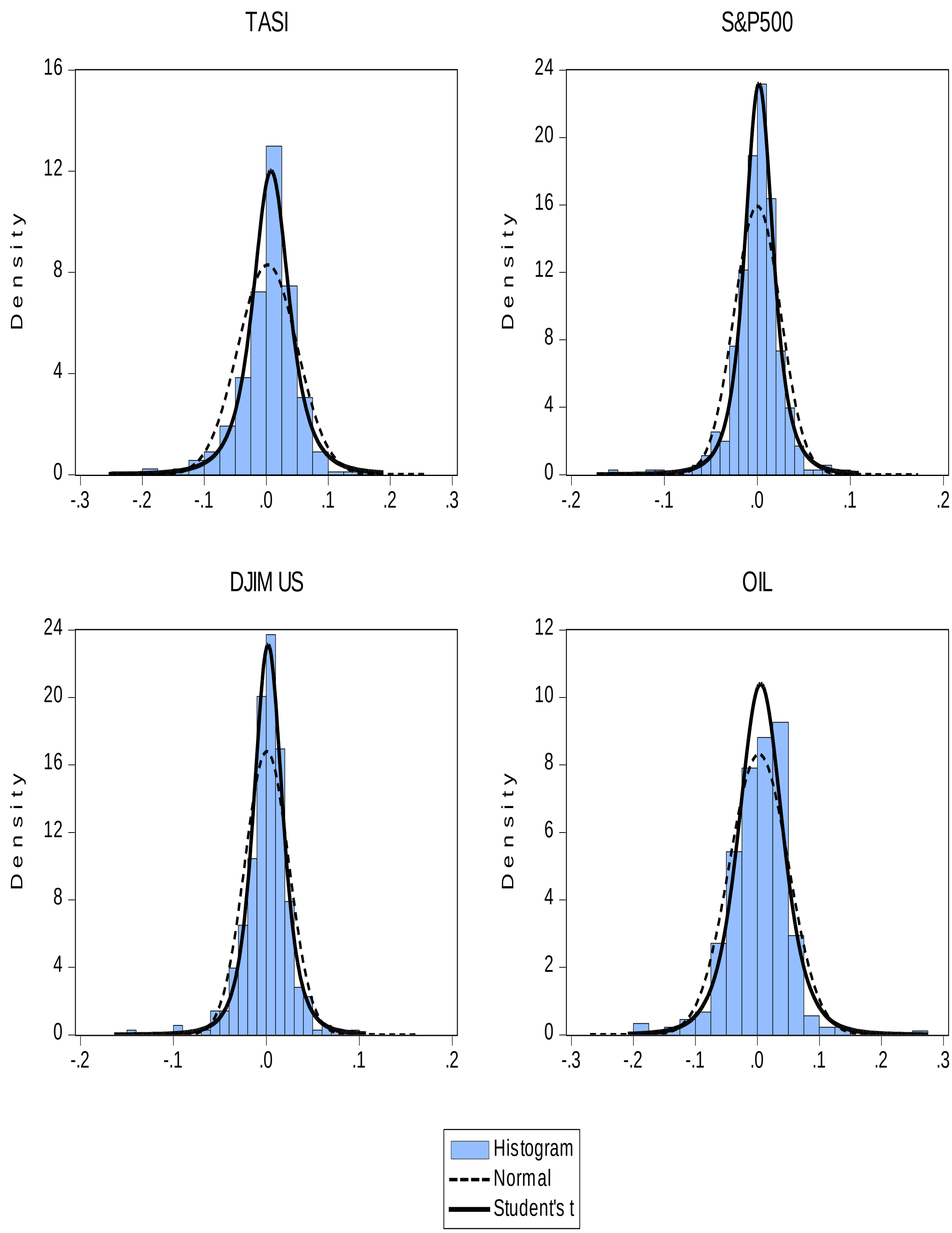
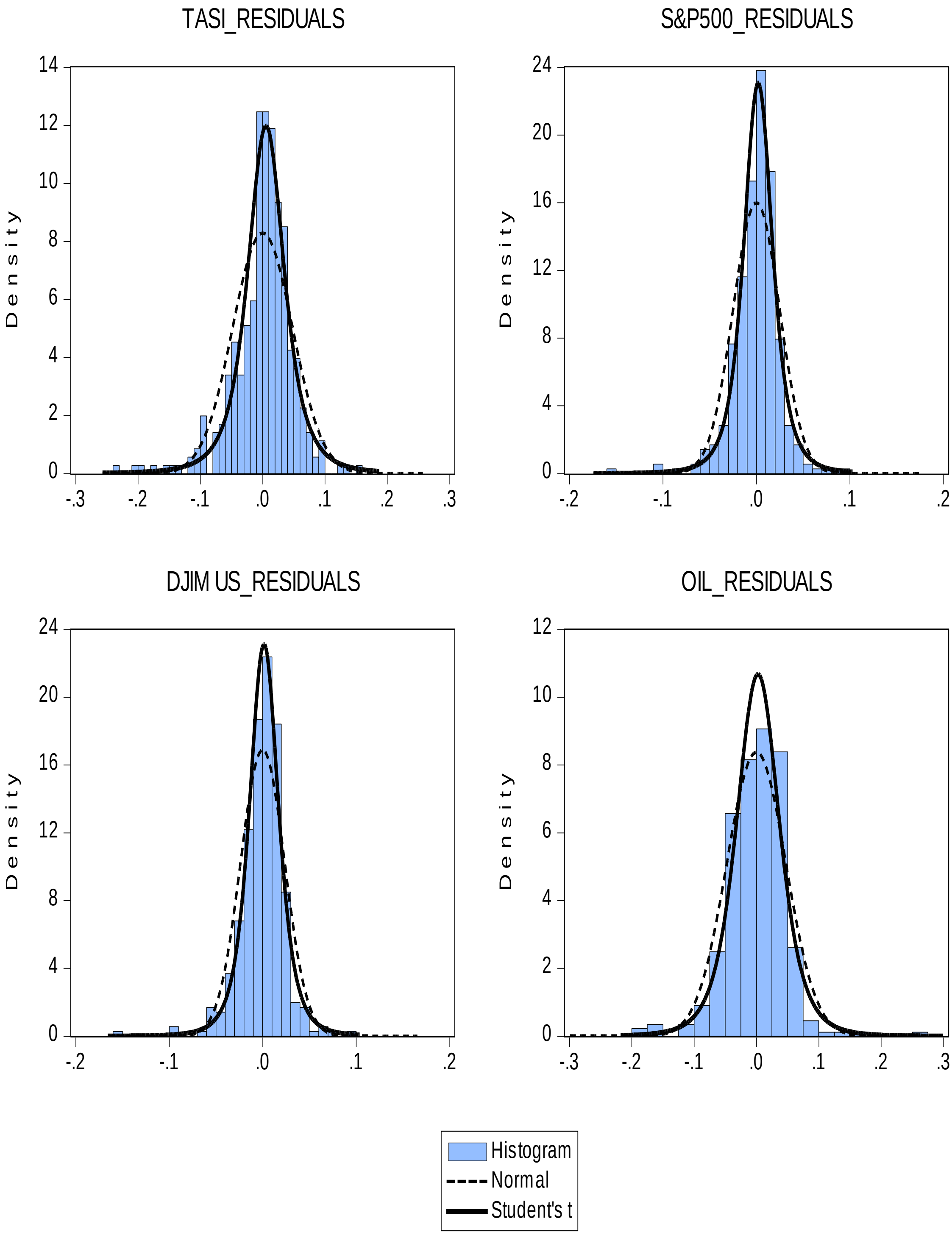


Figure 5: Normal distribution vs. t-distribution for the residuals



Therefore, this study adopts the t- error distribution which is also believed to be the best performing type of error distribution recommended by empirical studies as a good type of distribution that can account for the fat-tailed property (Bollerslev; 1987, Baillie and Bollerslev; 1989, Hamilton and Susmel, 1994, Wilhelmsson; 2006).

5.2.1 GARCH(1, 1):

In order to achieve the aims of this study, GARCH model is applied. The model is a simple GARCH (1, 1) having the oil return variable included in the conditional mean and variance equations as shown in equations (1) and (2). These equations are estimated to determine the effect of oil price changes on the mean and the variance of the stock prices of the selected samples. The expected effect of oil price shocks on the price of Saudi stocks is positive, whereas it is expected to be negative on the price of US stocks. However, the increase in the wealth of important Islamic investors in Saudi Arabia and the rest of oil-exporting countries in GCC might offset the negative effect on the price of some of stocks in the US market especially those of DJIM US. This is because DJIM US composes of Islamic compliant companies that attract Islamic capitals around the world.

In this study, each of the estimated series exhibited evidence of ARCH effects, therefore estimating a GARCH model is appropriate. GARCH (1, 1) is estimated using the following equations:

$$R_{i,t} = \mu + \alpha_1 R_{i,t-1} + \alpha_2 Oil_{t-1} + \varepsilon_{i,t} \qquad (1)$$

$$h_t = \omega + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 Oil_{t-1} \qquad (2)$$

In equation (1), $R_{i,t}$ is the return on series *i* between time *t* and *t-1*, μ is a constant, $\varepsilon_{i,t}$ is the error term for the return on series *i* at time *t*. The term Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. The term $R_{i,t}$ is the stock index return on Tuesday, whereas Oil_{t-1} is the oil return on Friday from the previous week. Equation (1) was estimated, and the residuals are examined for the presence of Heteroscdasticity (ARCH effects) using the test described in (Engle 1982). Equation (2) is the conditional variance model which estimates the parameters of the variance. In equation (2), *h* is the conditional variance at time t, ε^2 is the squared error term at time t-1, and *Oil* is the oil return at time t-1. Each of ω, β_1, β_2 is a non-negative parameter to be estimated, and β_3 is to capture the oil price changes effect on the market return volatility.

Price shocks and uncertainty in the oil market can have a short-term and a long-term effect on the stock prices. In the short-term, they can have direct influence on the investors' sentiment and investment decisions which can be reflected on the stock prices. In the long-term, high oil prices that are not offset by global economic expansion can depress the companies' profits which in turn affect the stock prices. The model specification in equations (1) and (2) allows the oil price changes to affect the expected return and volatility of the examined indices where the expected relationship depends on whether the country is an oil-exporter or –importer (Park and Ratti 2008).

Volatility, representing the risk of the market, is a good measure of the information flow, and the investor's perception of new information will alter their expectation which can cause the stock prices to change. News of oil supply interruption in an oil-exporting country due to a serious political conflict, a threatening war or workers strikes are examples of information that can have spillover effect to the stock markets. They can make the prices of some stocks disperse from the average price particularly those of the oil-related companies. This model specification explores the response of the stock market index of oil-exporting and –exporting countries towards the recent oil price shocks. But, what is more motivating is to reveal whether the adverse effect of high oil prices on the price of the U.S. companies in the Islamic index DJIM US can be offset because of the Islamic funds that are boosted by the oil revenues particularly in GCC.

5.2.2 GARCH-M (1, 1)

The estimated stock market volatility that depends on oil return variable can also enter the mean equation using GARCH-in-mean model (GARCH-M). This model adds a Heteroscdasticity term into the mean equation allowing the conditional mean to depend on its own conditional variance as shown in equations (3) in order to explore the relationship between risk represented by the volatility driven by oil return and return in the selected samples. GARCH-M specification essentially evolved from ARCH-M which was introduced by Engle, Lilien and Robins (1987). But, due to the popularity of GARCH than ARCH, it is more common to use GARCH-M rather than ARCH-M. Estimating GARCH-M (1, 1) is similar to GARCH (1, 1), yet the difference here is having the conditional standard deviation including in the mean equation as shown in the following equation (3).

$$R_{i,t} = \mu + \alpha_1 R_{i,t-1} + \alpha_2 Oil_{t-1} + \alpha_3 \sqrt{h_{t-1}} + \varepsilon_t \qquad (3)$$

$$h_t = \omega + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 Oil_{t-1} \qquad (4)$$

The term $\sqrt{h_{t-1}}$ is the square root of the conditional variance. In equation (4), oil price changes are allowed to explain the stock market volatility so that the latter is set to be conditional on its own lag, the lag of the squared error term and the lag of oil price changes. Hence, equation (3) in this model specification allows risk represented by the conditional volatility generated by equation (4) to directly relate to the expected return of the selected stock market. Theoretically, investors take higher risk only if they can get compensated by higher expected return. If this is empirically true in the examined samples then the relationship between the conditional variance and the expected return should be positive.

In both GARCH and GARCH-M, the conditional variance is expected to be positive, and in order to achieve this expectation the estimated parameters therefore is required to be non-negative. Also, the sum of coefficients of the ARCH and GARCH terms in the conditional variance specification have important implications regarding the role that shocks play in determining the persistence of volatility. The extreme case is when the sum is 1 indicating that shocks to the current volatility is permanent, and this process is assumed to be integrated GARCH (IGARCH). When the sum is less than unity, which is a requirement for a covariance stationary process, it indicates that shocks eventually die out, so the closer the summation to unity the more persistent the shock is.

5.3 GARCH Forecasting:

Because the main purpose of estimating an econometric model is to enable the econometricians to compute the forecasts of the series. Therefore, this section aims to find whether the examined stock market indices can be better forecasted using oil variable during the times of high oil prices. GARCH models, in particular, are popular forecasting models especially in the case of the financial time series (Harris and Sollis 2003). GARCH model has the privilege of allowing econometricians to compute the forecasts of the conditional mean as well as the conditional variance.

The accuracy of a particular model that compute the forecasts of the conditional mean of a series can be evaluated by firstly estimating the model of a subsample from the total sample of the data. Then, the generated forecasts can be compared with the actual future values of the series using the standard measure of forecast RMSE. The optimal forecast of a series is the forecast that minimize the expected value of the squared forecast error of that series.

But, the case is slightly different when forecasting the conditional variance of a time series, because the actual values of the conditional variance of the series are not observable and hence not available for comparison. However, the traditional method to go around this problem is to use the squared value of the return as a proxy for the actual value of the conditional variances of the series (ibid). Hence, the squared values can be compared to the forecasts of the conditional variance in the same way as with the conditional mean.

The presentation of the GARCH forecasting model is shown in equations 5 and 6. In the case of the equation (1), the optimal h-step ahead forecast can be as follows:

$$E\left(R_{i,T+h} \middle| \Omega_T\right) = \mu + \alpha_1 R_{i,T+h-1} + \alpha_2 Oil_{T+h-1} \qquad (5)$$

Where the letter Ω_T is the relevant information set. For computing the optimal forecast of the conditional variance, the same methodology as for the conditional mean forecasts can be used. Hence, the optimal one-step ahead of the conditional variance h_T can be given by the following

$$E(h_{T+1}|\Omega_T) = \omega + \beta_1 u_T^2 + \beta_2 h_T + \beta_3 Oil_T \qquad (6)$$

In this empirical study, the three market indices returns are forecasted using two models. The first model is GARCH (1, 1) with the oil variable included in the mean and the variance equations. The second model is GARCH (1, 1) without the oil variable. Then, RMSE evaluates what model can generate more accurate forecasts for each market index. RMSE can be calculated using the following formula.

$$RMSE = \sqrt{\sum_{t=T+1}^{T+h} \left(\hat{R}_t - R_t\right)^2 / n} \qquad (7)$$

Each model is estimated using the first 300 observations from 3 September 2002 to 27 May 2008. Then, the forecasts of the conditional mean and conditional variance are computed using the rest of the 55 observations from 3 June 2008 to 16 June 2009. In measuring the accuracy, the lower RMSE the more accurate the forecast of the conditional mean or the conditional variance is. If oil return manages to minimize the RMSE, it will mean that the index return is better forecasted using the oil return and vice-versa.

6. Results:

This section displays the results of this chapter. It firstly presents figure 4 that shows the graphs of the stock market indices and the oil prices movement overtime for the selected interval. It then goes on to exhibit the descriptive statistics of all of the series. The last part of this section, divided into two sub-sections, presents the GRACH models results in tables. Sub-section 6.1 displays the main results of this study, whereas sub-section 6.2 demonstrates the results that include oil volatility variable in the conditional variance in order to check the possibility of omitting an important explanatory variable in the conditional variance equation. Sub-section 6.3 exhibits RMSE results of the forecasts of the series computed using GARCH models. Throughout this section, interpretation for all of the tables and graphs are provided.

Figure 6: TASI, DJIM US, S&P500 and Oil prices movement from 09/2002 to 06/2009

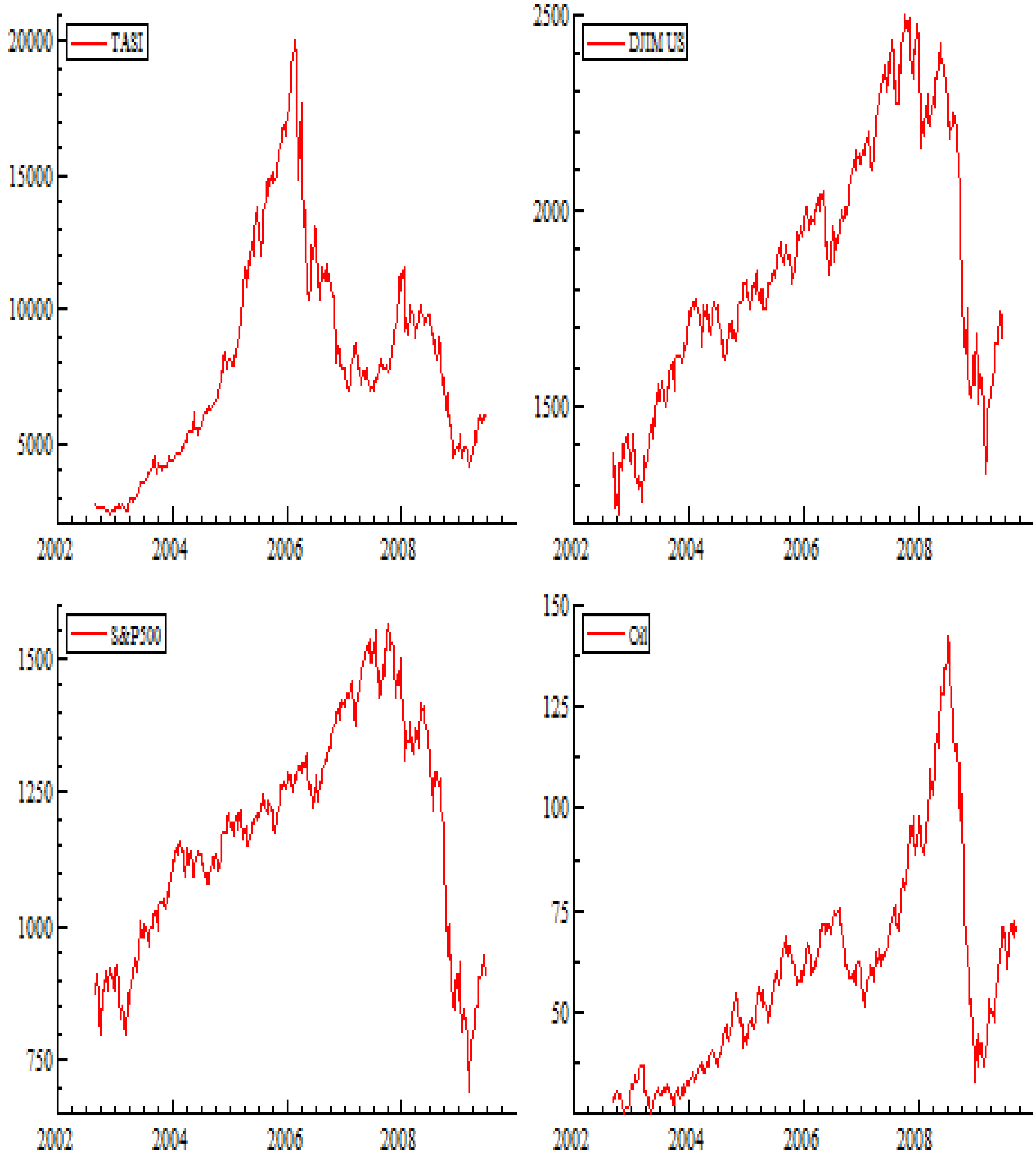


Figure 4 presents four graphs for the price movements of all of the selected samples TASI, DJIM U.S., S&P500 indices and the crude oil prices. It seems that TASI index was experiencing a sharp increase in prices commencing in 2002 the year when Tadawul had started allowing investors to trade online which has made it a lot easier for investor to enter the market and trade. Due to the lack of the investment opportunities in Saudi for those who hold small amount of savings, online trading has opened the door for their savings to flow in such a market. People, outside the market, observing others generating high profits from TASI have led them to enter the market too. A sharp increase in prices consequently took place between late 2002 to the beginning of 2006; meanwhile, the oil prices as shown in the graph -labelled oil- were slightly increasing overtime and fluctuating from around $50 to $75 per barrel between 2004-2006 before it took off in 2007 reaching around $140 in the mid of 2008. The sharp increase in TASI index was followed by a tragic crash in the index falling from 20,000 to around 10,000 points in mid 2006. In 2008, TASI revived simultaneously with the oil price increases; however, it experienced another sharp decline during the time of the recent financial crisis.

DJIM U.S. and S&P500 exhibit similar price movements with steady rising in the index from 2002 till 2007. It appeared that the rise in oil prices since 2007 depressed the two U.S. stock exchanges due to the fact that higher oil prices have indirect reverse impact on stock prices in countries that depend on the foreign oil such as the U.S. Thus, the two indices were trying to resist the sharp increase in oil prices until the sharp decline occurred in 2008 after the reveal of the financial crisis. It is clearly evident that TASI, DJIM U.S. and S&P500 indices and the oil prices all fell sharply during 2008, and the oil price was the last to start declining.

Table 2 presents the descriptive statistics of the selected sample to give general insight about the data. It appears that TASI has the highest mean 0.22% associated with the highest risk represented by the standard deviation 4.81% between the stock indices. Although DJIM US and S&P500 exhibit almost similar risk, yet the former with a slightly higher risk record a clear higher mean of return 0.12% than the latter which has a mean return of 0.002%. The statistics of the oil return is very similar to TASI's results where its mean return is 0.23% with high risk being 4.79%. From the descriptive statistic shown above, it can be seen that DJIM US is preferred to others as it generated the higher mean of return while maintaining a reasonable low risk in comparison to others presented in the table.

All the data in the table2 exhibit negative skewness and high positive Kurtosis. The negative skewness indicates that the tail on the left side of the probability density function is longer than right side which is a sign of asymmetric distribution. The positive Kurtosis indicates that the tails are fatter with higher peak than in the case of normal distribution. The J-B test confirms the non-normality of the data by rejecting the null hypothesis that the data is normally distributed. ARCH test shows that ARCH effects exist in the indices which indicate that GARCH model can be considered.

Table 8: Descriptive statistics

Market	Data	Mean	Max	Min	STDV	Skew	Kurt.	J-B Test	ARCH(1)
TASI	Return	0.0022	0.1601	-0.232	0.0481	-1.093	6.7655	279.58 (0.0000)	8.72 (0.0032)
	Residuals	---	---	---	---	-1.0768	6.7186	271.59 (0.0000)	---
S&P500	Return	0.00002	0.0986	-0.158	0.0252	-1.052	9.5388	695.96 (0.0000)	5.48 (0.0193)
	Residuals	---	---	---	---	-1.1209	9.8129	756.62 (0.0000)	---
DJIM US	Return	0.0012	0.1151	-0.149	0.0272	-0.576	5.6438	252.61 (0.0000)	3.01 (0.0828)
	Residuals	---	---	---	---	-0.9466	9.2753	631.92 (0.0000)	---
Oil	Return	0.0023	0.2513	-0.191	0.0479	-0.379	6.6038	200.08 (0.0000)	----
	Residuals	---	---	---	---	-0.1743	7.7426	332.61 (0.0000)	---

The sample of daily return is weekly from 3 Sep 2002 to 16 June 2009. Max stands for the maximum, Min for the minimum, STDV for the standard deviation, Skew for Skewness, Kurt for Kurtosis, J-B Test is the Jarque and Bera test, Obs is the number of observations, and Res for residuals. The numbers in parentheses are the P-values.

6.1 Stock indices and oil returns:

As shown in Table3, TASI seems to be sensitive to oil price changes. In GARCH(1, 1), oil returns significantly affect the stock market expected return and its volatility at the 5% and 10% level of significance, respectively. Its effect on the mean return is positive while the opposite is on the conditional variance. This result indicates that good news about the oil return can possibly be a sign of generating higher returns as well as reducing the risk by reducing the market's volatility which in return enhances the stability of the market. So far, increase in oil returns positively contributes to TASI returns.

But the question here is going to be about the risk return trade off in TASI, and whether the risk in TASI gets compensated by higher return. GARCH-M comes in to play where the square root of the conditional variance is the risk representing the uncertainty in the market. The results of GARCH-M (1, 1) model_1 shows that market's volatility exert significant impact on the expected return in a negative way indicating that TASI's expected return is affected by TASI uncertainty. The negativity could possibly mean that investors in TASI are not that type of risk averse, and hence investors might end up lowering their mean returns by enduring higher risk. In other words, it is not necessary that bearing a higher risk is compensated by a higher return in the context of TASI as believed in the mainstream theory. In sum, while oil returns significantly reduces the TASI's volatility, uncertainty exerts a negative impact on the market expected return. It shows that oil return can be an important element in TASI in terms of predicting the volatility as well as the expected returns.

However, more things can be learnt from GARCH-M (1, 1) Model_2. The model reveals that when the conditional mean allows the oil return to enter its equation, the significance effect of oil returns in the mean equation disappears as a result of the presence of the conditional standard deviation in the mean equation. This actually demonstrates that the effect of the oil return on the TASI return can be accounted for by the conditional standard deviation of the market.

In the light of the different models and results shown above, one can conclude that stability in oil markets is important to enhance the stability of TASI expected return; thus, an increase in oil returns reduces risk. Furthermore, oil return can be a significant factor for TASI's expected returns with positive impact. This kind of results are not surprising because Saudi Arabia's economy is heavily dependent on oil and petroleum-related industries as it is the world's largest producer and exporter of total petroleum liquids, and the world's second largest crude oil producer.

Table 9: TASI results

	GARCH (1, 1)	GARCH-M (1, 1)	
		Model_1	**Model_2**
Mean Equation	Coff	Coff	Coff
$\sqrt{h_{t-1}}$	-----	-0.2735 (0.0279)**	-0.2380 (0.0644)*
μ	0.006370 (0.0003)***	0.0165 (0.0001)***	0.0147 (0.0011)***
R_{t-1}	0.104804 (0.0846)*	0.0897 (0.1341)	0.0879 (0.1448)
Oil_{t-1}	0.073735 (0.0343)**	-----	0.0439 (0.2461)
Variance Equation			
ω	0.0002 (0.0057)***	0.0002 (0.0056)***	0.0002 (0.0077)***
ε_{t-1}^2	0.3871 (0.0006)***	0.3319 (0.0004)***	0.3401 (0.0004)***
h_{t-1}	0.5931 (0.0000)***	0.6485 (0.0000)***	0.6388 (0.0000)***
Oil_{t-1}	-0.0039 (0.0648)*	-0.0037 (0.0191)**	-0.0035 (0.0403)**
R^2	0.003413	0.009798	0.020695
AIC	-3.601224	-3.608131	-3.604831

The table presents the results of a model specification of GARCH(1, 1) and two specification models of GARCH-M(1, 1). For the mean equation, the term $\sqrt{h_{t-1}}$ is the square root of the conditional variance at time t-1, μ is a constant, R_{t-1} is the lag return of the dependent variable, Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. For the variance equation, the term ω is a constant, ε_{t-1}^2 is the squared error term at time t-1, h_{t-1} is the conditional variance at time t-1, and *Oil* is the oil return at time t-1. The term Coff means coefficient. AIC = Akaike Information criterion and R^2 is R-squared. P-values are in parentheses and the signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

From the results of GARCH (1, 1) shown in table4, it is clear that oil price changes have opposite effects on S&P500 to those exerted on TASI. There is a significant positive relationship between the oil returns and volatility at 10% level of confidence while negative relationship is detected between the oil return and mean return of S&P500 at the 10% level of confidence as well.

GARCH-M (1, 1) model_1 shows that conditional standard deviation insignificantly entered the mean equation, indicating that S&P500 does not pay for the risk of uncertainty. However, oil return in Model_2 remains significant despite the presence of the insignificant conditional standard deviation term.

The graphs show that the fluctuations of prices of S&P500 index look very similar to the fluctuation of the oil prices; hence S&P500 and oil prices seem to be moving together. Similar to the case of DJ IMUS, there was a constant increase in the two graphs from 2002 till almost 2008, and then a sharp decline had happened to both of them during the mid of 2008 due to the recent financial crisis. Furthermore, S&P500 price index levelled for a while between 2007 and 2008, and only fluctuating between 1566 and 1309.

In sum, the GARCH models present evidences suggesting that oil return has a negative significant impact on S&P500 expected return. The evidences also suggest that stability of the market seems to be having some dependency on the stability of the oil market because the oil return is positively significant in the variance equations. Hence, oil shocks positively correlate with the volatility of the stock market as well as negatively affect the mean return.

In the light of the different models and results shown above, one can conclude that these results are in line with those of (Sariannidis, Giannarakis et al. 2009), which found that oil returns affect the S&P500 return in a negative way, and oil shocks create more volatility in this market. Our finding also is supporting previous empirical evidence that showed the relationship between oil and U.S. stock market.

Table 10: S&P500 results

	GARCH (1, 1)	GARCH-M (1, 1)	
		Model_1	**Model_2**
Mean Equation	Coff	Coff	Coff
$\sqrt{h_{t-1}}$	-----	-0.062816 (0.6493)	-0.045946 (0.7399)
μ	0.002784 (0.0012)***	0.003670 (0.1274)	0.003516 (0.1397)
R_{t-1}	-0.117474 (0.0315)**	-0.111945 (0.0444)**	-0.118356 (0.0333)**
Oil_{t-1}	-0.034070 (0.0880)*	-----	-0.033462 (0.1001)*
Variance Equation			
ω	8.46E-06 (0.1705)	7.75E-06 (0.1681)	8.44E-06 (0.1694)
ε_{t-1}^{2}	0.104205 (0.0160)**	0.099103 (0.0147)**	0.103156 (0.0158)**
h_{t-1}	0.873578 (0.0000)***	0.879953 (0.0000)***	0.874581 (0.0000)***
Oil_{t-1}	0.000540 (0.1039)*	0.000532 (0.0940)*	0.000550 (0.0923)*
R^2	-0.023259	0.000465	-0.019432
AIC	-4.978225	-4.972839	-4.972885

The table presents the results of a model specification of GARCH(1, 1) and two specification models of GARCH-M(1, 1). For the mean equation, the term $\sqrt{h_{t-1}}$ is the square root of the conditional variance at time t-1, μ is a constant, R_{t-1} is the lag return of the dependent variable, Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. For the variance equation, the term ω is a constant, ε_{t-1}^{2} is the squared error term at time t-1, h_{t-1} is the conditional variance at time t-1, and *Oil* is the oil return at time t-1. The term Coff means coefficient. AIC = Akaike Information criterion and R^2 is R-squared. P-values are in parentheses and the signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

From table5, it is evident that oil returns exert no significant effect on the DJ IMUS whatsoever. Model_1 shows that conditional standard deviation insignificantly entered the mean equation indicating that DJ IMUS does not pay for bearing higher risk of uncertainty. Although it is believed that a large number of the capitals investing in ISMI in the western markets are coming from the Gulf countries which are the major oil-producer countries, yet Model_2 indicate that fluctuations in the oil markets does not necessarily bother DJ IMUS. Stability of the market seems to be independent of the stability of the oil market. A better explanation can possibly be that DJ IMUS is more efficient in the way that oil market information is well reflected in the DJ IMUS prices so this information does not earn the investor any abnormal profit, nor altering the risk of a portfolio.

The graphs show that the fluctuations of prices of DJIM US index look very similar to the fluctuation of the oil prices; hence, DJIM US and oil prices seem to be moving together. There was a constant increase in the two graphs from 2002 till almost 2008, and then a sharp decline occurred to both of them in 2008 during the recent financial crisis. However, the only difference seemed to be that DJIM US price index levelled for a while between 2007 and 2008, and only fluctuating between 2491 and 2160. Furthermore, the study found out that having oil variable included in the variance equation does not alter the insignificance of the risk on DJIM US expected return.

In the light of the different models and results shown in table5, one can conclude that fluctuation in oil market is well predicted and reflected in the prices and hence has no effects on the stability of DJIM US expected return. As a result, predictions by utilising oil market information in the context of DJIM US are almost impossible, according to the results. DJIM US can possibly be used as an investment vehicle to hedge against oil return’s changes.

Table 11: DJ IMUS results

	GARCH (1, 1)	GARCH-M (1, 1)	
		Model_1	**Model_2**
Mean Equation	Coff	Coff	Coff
$\sqrt{h_{t-1}}$	-----	-0.0464 (0.7970)	-0.0567 (0.7487)
μ	0.0028 (0.0033)***	0.0035 (0.3136)	0.0038 (0.2615)
R_{t-1}	-0.0764 (0.1666)	-0.0765 (0.1694)	-0.0777 (0.1625)
Oil_{t-1}	-0.0241 (0.2634)	-----	-0.0245 (0.2543)
Variance Equation			
ω	1.66E-05 (0.0933)*	1.63E-05 (0.0929)*	1.64E-05 (0.0978)*
ε^2_{t-1}	0.0891 (0.0169)**	0.0882 (0.0169)**	0.089470 (0.0169)**
h_{t-1}	0.8678 (0.0000)***	0.8693 (0.0000)***	0.867893 (0.0000)***
Oil_{t-1}	0.0003 (0.4643)	0.0003 (0.4626)	0.000343 (0.4112)
R^2	-0.015327	0.000283	-0.012338
AIC	-4.909609	-4.941955	-4.939006

The table presents the results of a model specification of GARCH(1, 1) and two specification models of GARCH-M(1, 1). For the mean equation, the term $\sqrt{h_{t-1}}$ is the square root of the conditional variance at time t-1, μ is a constant, R_{t-1} is the lag return of the dependent variable, Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. For the variance equation, the term ω is a constant, ε^2_{t-1} is the squared error term at time t-1, h_{t-1} is the conditional variance at time t-1, and *Oil* is the oil return at time t-1. The term Coff means coefficient. AIC = Akaike Information criterion and R^2 is R-squared. P-values are in parentheses and the signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

6.2 Including Oil volatility in the conditional variance:

From the results shown in sub-section 6.1, we can see that oil return significantly affect the volatility of S&P500 and TASI which is in line with previous findings (Hammoudeh and Aleisa, 2002; Vo, 2011). The aim of this chapter is to investigate the effect of oil returns on the selected stock markets; however, it can be argued that the estimate of oil return's effect on the market's volatility is biased due to the possibility of omitting a relevant variable which can be the oil volatility. It is theoretically accepted that oil volatility might be an important explanatory variable that should be included in the conditional variance equation as Malik and Hammoudeh (2007) indicate that the relationship between stock market and oil market can also exist between second moments. Hence, in order to investigate this matter of biased estimates, this sub-section employs oil volatility in the GARCH specifications. Therefore, the second moment of oil return is allowed to enter the conditional variance equation to estimate the second moment of the three selected stock market indices.

In this section, the tables 6, 7 and 8 present GARCH models incorporating the oil volatility in the conditional variance in combination with oil price shocks. While everything remains the same in each specification, the conditional variance models will be as follows:

$$h_t = \omega + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 Oil_{t-1} + \beta_4 Oil_{t-1}^2 \qquad (8)$$

While the mean equation remains the same as in equation (1) for GARCH(1, 1) and equation (3) for GARCH-M(1, 1), the new term added to the variance equation is Oil_{t-1}^2 as presented in equation (8). The term Oil_{t-1}^2 is the oil volatility which is simply defined as the oil return squared. This definition of volatility is widely used in the literature (e.g., Jorion (1995), see also Poon and Granger (2003) for a survey of literature on volatility forecasting). Gębka (2012) explained that, on theoretical grounds, there is no method of volatility estimation clearly dominates the others. However, he explained that the definition of squared return has the ability to capture the contemporaneous shocks to the volatility (ibid). Hence, this definition has the advantage that makes it preferred in this study over the other definitions.

Also, it should be noted that there is a weak correlation between oil return and oil volatility but negative with value of -0.1211. Thus, it should not be a problem of Multicollinearity. The inclusion of oil volatility can tell us whether the level of return or volatility of oil is more important in estimating the stock market volatility in this chapter.

It is clear from the results shown in table 6 that while oil return effect remains the same as before the inclusion, oil volatility is statistically insignificant across the three models. There is no indication of specification error in terms of omitting the oil volatility in the context of TASI as the AIC's value is higher than when the oil volatility is not included. The AIC shows that including the oil volatility does not improve the goodness of fit of the models.

Table 12: TASI results

	GARCH (1, 1)	GARCH-M (1, 1)	
		Model_1	**Model_2**
Mean Equation	Coff	Coff	Coff
$\sqrt{h_{t-1}}$	----	-0.273051 (0.0197)**	-0.226304 (0.0712)*
μ	0.006561 (0.0002)***	0.016244 (0.0000)***	0.014073 (0.0013)***
R_{t-1}	0.103566 (0.0891)*	0.093156 (0.1200)	0.090773 (0.1337)
Oil_{t-1}	0.079671 (0.0664)*	----	0.048414 (0.2857)
Variance Equation			
ω	0.000165 (0.0779)*	0.000166 (0.0443)**	0.000152 (0.0717)*
ε^2_{t-1}	0.387701 (0.0016)***	0.351007 (0.0008)***	0.356492 (0.0009)***
h_{t-1}	0.560032 (0.0000)***	0.596764 (0.0000)***	0.592138 (0.0000)***
Oil_{t-1}	-0.005530 (0.0361)**	-0.006346 (0.0063)***	-0.005662 (0.0196)**
Oil^2_{t-1}	0.067288 (0.2175)	0.056554 (0.2016)	0.059353 (0.2131)
R^2	0.004429	0.008255	0.019748
AIC	-3.611382	-3.618316	-3.615429

The table presents the results of a model specification of GARCH(1, 1) and two specification models of GARCH-M(1, 1). For the mean equation, the term $\sqrt{h_{t-1}}$ is the square root of the conditional variance at time t-1, μ is a constant, R_{t-1} is the lag return of the dependent variable, Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. For the variance equation, the term ω is a constant, ε^2_{t-1} is the squared error term at time t-1, h_{t-1} is the conditional variance at time t-1, *Oil* is the oil return at time t-1, and Oil^2_{t-1} is the oil volatility. The term Coff means coefficient. AIC = Akaike Information criterion and R^2 is R-squared. P-values are in parentheses and the signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

For S&P500, Table 7 tells a slightly different story from TASI's. While oil return remains significant with the same signs, oil volatility is statistically significant at the 90% level of confidence with a positive sign. The only change of the oil return effect is that its significance has increased from 90% to 95% level of confidence. Apart from that, no significant change has been recorded after the inclusion of the oil volatility variable except the disappearance of the oil return significance in the mean equation in GARCH-M (1, 1) model_2. However, AIC indicates that these specifications are not better than the ones that omitted the oil volatility.

Table 13: S&P500 results

	GARCH (1, 1)	GARCH-M (1, 1)	
		Model_1	Model_2
Mean Equation	Coff	Coff	Coff
$\sqrt{h_{t-1}}$	----	-0.143222 (0.3140)	-0.112850 (0.4298)
μ	0.002629 (0.0026)***	0.004798 (0.0524)**	0.004419 (0.0743)*
R_{t-1}	-0.111461 (0.0423)**	-0.108590 (0.0525)**	-0.113553 (0.0419)**
Oil_{t-1}	-0.037032 (0.1004)*	----	-0.034748 (0.1333)
Variance Equation			
ω	1.53E-06 (0.8278)	1.32E-06 (0.8407)	1.76E-06 (0.7955)
ε^2_{t-1}	0.085402 (0.0318)**	0.075276 (0.0328)**	0.080402 (0.0332)**
h_{t-1}	0.861772 (0.0000)***	0.870267 (0.0000)***	0.864488 (0.0000)***
Oil_{t-1}	0.000662 (0.0370)**	0.000701 (0.0185)**	0.000719 (0.0211)**
Oil^2_{t-1}	0.010239 (0.0946)*	0.010394 (0.0717)*	0.010423 (0.0806)*
R^2	-0.026753	0.004517	-0.015846
AIC	-4.984576	-4.980552	-4.980664

The table presents the results of a model specification of GARCH(1, 1) and two specification models of GARCH-M(1, 1). For the mean equation, the term $\sqrt{h_{t-1}}$ is the square root of the conditional variance at time t-1, μ is a constant, R_{t-1} is the lag return of the dependent variable, Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. For the variance equation, the term ω is a constant, ε^2_{t-1} is the squared error term at time t-1, h_{t-1} is the conditional variance at time t-1, *Oil* is the oil return at time t-1, and Oil^2_{t-1} is the oil volatility. The term Coff means coefficient. AIC = Akaike Information criterion and R^2 is R-squared. P-values are in parentheses and the signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

For DJIM US, it seems as if the oil volatility is playing an important role according to the results shown in table 8. The variable appears to be significant at the 5% level of confidence across the models. Moreover, oil return has become a statistically significant variable in the GARCH-M models. However, the AIC shows that the inclusion of oil volatility has not improved the model. Thus, GARCH models for DJIM US presented in table 5 are preferred to the ones in table 8. To underpin this inference, the same GARCH models were separately run by incorporating only the oil volatility in the conditional variance without the oil return.

Table 14: DJIM US results

	GARCH (1, 1)	GARCH-M (1, 1)	
		Model_1	**Model_2**
Mean Equation	Coff	Coff	Coff
$\sqrt{h_{t-1}}$	----	-0.144693 (0.4212)	-0.121301 (0.4968)
μ	0.002556 (0.0061)***	0.005062 (0.1340)	0.004722 (0.1566)
R_{t-1}	-0.076066 (0.1625)	-0.079212 (0.1488)	-0.078367 (0.1520)
Oil_{t-1}	-0.029206 (0.2230)	----	-0.027877 (0.2488)
Variance Equation			
ω	6.74E-06 (0.5207)	6.39E-06 (0.5230)	6.13E-06 (0.5450)
ε_{t-1}^2	0.052602 (0.0979)*	0.048281 (0.0990)*	0.049275 (0.0996)*
h_{t-1}	0.867943 (0.0000)***	0.872458 (0.0000)***	0.871410 (0.0000)***
Oil_{t-1}	0.000584 (0.1565)	0.000644 (0.0950)*	0.000651 (0.0998)*
Oil_{t-1}^2	0.012936 (0.0501)**	0.012866 (0.0362)**	0.013166 (0.0397)**
R^2	-0.018188	0.003582	-0.011186
AIC	-4.963309	-4.960992	-4.958773

The table presents the results of a model specification of GARCH(1, 1) and two specification models of GARCH-M(1, 1). For the mean equation, the term $\sqrt{h_{t-1}}$ is the square root of the conditional variance at time t-1, μ is a constant, R_{t-1} is the lag return of the dependent variable, Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. For the variance equation, the term ω is a constant, ε_{t-1}^2 is the squared error term at time t-1, h_{t-1} is the conditional variance at time t-1, *Oil* is the oil return at time t-1, and Oil_{t-1}^2 is the oil volatility. The term Coff means coefficient. AIC = Akaike Information criterion and R^2 is R-squared. P-values are in parentheses and the signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

The results shown in table 9 indicate that the oil volatility has no effect and its significance disappears completely after the exclusion of the oil return. In sum, all the results show that oil return is the right level to be used in this chapter to investigate the oil effects on the selected stock markets returns.

Table 15: DJIM US having only oil volatility in the conditional variance equation

	GARCH (1, 1)	GARCH-M (1, 1)	
		Model_1	**Model_2**
Mean Equation	Coff	Coff	Coff
$\sqrt{h_{t-1}}$	----	-0.004805 (0.9809)	-0.016119 (0.9346)
μ	0.002301 (0.0177)***	0.002270 (0.5490)	0.002592 (0.4859)
R_{t-1}	-0.070225 (0.2006)	-0.070143 (0.2051)	-0.070253 (0.2015)
Oil_{t-1}	-0.026135 (0.2906)	----	-0.026246 (0.2884)
Variance Equation			
ω	1.17E-05 (0.2689)	1.23E-05 (0.2473)	1.17E-05 (0.2695)
ε_{t-1}^2	0.0549 (0.0947)*	0.0567 (0.0908)*	0.054693 (0.0961)*
h_{t-1}	0.8678 (0.0000)***	0.8652 (0.0000)***	0.8681 (0.0000)***
Oil_{t-1}^2	0.010465 (0.1062)	0.010172 (0.1134)	0.010459 (0.1109)
R^2	-0.014496	-0.000584	-0.013511
AIC	-4.962100	-4.959167	-4.956452

The table presents the results of a model specification of GARCH(1, 1) and two specification models of GARCH-M(1, 1). For the mean equation, the term $\sqrt{h_{t-1}}$ is the square root of the conditional variance at time t-1, μ is a constant, R_{t-1} is the lag return of the dependent variable, Oil_{t-1} is the return on oil prices at time *t-1*. The weekly observation is on every Tuesday for the stock markets and every Friday for the oil market. For the variance equation, the term ω is a constant, ε_{t-1}^2 is the squared error term at time t-1, h_{t-1} is the conditional variance at time t-1, and Oil_{t-1}^2 is the oil volatility. The term Coff means coefficient. AIC = Akaike Information criterion and R^2 is R-squared. P-values are in parentheses and the signs (***),(**),(*) are the level of significance of 1%, 5% and 10%, respectively.

6.3 The Evaluation Measure for the Forecasting results:

The results presented in table 10 are those of the standard measure of forecast accuracy RMSE. Table 10 shows the RMSE results of the forecasts of the conditional mean and the conditional variance of the three examined indices. It is clear from the results that the forecasting GARCH model after the incorporation of the oil return produces more accurate forecasts of the conditional mean and the conditional variance in TASI. This is because including oil return in the model lowers the RMSE in both the conditional mean and the conditional variance of TASI. Whereas in the case of S&P500 and DJIM US, RMSE is higher when the oil return is included in the mean and the variance equations indicating that both indices' future expected returns and volatility are better forecasted without the oil return.

Table 16: RMSE results.

	TASI	S&P500	DJIM US
RMSE for the conditional mean			
Oil	0.0534	0.0269	0.0249
None-Oil	0.0542	0.0253	0.0235
RMSE for the conditional variance			
Oil	0.066	0.047	0.042
None-Oil	0.067	0.045	0.040

This table presents the results of RMSE (a forecast evaluation measure) for forecasts from GARCH (1, 1) model with and without oil return for TASI, S&P500 and DJIM US. The term Oil refers to the estimation of GARCH using the oil variable, None-Oil refers to the estimation of GARCH without the oil variable. Estimating the forecasting GARCH model with- and without oil variable is for exploring whether the dependent variable is better forecasted using the oil variable or not. The dependent variable is better forecasted using the oil variable if its inclusion in the forecasting GARCH model makes RMSE smaller and vice-versa. This applies to the mean and the variance equation separately.

7. Analysis and discussion:

7.1 General overview:

This section analyses the results in the light of the aims of this chapter, analysing the impact of oil price changes on different stock market indices adopting different principles; the Islamic and the conventional principles. In this study, the data used are weekly data, so it is expected that a weekly observation is enough for the stock market returns to possibly reflect and absorb, if it can, the effects of changes in the oil prices. The use of weekly data is also useful to overcome the problem of the matching trading days between the stock and oil markets. The increase in oil prices means higher revenue for the economy because the government can sell it at higher prices. If the current oil price rose higher than the previous week price, it means a positive growth indicating that the return generated by the oil producer from the previous to the current week is positive. Thus, increase in current prices means higher return in the sense that the oil is currently worth more than it was when purchased or previously valued.

Oil plays a key role in the modern economy as it is one of the most important production factors in the economy, and that its price shocks have great influence on the economy (Hamilton, 1983; Gilbert and Mork 1984; Mork, Olsen, and Mys en, 1994). The effect of oil price is asymmetric where oil price increases are much more influential than oil price decreases (Mork, 1989; Mork, Olsen, and Mysen; 1994; Hamilton 1996, 2000; and Balke, Brown, and Yucel, 1999). Since 2000, the world oil prices have been substantially higher than those of the 1990s. So it is reasonable to expect that the stock markets would be exposed to shocks in oil market especially in countries like Saudi Arabia the largest oil exporters and US the largest oil importer[32]. In theory, there is an economic explanation for why stock returns and volatility can be affected by oil price changes. Since the stock price is the present value of expected future cash flow, any external factor such as increase in oil prices affects the cash flow through corporate earning and production cost or the interest rate through inflation and monetary policy should eventually cause a change in the stock prices (Roger, Ronald et al. 1996; Mussa 2000). Jones et al (1998) indicate that since asset prices are the present discounted value of future net earnings of firms, oil price shocks should be absorbed into stock prices and returns.

And based on the fact that the information transmission between markets can be related through return as well as volatility (Clark, 1973; Tauchen and Pitts, 1983; and Ross, 1989), the link between oil and stock markets can also be in volatility as well as return. Vo (2011) explains that while volatility is a good measure of information flow, exploring information flow may generate new insights and that shocks to either market help predict not only volatility in their own market but also that in the other market. To explain how markets can be informationally linked, Roger, Ronald et al. (1996) put forward three scenarios. When the relevant information affecting each of the two markets is informationally segmented from the other, the prices of oil and stock markets will be unrelated. When the information induces common price movement in both markets, no market-specific shocks will exist. While these two scenarios are extreme and unlikely events, the interesting phenomenon of market price and volatility spillovers between the two markets actually lies between these two extremes. Moreover, Malik and Ewing (2009) offered two economic explanations for why spillover effects exist between oil and stock markets. The first is that they may exist as a result of cross-market hedging and changes in common information, which may simultaneously alter

[32] Saudi Arabia exports 6.25 million barrels per day, followed by Russia (4.89) and Iran (2.296). US imports 9.012 million barrels per day, followed by China (4.081) and Japan (3.444) (Energy Information Administration; EIA 2009).

expectations across markets. The second is the financial contagion where a shock to one country's asset may cause changes in asset prices in another country's financial market.

The recent increase in oil prices, since 2000, has attracted economists to investigate its effect on the stock markets. For example, Driesprong et al.(2008) find that stock returns of many developed market tend to be lower after oil price increases and higher if the oil price falls in the previous month. Malik and Ewing (2009)find evidence of significant transmission of shocks and volatility between oil prices and the returns in some equity market sectors of the Dow Jones, Vo (2011), examining S&P500 and oil market, finds that innovations that hit either market can affect the volatility in the other market.

7.2 Analysis of the model specifications of the methodology:

For the aims of this chapter, GARCH model is found very useful tool for modeling the stock market time series as they often exhibit volatility clustering. Since stock prices are reflecting the results of trading among buyers and seller at the stock market, various sources of news and other exogenous economic events such as oil price shocks may have an impact on the series pattern of asset prices (Gujarati and Porter 2009).

Thus, GARCH (1, 1) is employed since there is a possibility of shock spillover from oil market to the return and volatility of the stock markets. Equation (1) is a mean equation to investigate the effect of oil price shocks on the return of the stock markets, and that higher oil price could positively or negatively affect the return of the stock market depending on whether the country is an oil exporting or importing. Equation (2) is a conditional variance equation modeling the varying variance utilising the oil return to explore the impact of the oil price shocks on the volatility of the stock markets. Investors in stock market should be concerned about such volatility because high volatility could mean either huge losses or huge gains which in turn lead to great uncertainty as well as difficulties for companies to raise capital in such volatile capital markets.

In finance, the stock return may depend on its volatility (risk). To model such phenomena, the GARCH-M model is also employed adding a Heteroscdasticity term into the mean equation as shown in equation (3). The new term added in the mean equation is simultaneously estimated using the conditional variance equation (4). While the conditional variance of the stock market is allowed to depend on the lag of the oil return, the estimated varying variance is allowed to estimate the expected return of the stock market. GARCH-M model implies that there are serial correlations in the data series itself which were introduced by those in the volatility $h_t$process in equation (4). A positive significant risk-premium (α_3 in equation 4) indicates that data series is positively related to its volatility.

GARCH models are characterised by their ability to capture volatility clustering, and that a common objective of conditional variance modelling is to generate forecasts for the conditional variance process over a future time horizon. One of the main purposes of forecasting volatility, that this chapter is interested in, is for risk management. For risk management, forecasting volatility is mainly estimated to measure the potential future losses as investors must be concerned about these potential losses of their portfolios. Thus, since oil return exerts significant effect on the return and volatility of TASI and S&P500, this chapter was motivated to examine the ability of this oil variable to forecast the volatility of the stock markets during this period of high oil prices.

Therefore, GARCH-Forecasting model is employed, presented by equations (5) and (6) to find out whether these stock markets are better forecasted using this oil variable. The generated forecasts are then compared with the actual future values of the series using the standard measure of forecast RMSE presented in equation (7). The lower RMSE the more accurate the forecast of the conditional mean or the conditional variance is. Thus, if oil return manages to minimize the RMSE after its inclusion to the forecasting model, it will indicate that the series is better forecasted using the oil return.

As the markets can be informationally linked, the volatility generated in the oil market is then expected to have spillover effect on the volatility of the stock market especially during the time of high oil prices. This indicates that the volatility between the two markets can be linked. In fact, it is not surprising that the relationship between stock market and oil market exists between second moments as this relationship would have important implications for portfolio managers for making optimal portfolio allocation (Malik and Hammoudeh, 2007). Hence, GARCH model is also employed to empirically analyse the possible volatility transmission from the oil market to the stock markets, presented by equation (8).

Oil volatility is simply defined in this chapter as the oil return squared which is widely used in the literature (e.g., Jorion (1995), see also Poon and Granger (2003) for a survey of literature on volatility forecasting). This definition of squared return is appropriate for this study since it has the ability to capture the contemporaneous shocks to the volatility (Gębka 2012). Since the aim of this chapter is to empirically analyse the effect of oil price shocks on the expected return and volatility of the stock markets, the first moment of oil return appear in the mean and variance equations in equations (1-7). However, since there is a possibility that the relationship between the stock market expected return and the oil return exist between second moments, it makes it appealing to have the second moment of oil return in combination with its first moment included in the conditional variance equation as shown in equation (8). The correlation between oil volatility[33] and the absolute value of oil return is very high (0.89) which means that each one can substitute for the other. So the possibility that the absolute value of oil return should appear in the models instead of the squared return was not considered as both can be substitute for another.

7.3 Analysis of the results of the stock market indices:

In the light of the results in the tables shown above in section 5, it can be seen that the relationship between oil return and the expected return and volatility of stock market indices exist only in TASI and S&P500. The stock market's response to oil price shocks partly depend on whether the country is oil-importing or –exporting, so that any stock market should be initially exposed to its respective economy's state (Park and Ratti 2008). Hence, the effects of oil price changes appear to be different on each of the two markets.

The oil price shocks positively affect the return of TASI and negatively affect its volatility, whereas the opposite is for S&P500. Arouri et al. (1974) find empirical evidence of the existence of significant shock and volatility spillover between the world oil prices and GCC stock markets including TASI, whereas Vo (2011), examining S&P500 and oil market, finds that innovations that hit either market can affect the volatility in the other market. Interestingly, although DJIM US is an index tracking the performance of US companies, it remains unaffected by oil price changes which becomes the main motivate for the analysis of this study.

[33] Volatility of return is actually defined as the expected value of the squared difference between the actual return and the expected return: $Vol\ (R_t) = \ E\big(R_t - E(R_t)\big)^2$. Since the mean value of daily returns will be very close to zero, it can be assumed to be equal zero $E(R_t)$ = 0, then $Vol\ (R_t) = E(R_t)^2$. With rational expectation, the expected value of a variable equals its actual value:$E(x_t) = x_t$. Hence,$Vol\ (R_t) = {R_t}^2$. As a result, the squared return can be a good measure of volatility.

The risk of omitting a relevant important is very low and negligible as this chapter investigated the possibility of the oil volatility variable being an omitted important explanatory variable that should be included in the conditional variance. The results in tables 6, 7 and 8 clearly show that oil return is the right variable to explain the relationship between oil and stock markets and preferred to oil volatility. No significant change has been observed for p-values after the inclusion of oil volatility. At the same time, the oil return plays an important role in the forecasting of TASI's expected return and volatility. As shown in table 10, the oil return helps minimising the RMSE when forecasting the future expected return of TASI. Also, predicting the volatility of TASI is more accurate when taking oil price changes into account. On the other hand, S&P500 and DJIM US are better forecasted without the oil variable in terms of both the future expected return and volatility according to RMSE.

7.3.1 Analysing the results of TASI:

For analysing the results of the effect of oil returns on the expected return of TASI, it is important to realise that Saudi Arabia has almost one-fifth of the world's proven oil reserves and it is the largest producer and exporter of total petroleum liquids in the world. Therefore, significant interaction between the two markets comes as no surprise. By investigating GCC stock markets, Malik and Hammoudeh (2007) explain that oil exports primarily determine their foreign exchange earnings and government spending which both play a key role in determination of aggregate demand. They also add that Changes in aggregate demand can influence domestic output and price level, thus leading to changes in corporate earnings, and eventually affecting stock prices. This aggregate demand effect can also indirectly impact stock prices through its influence on expected inflation, which in turn affects the present discount rate.

The rise in oil prices has two positive effects in TASI. One is that on the petrochemical companies as their earning profits will increase. The other is on other companies as the aggregate demand will increase due the increase in the government expenditure. The Saudi government and its institutions, which heavily depend on oil revenue, have always been placed in the top 10 investors in TASI. Hence, it is not surprising that TASI's expected return is positively affected by oil prices changes while the increase in latter help stabilising the stock market. The top 10 wealthy investors in TASI, according to Falcom Research[34], hold SR 543.6 billion (around $144.9 billion) worth of shares accounting for 44% of the total market capitalisation of SR 1.2 trillion ($ 320 billion) in September 2009. In line to this finding, Park and Ratti (2008) find that an oil price shock has a positive and statistically significant impact on the real stock returns of Norway, an oil exporting country, a stock market that is comparable to TASI.

The results of this chapter also observed a shock spillover from the oil market to the volatility of TASI. In fact, the existence of significant shock and volatility spillover between the world oil prices and GCC stock markets including TASI is previously observed by Arouri et al. (1974). In this chapter, the significant relationship between oil return and the volatility of TASI is found negative indicating that the higher the oil prices the lower the volatility. This negative relationship can be attributed to the fact that Saudi Arabia's oil revenue contributes high percentage to its GDP, according to EIA. Since the stock market and the oil market can be informationally linked, the increase in oil returns should represent a good indication for the future of TASI. The reality in Saudi Arabia can tell that increase in oil prices should enhance the economy and, in turn the investor's behaviour in TASI should also be stimulated. Therefore, higher oil prices are found to be stabilising TASI by lowering its volatility as well as enhancing its expected return. This was indicated by GARCH (1, 1) results in table 3 which indicate that there is a positive relationship between the returns of oil market and TASI, while there is an inverse relationship between oil return and TASI's conditional variance.

The significant risk-return trade off exist in TASI but with a negative sign showing that the higher the uncertainty the lower the return. Thus, enduring higher risk in the market generally seems not to be compensated with higher return. In fact, Baillie and DeGennaro (1990), Nelson (1991), and Glosten et al. (1993) has detected a negative mean-variance trade-off. While the mainstream theory expects a positive risk-return relationship, other researchers, however, such as Abel (1988) Backus and Gregory (1993) believe that the relations can be otherwise.

Therefore, TASI investors, according to this study's results, should not expect to benefit from taking higher risk and speculation in the market which might imply that investors would be better off going for long-term investment strategy. This is because if the

[34] See Falcom List of Wealthy Investors research published in 15 November 2009. Falcom is an investment bank located in Saudi Arabia.

market does not compensate for the higher the risk that the investors take, then being a long-term investor receiving dividends and selling the share at higher prices in a long-run period will be more appealing.

7.3.2 Analysing the results of S&P500:

For analysing the results of oil returns on the expected return of S&P500, it is important to realise that US is the largest oil consumer in the world. Hence, it comes as no surprise that the oil price shocks significantly affect the expected return and volatility of S&P500. Roger, Ronald et al. (1996) explains that since US is a net importer of oil, higher oil prices would adversely affect the balance of payments, putting downward pressure on the U.S. dollar's foreign exchange rates, and upward pressure on the expected domestic inflation rate. Thus, a higher expected inflation rate is positively related to the discount rate and as a consequence is negatively related to stock returns.

Consequently, US companies get negatively affected by the increase in oil prices, and that can explain the negative relationship between the oil return and the expected return of S&P500 as the imported oil in US accounts for two-third of its consumption. Unfortunately, no statistical information are available, to the knowledge of the author, to show at least the type of large funds that invest in S&P500 in order to understand the type of investors presented in the market so that it can somehow help analysing the results from investors perspective. Although, the costs are not expected to react immediately to the increase in oil prices or at least as quick as the react of the corporate earnings to the increase in costs, yet the investors' sentiment and behaviour are expected to shortly respond according to the expected impact on corporate earnings. Chen (1973) finds a strong and robust evidence from S&P500 that a higher oil price does push the stock market into bear territory. Park and Ratti (2008) find that shock in oil prices exerts negative and statistically significant impact on the real stock return of S&P500.

Again, since stock markets and oil market can be informationally linked, the significant effect of oil return on the volatility of S&P500 is expected. Such an increase in oil prices would eventually lead to lowering the value of the shares the investors hold in S&P500. The expected reaction of such investors could possibly be the option of withdrawing from the market by selling off the shares before their assets prices decline. Therefore, increase in oil prices can be a reason for increasing uncertainty in the stock market. Such behaviour of investors can be, in turn, another reason for the prices to fall as well as the index expected return**.** Therefore, this increase leads to a decline in the stocks prices of S&P500 while it creates more uncertainty in the market by increasing its volatility. This was indicated by the results generated from GARCH (1, 1) in table 4 where there is a significant negative relationship between oil and S&P500 expected returns; meanwhile, a positive significant relationship is detected between oil return and conditional variance. This finding is in line with Sadorsky (1999) who found that positive shocks to oil price depress the real stock returns of S&P500. The findings of Vo (2011), examining S&P500 and oil market, confirmed that innovations that hit oil market can affect the volatility in the stock market.

When Investors are risk-neutral, then no significant risk-return trade off is expected to exist. However, the insignificant risk-return relationship in S&P500 could be accounted for by the fact that the return used in this study is not the excess return that is provided over the risk-free rate which most of the previous studies used. Moreover, the small sample size could be the factor that prevents the investigation methodology from detecting the risk-return trade off.

7.3.3 Analysing the results of DJIM US:

Both S&P500 and DJIM US are indices that track the performance of US companies. The companies listed in both indices are exposed to the same economy. Therefore, the economic explanation for the link between the companies in DJIM US and oil prices should be not significantly different from that of S&P500. The difference between the two market indices is that DJIM US tracks the performance of US companies that are in compliance with Islamic law. This makes this index attracts the Islamic capitals around the world.

Inversely to CSMI, DJIM US surprisingly seems to be immune to the oil market fluctuations. In simple words, oil returns failed to exert significant influence on DJIM US expected return or volatility. Although U.S companies are negatively affected by the increase in oil prices as expected and shown in S&P500 results, yet some other US companies in DJIM US interestingly seem to be unaffected by oil price changes during the same period. This is an interesting observation in this chapter. In order to explain that recall the fact that the high growth in GCC’s revenue caused by oil-related boom has led to a great expansion in the Islamic funds worldwide. Therefore, it is highly possible that Islamic compliant US stocks in DJIM US have actually managed to attract and return the wealth from the oil exporters (GCC) back to the oil importer (US) through Islamic funds which eventually make DJIM US unaffected. In other words, the increase in oil prices adversely affect the profits of US companies, but the tendency of the increased wealth of the Islamic investors to invest in Islamic funds might be the reason behind offsetting the adverse effect on the price of Islamic compliant stocks of DJIM US. Hence, the positive effect of high oil price on Islamic funds cancels out the negative effect of high oil prices on the Islamic compliant US stock prices of DJIM US.

Similar to that, Maghyereh (2004) reported that oil return exerted no significant impact on 22 emerging markets. Similar to DJIM US, the Dow Jones Sustainability U.S. (DJSI US) index has social responsible criteria based on which a company should pass in order to be listed in the index. Although, DJIS US is similar to DJIM US in the sense that both have some restrictions imposed on the investment opportunities based on people beliefs, Sariannidis et al. (2009) found out that the social responsible index is yet concerned about oil and reacts to the oil returns but with a month delay. This relationship is found to be negative parallel to the S&P500.

Therefore, it is possible to assume that investing in DJIM US can be a safe place for portfolios during the time of high oil prices. The GARCH (1, 1) results in table 5 show that oil price changes exert no significant impact on the mean return or the conditional variance. Although, DJIM US is an index solely created to meet the needs of Muslim investors who only seek financially rewarding investments that are Shari'aah compliant, it is not guaranteed that it remains resistant to the factors affecting non Shari'aah compliant U.S companies. However, it is not surprising that if the expected investor's behaviour differs due to the fact that major Islamic capitals are coming from the Muslim world especially the GCC where the oil price changes' direct impact on the economy and the investors' pockets are believed to be exactly the opposite from the impacts exerted on the U.S. economy.

However, another explanation for the insignificant relationship between oil prices changes and DJIM US returns could possibly be the fact that investors in DJIM US construct long-term investments. Long-term plans usually do not respond to short-time events that might influence the behaviour of some investors. Also, another fact might be responsible for the different attitude of DJIM US towards oil returns is that the quarterly review conducted by the board of Muslims scholar which results in having some companies ejected from the index while others newly enter the index. This frequent filtering may happen to safe the index portfolio from the impact of oil effects on the companies. For example, the Dow Jones Islamic Index managed to safe investors around the world large losses from the collapse of WorldCom and Tyco companies because these two companies were ejected from the index, due to violating the Islamic criteria, well before their collapse.

In terms of the insignificant relationship between risk and return in the case of both S&P500 and DJIM US, a comparable empirical work conducted by Mohd and Majid (2006) comparing ISMI and CSMI in the context of Malaysia is consistent with this chapter's results. Using GARCH models, they found that risk has no significant effect on the returns of neither of the two markets. In contrast, Hassan (2002), investigating the broader index DJIM, found a significant positive risk-return trade off.

As far as finance is concerned, risk-return trade off is a fundamental principle. The mainstream theory implies a positive trade off between the excess return on the market portfolio and the variance of its return, so that the higher the risk the higher the expected return. In the literature, however, there is still ongoing debate about this particular relationship between risk and stock return. Mixed evidence are presented in the literature where some authors find a significant positive relationship such as Harvey (1989), Campbell and Hentschel (1992), and Guo and Whitelaw (2006), others find it significantly negative such as Campbell (1987), Glosten, et al. (1993), and Brandt and Kang (2004), and the remaining concluded that the relationship is weak and insignificant such as French, et al. (1987) and Baillie and DeGennaro (1990). In fact, the literature has failed to reach a definitive conclusion on this relationship.

8. Conclusion:

In the recent years, the oil market has been experiencing wide oil price swings. This is widely believed to represent an important fact that influences the economies around the world either positively or negatively. This chapter investigates the influence of the shocks in crude oil prices on the return and volatility of ISMI and CSMI. High oil prices can exert positive effect on some economies whereas others can be negatively affected at the same time. This study was motivated to find out whether this coexistence of opposite effects can cancel out each other since the means of transmission exists. More specifically, Islamic funds represent a means of transmission between the increased wealth of Islamic investors in GCC by oil-related boom and some of U.S. companies in

DJIM US that are in compliance with Islamic rules. High oil prices put pressure on the prices of U.S. companies in DJIM US; however, the tendency of the wealthy Islamic GCC investors to invest in Islamic funds can possibly cancel out this negative effect. This empirical study also compares the results of DJIM US to those of non-Islamic compliant stocks in S&P500 and TASI. The last two markets indices are different in terms of the expected impact of oil price on their companies' net profit.

This chapter managed to achieve its proposed aims by conducting ARCH and GARCH models. The interval chosen to be investigated is from September 2002 to April 2009 utilising weekly data. During this period, the world oil prices had been substantially higher than those of the 1990s. For CSMI, two stock market indices are examined; TASI and S&P500 in order for each to reflect the oil exporting-and importing economies, respectively. DJIM US represents ISMI; only one index was chosen due to the limitation in the availability of Islamic indices.

The results revealed that increase in oil prices represents good news for TASI as it enhances its mean return and lowers its volatility. The opposite is for S&P500, when oil price goes up the volatility is higher and the mean return is lower. Although U.S. companies are negatively affected by higher oil prices as proved in S&P500, DJIM US remains unaffected by changes in oil price during the same period. This can be explained by the fact that tendency of Islamic funds to invest in ISMI such as DJIM US can transmit the positive effect of the high oil prices from GCC to the U.S. companies in DJIM US. The latter remains unaffected because the transmitted positive effect cancels out the negative effect of oil price on the U.S companies that are in compliance with Islamic rules. In contrast to TASI, future expected returns and volatility of DJIM US and S&P500 are not better forecasted by the oil variable.

The results also underline the fact that the effect of the oil returns on the stock market returns depends on the state of the economy in the context of the conventional markets, so that it differs if the economy import the oil from abroad from if the economy depends heavily on the revenue generated from exporting oil. The findings support this fact by revealing that TASI and S&P500 responds to oil price changes differently according to the economic state of each market. The high returns help stabilising TASI as well as enhancing the expected return; whereas, S&P500 showed the opposite response. It also seems that the change in oil prices is an important element in predicting the movements in the stock market prices of the oil-exporting economy as in TASI.

Although the risk return trade-off is fundamental to finance, the empirical evidences, shown in this study, do not support it. The risk return significant relationship is only detected in TASI where the evidence proposed a negative relationship between expected return and risk. However, Lundblad (2007) pointed out that not necessarily the existing mixed findings are clear evidence against the hypothesised relationship. Instead, the mix findings can be a result of a statistical artefact of small samples.

This study contributes to the literature on Islamic finance where it attempts to investigate the difference between the emerging ISMI and the already existing CSMI. It has always been a main concern for observers as well as potential investors whether restricting the investments to Islamic rules will make the Islamic market different in terms of performance and behaviour. It is also to the advantage of policy makers, investors and fund managers to take into consideration such differences when making long-term plans and strategies.

Given the fact that the two classified markets have different attitude toward the oil market fluctuations, identifying the different factors that drive each market can be a topic for further investigation.

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Chapter 4. Day of the Week Effect on DJIM US: Evidence from GARCH models

1. Introduction

Seasonality[35] has increasingly become a major area of interest to researchers in economics and finance in the last few decades. At the same time, the existence of seasonality has driven the statistical offices to publish seasonally adjusted data.

According to Hylleberg (1992, p. 4), seasonality can be defined as:

> *the systematic, although not necessarily regular, intra-year movement caused by the changes of the weather, the calendar, and timing of decisions, directly or indirectly through the production and consumption decisions made by agents of the economy. These decisions are influenced by endowments, the expectations and preferences of the agents, and the production techniques available in the economy.*

The regular patterns reappearing every calendar year have important implications for the economic data, so identifying the causes of seasonal fluctuations in order to better interpret time series and econometric analysis involving seasonal components and seasonal adjusted series is vital (Granger 2001).

It is clear that the definition of seasonality points out the characteristic features of the seasonal components, their causes, and the economic contents. Granger (2001), in addition, listed four classes of causes of seasonal fluctuations in economic data (which he described as basic causes, which might not be complete). The four classes are summarised as follows:

a. Calendar:

   Public holidays that affect some series related to production, such as Christmas and Easter.

b. Timing decision:

   Decisions made by individuals or institutions that may cause seasonal effects such as school vacation, ending of university sessions, payment of company dividends, and the choice of a tax year or accounting period.

[35] Seasonality can also be referred to by the term "seasonal component"

c. Weather:

Weather changes that directly affect different economic series related to agriculture production, construction and transportation, such as actual changes in temperature, rainfall and other weather variables.

d. Expectation:

Expectation of certain seasonal patterns leads to making plans which then can cause an actual seasonal in a series or another variable such as toy production in expectation of a sales peak during the Christmas period and expectation of bad or good weather especially for those who wants to choose a destination for vacations.

A seasonal component can simply have an impact on the financial or economic data by exhibiting a constant shape that is regularly repeated according to the occurrence of that component. As it is generally believed that seasonality exists in economic data such as production, sales, inventories, consumptions and imports and exports amongst others, researchers interestingly have also empirically observed the existence of seasonality effects in stock market returns, such as the Monday, weekend and January effects, while others observed holiday effects as well (Granger 2001). Thus, it is important for investigating seasonality in the stock market to consider EMH, proposed by the asset pricing dominant paradigm CAPM, which requires that the capital market returns should be characterised in such a way that all subsequent returns represent random departures from the previous one (Dimson 1988). In other words, there should not be any ex-post regularities characterising the capital market returns, and thus the returns should simply be a random walk variable. The presence of market regularity, such as seasonality, represents a violation of that EMH, implying informational inefficiency due to the fact that investors can exploit the market regularities to generate abnormal returns (Dimson 1988).

Rozeff and Kinney (1976), who observed one of the first empirical regularities in the modern capital markets, revealed that simple random walk does not hold in their examined data, and found out that the mean return distribution is higher in January in comparison to other months of the year. However, according to them, the seasonal patterns that they observed do not necessarily earn investors abnormal returns. In other words, data exhibiting seasonality patterns does not necessarily violate the efficient market hypothesis (EMH), because investors, according to the empirical results, cannot develop a trading strategy exploiting the seasonality in the series to earn abnormal return.

After that, particularly in the early 1980s, anomalies with regard to the joint hypothesis of the CAPM and EMH were increasingly reported by finance researchers, such as weekend effects by French (1980) and firm size effects by Banz (1981) and Reinganum (1981). Thus, seasonality has since become an important topic that attracted many researchers' attention in the literature of finance due to its potential effect of generating abnormal returns in the equity markets (Mills 1992). Also, the presence of seasonality in the equity markets, affecting the return distribution, is an important issue to be investigated due to its important implications for the EMH.

This chapter focuses only on one of the most common calendar anomalies: the day-of-the-week effect (DOWE), which can cause regular seasonal fluctuations in stock market returns. In fact, DOWE, which has been extensively investigated in various markets, actually refers to the tendency of stocks to regularly exhibit large or small returns on certain trading days relative to others.

Pioneer studies focusing on the US markets observed calendar anomalies in the stock markets demonstrating that DOWE exists, thus the distribution of the stock returns can vary according to the day of the week (Cross 1973; French 1980; Gibbons and Hess 1981; Keim and Stambaugh 1984; Rogalski 1984; Wingender and Groff 1987).

Other studies revealed that DOWE is not a specific characteristic of the US market, but rather a global phenomenon existing in other developed markets (Jaffe and Westerfield 1985; Barone 1990; Solnik and Bousquet 1990; Chang, Pinegar et al. 1993; Davidson and Faff 1999). Moreover, other researchers also observed DOWE in the developing markets (Aggarwal and Rivoli 1989; Wong, Hui et al. 1992; Agrawal and Tandon 1994; Alexakis and Xanthakis 1995; Coutts, Kaplanidis et al. 2000; Oguzsoy and Guven 2003; Ajayi, Mehdian et al. 2004; Yakob, Beal et al. 2005; Basher and Sadorsky 2006; Malambo and Biekpe 2006).

The GCC stock markets have also exhibited DOWE (Al-Loughani and Chappell 2001; Al-Loughani, Al-Saad et al. 2005; Seyyed, Abraham et al. 2005). It should be borne in mind that the working week in the Gulf markets does not start on Monday as most markets do, but on Saturday (some end on Wednesday, such as TASI).

In summary, it seems that DOWE is an international phenomenon that exists in many stock market indices across the world; hence, any other new market index, yet to be investigated, such as ISMI, should be no different. In comparison to CSMI, studies on seasonality in ISMI are relatively new. The most popular seasonality empirically observed in ISMI is the holy month of Ramadhan, the ninth month of the Islamic calendar. It is a month of fasting, spiritual training and discipline followed by a day of celebration called “Eid”. The fact is that there are only limited studies in the literature investigating seasonality in ISMI, and those tentative efforts mainly focussed on the effect of the month of Ramadhan (Husain 1998; Oguzsoy and Sibel 2004; Seyyed, Abraham et al. 2005).

In the Islamic calendar[36] Friday is considered a holy day (equivalent to Sunday for Christians). Saturday and Sunday are also considered to be religious days in the Arab world, but only for Judaism and Christianity (respectively). Worldwide, Saturday and Sunday generally comprise the weekend, and Friday is a weekly working day on which most stock markets are open for trade. Friday is a weekend day in most Muslim countries (the second day of the weekend varies; some countries use Saturday, some use Thursday).

On Friday, Muslims tend to be occupied with Islamic rituals and social activities. This overlap between religious activities and trade can have a potential impact on ISMI, which trades on Friday. To the knowledge of the author, there has been no empirical study examining DOWE in ISMI from an Islamic perspective. An example of an Islamic viewpoint can be investigating the effect of Friday as a Muslim holy day on the ISMI.

In ISMI, Friday seems to have more characteristics to be investigated rather than only being the end of the week. Therefore, this chapter continues to investigate ISMI, as it is the overarching aim of this thesis to provide empirical essays looking into ISMI. This chapter investigates DOWE in the Dow Jones Islamic Market Index in the US (DJIM US). The trading days in this market are from Monday to Friday, with daily trading hours from 9:30 to 17:15. Empirical studies on CSMI repeatedly observed low returns on Monday and high returns on Friday (French 1980; Agrawal and Tandon 1994; Mills and Coutts 1995). This study investigates all the days of the week in order to explore

[36] More details about the Islamic calendar and Friday are presented in section 2.

any regularity of returns on Friday, the Muslim holy day, in comparison to other normal days.

DJIM US is designed to offer the Muslims an index that enables them to invest in the equity market while not violating their religious obligations. This index logically attracts large Islamic funds and Muslim individuals to invest in it. Thus, the importance of Friday to the Muslims in addition to the fact that Friday is a trading day in DJIM US are the motives for this chapter to investigate DOWE. It is expected that Friday will have certain characteristics in ISMI different from those in CSMI. The market on Friday may suffer from less liquidity due to the fact that Muslim investors are expected to be engaged in religious and social activities rather than trading in the market. Consequently, less liquidity in a market can drive stock prices to decline (Amihud and Mendelson 1991).

Previous studies employed different methodologies to investigate seasonality. Al-Loughani and Chappell (2001) summarised and described the methodologies used previously by dividing them into four groups. The first applies the standard *t*-and *F*-tests or ANOVA in an attempt to investigate the significance and equality of mean returns. However, this methodology is criticized because it does not take into account the time series properties of the sample data. In this methodology, the mean and the variance of the returns are generated either by calculating them for each day or by estimating the coefficient by the following regression equation:

$$R_t = \beta_1 + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \varepsilon_t \quad (1)$$

The second group used the same previous method to generate the mean and the variance. The difference is that this methodology uses *t*-statistics and X^2, the chi-square test of significance, calculated using heteroscdasticity-consistent standard errors, as suggested by White (1980), in order to test the hypothesis. This methodology is subject to criticism due to its neglect of checking the appropriate time series distribution of the data employed, whereas Chang et al. (1993) checked the properties of the time series and found out that the regression residuals are auto-correlated, heteroscedastic (non-constant variance) and not normally distributed. The third group suggested using t- and F-test or ANOVA if the returns are normally distributed. If not, then nonparametric tests are the appropriate method to investigate the presence of DOWE.

The fact is that returns of the financial data statistically tend to be highly leptokurtic relative to the normal distribution, and the variance is not constant over time. Hence, the fourth group of researchers used GARCH models to investigate the existence of DOWE allowing the variance to be varying over time. While previous methodologies did not investigate the variation of returns volatility across days of the week, GARCH models allow researchers to examine the stock returns behaviour in terms of volatility as well as returns.

The aim of this empirical essay is to mainly investigate DOWE in ISMI proxied by DJIM US, while the popular conventional index Dow Jones Industrial Average DJIA is also utilised in the investigation as a complement for the study. Although the literature is full of studies investigating DOWE in the conventional market, especially S&P500, DJIA is mainly used here for the purpose of getting a flavour of what effect a Friday dummy variable might have on the conventional Dow Jones stock market. Therefore, this chapter uses GARCH and GARCH-M models to investigate DOWE in DJIM US and its 10 sub-indices as well as DJIA, an index that does not have sub-indices, with the intention of exploring the differences between the Islamic and conventional markets in terms of Friday effect.

The following section provides the background and the motivation of this chapter. The third section reviews the literature of studies that investigated calendar anomalies in the stock markets. Section four presents the data and its descriptive statistics, then section 5 explains the econometric methodology applied in this study. Section 6 presents the actual empirical results expressed in tables. Section 7 analyses and discusses the results. The final section concludes the chapter.

2. Background

This section briefly provides the necessary information about the Islamic calendar, its origin and its holy day (Friday). It also explains the importance of Friday to Muslims, and what Muslims are expected to do on this day.

The main aim of this section is to determine the extent to which Friday "holiness" might shape the behavior of Muslim investors on that particular day, and to show the importance of empirically investigating Friday effects on ISMI and comparing it to its effect on the counterpart CSMI.

Therefore, the following three subsections are provided to talk about the Islamic calendar, Islamic ruling on Friday and the virtues of Friday in Islam.

2.1 Islamic calendar:

The Islamic calendar is a lunar calendar consisting of 12 months in a year of 345 or 355 days. It is used as the spiritual calendar of all Muslims, to determine the proper day on which to celebrate Islamic holy days and festivals. The Islamic calendar begins with the migration of the Prophet Mohammed (pbuh) in 622 AD from Makkah to Yathreb (subsequently known as Al-Madinah). These two cities are located in Al-Hejaz (west of Saudi Arabia). The importance of this calendar comes from the importance of the long-term implications of the migration of the Muslims from Makkah to Al-Madinah. The migration was induced by the oppression exercised by the people of Makkah on the small Muslim community. After the migration, the Prophet (pbuh) and his companions enjoyed independence and freedom, and established an Islamic state. In 638 AD, the second Caliph ("successor") of the Prophet (pbuh), Omar Ibn Al-Khattab, decided to introduce an Islamic calendar called *Hijrah*[37]. The idea came into existence after the Caliph had received a complaint from one of his officials about the absence of dates on the correspondence. This absence made it difficult to determine which instructions received from the Caliph were most recent (Arabs traditionally referred to years in terms of significant events that occurred in them, e.g. "the Year of the Elephant", when an army invaded Hejaz with an elephant). 7 December 2010 marked the beginning of the Hijrah year 1432.

The calendar has a holy month as well as a holy day. The holy month is the ninth month of the year, which is called Ramadhan, whereas every Friday is considered a holy day. While a few previous studies have investigated the Ramadhan effect (Husain 1998; Oguzsoy and Sibel 2004; Seyyed, Abraham et al. 2005), this study focuses on Friday, a novel concept in Islamic finance literature. The doctrine of a holy day exists in the three Abrahamic religions (Judaism, Christianity and Islam). Each religion has a different holy day (Saturday, Sunday and Friday respectively). The main Islamic ritual on Friday is to attend the mosque at noon, listening to the sermon (*Khutba*) followed by a special congregational prayer. Muslims gather in the mosque on Friday to witness *Jummah*[38]

[37] Hijrah is an Arabic word meaning "migration".
[38] *Jummah* refers to the *Khutba* and the prayer together.

(“congregation”). As with all of the five daily prayers, the time of *Jummah* varies slightly throughout the year, depending on the position of the sun in the sky.

2.2 Islamic ruling on Friday prayer:

The Quran and the *Sunnah*[39] of the Prophet (pbuh) are the main sources for rules and regulations in Islam, and hence Muslims act according to their injunctions. There follows an explanation of the position of Friday in Islam from these two Muslim sources.

Friday prayer is obligatory upon every individual Muslim[40] who endeavours to perform the prayer and attend the sermon, because God said in the Quran:

> *O you who believe! When the call is made for prayer on Friday, then hasten to the remembrance of God and leave off business; that is better for you, if you know.* (Quran 62:9)
>
> *And when the prayer is ended, then disperse in the land and seek of Allah's bounty, and remember Allah much, that ye may be successful.* (Quran 62:10)

It was also narrated from Hafsah[41] that the Prophet (pbuh) said:

> *Attending* Jummah *is a duty upon every pubescent* [i.e. adult].

It can be understood from the Quranic verses and the Prophet’s command that Muslim individuals are asked to forego normal activities when the time of Jummah comes, and attend the mosque.

2.3 The virtues of Jummah:

Firstly, Muslims believe that Friday is the best of the days according to the authentic narration of the Prophet Mohammed (pbuh), who said:

> *The best day during which the sun has risen is Friday. It is the Day Adam was created. It is the day when Adam entered paradise and also when he was taken out from it. It is also the day on which the Day of Judgment takes place.*

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[39] *Sunnah* is the habit or usual practice of the Prophet Mohammed (pbuh) referring to his sayings and living habits.

[40] For the prayer to obligatory, an individual must meet two conditions, one is to be sane, and the second is to reach the age of puberty.

[41] A wife of the Prophet (may God be pleased with her).

Secondly, Islam encourages and motivates Muslims to attend *Jummah*. It was narrated from Aws Al-Thaqafi[42] that the Prophet (pbuh) said:

> *Whoever does* ghusl [ritual bathing] *on Friday and* ... [his wife does likewise], *and sets out early, and comes close to the imam*[43] *and listens and keeps quiet, for every step he takes he will have the reward of fasting and praying* qiyaam[44] *for one year.*

Thirdly, the earlier the person comes to the mosque on Friday, the better they are in terms of rewards. It was narrated by Abu Hurayrah[45] that the Prophet (pbuh) said:

> *Whoever does bath on Friday like the bath for* janaabah[46] [i.e. "ghusl"; see above], *then goes to the prayer* [in the first hour, i.e. early], *it is as if he sacrificed a camel. Whoever goes in the second hour, it is as if he sacrificed a cow; whoever goes in the third hour, it is as if he sacrificed a horned ram; whoever goes in the fourth hour, it is as if he sacrificed a hen; and whoever goes in the fifth hour it is as if he offered an egg. When the imam comes out, the angels come to listen to the* Khutba.

Fourthly, during the day of Friday, Muslims are encouraged to recite Quran, particularly a chapter called *Al-Kahf*. It was narrated from Abu Sa'eed al-Khduri[47] that the Prophet (pbuh) said:

> *Whoever reads Surat al-Kahf* [lit. "The Chapter of the Cave"] *on Friday, he will be illuminated with light between the two Fridays.*

Fifthly, Muslims believe that there is an unspecified hour between Friday prayer and the sunset in which supplication is answered and accepted by God. It was narrated from Abu Hurayrah that the Prophet (pbuh) mentioned Friday and said:

> *On this day there is a time when no Muslim stands and prays, asking Allah for something, but Allah will grant him it.*

Abu Hurayrah continued saying that the Prophet (pbuh) gestured with his hands to indicate how short that time is. This hour is deliberately unspecified in order to encourage the Muslims to be occupied during this time, seeking this hour, supplicating to God for blessings and forgiveness.

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[42] A companion of the Prophet (pbuh).
[43] An imam is the one who leads the prayer, and delivers the sermon.
[44] *Qiyaam* means praying at night.
[45] A close companion of the Prophet (pbuh).
[46] *Janaabah* means "sexual impurity".
[47] He is one of the Prophet (pbuh) companions.

Given the spiritual importance Muslims attach to Friday, one can conclude that this day is supposed to mean a lot to Muslims, including investors. As shown in some verses, Muslims are encouraged to leave everything, including trade and business, and go to attend the *Jummah*. Although the Quran specifically gives the concession that people can return to trading after the congregational prayer (see above), in reality it is highly possible that Muslims get diverted from trading in the stock market on Friday, preferring to perform religious activities, resulting in creating a less liquid market. In fact, less liquidity and low trading volume are expected to characterise Friday in the stock market, resulting in forcing prices to decline, along with returns. A decline in prices would therefore be unsurprising, as a decline in asset liquidity should bring about a decline in asset prices (Amihud and Mendelson 1991). In other words, stocks that experienced larger declines in liquidity should consequently suffer larger price declines.

In summary, this section illustrated the importance of Friday as a holy day for Muslims. Muslim investors tend to be occupied on this day with ritual activities. This religious occupation raises the question of to what extent this may affect ISMI. This question can be answered by empirically investigating DOWE, and the Friday effects in particular, on ISMI, and comparing this to its effect on the counterpart CSMI.

3. Literature Review

Investigating the existence of calendar anomalies in the stock markets has been an interesting topic for researchers. An early general discussion of the behaviour of stock markets around the weekend was done by Fields (1931), who observed an immediate increase in stock prices before the weekend and a decline on Mondays in the context of DJIA for the period from 1915 through to 1930. From this point and for further investigation, he recommended future researches to extend the analysis by using all days rather than only Friday and Monday. After that, the earliest empirical studies came out quite a long time subsequently, investigating the existence of calendar anomalies in the stock market (Cross 1973; French 1980; Gibbons and Hess 1981; Keim and Stambaugh 1984; Rogalski 1984; Wingender and Groff 1987).

Cross (1973), focusing only on two days, stated that his article's objective was to document an example of non-randomness movements in stock prices. He particularly examined the distribution of price changes for S&P500 on Fridays and Mondays, and the relationship between these two days covering the period January 1953 to December

1970. He found evidence of negative average returns for Monday in contrast to Friday, which recorded positive average return. This finding is considered as an example of non-randomness in the movement of stock prices, indicating the existence of the weekend effect.

However, French (1980) extended the analysis of daily S&P500, as mentioned by Fields (1931), to all days of the week, covering the period from 1953 to 1977, by conducting two tests on S&P500; the calendar time and the trading time hypothesis. He defined the former as if the generating process of stock returns operates continuously, which means that return on Monday is expected to be three times higher than any other day of the week due to the fact that Monday represents three-calendar-day investment (from Friday close to Monday close). The latter hypothesis was defined as if the returns are only generated during active trading and each trading day has the same expected return. His aim was to examine these two processes, but the findings appeared to be inconsistent with both of them. Instead, he found evidence verifying previous findings, showing that average return on Monday was negative, while it is positive for other days, including Friday.

In confirmation of the findings of Cross and French, Gibbons and Hess (1981) re-examined the assumption that stock returns are constant across the trading days of the week. They examined the US stock market represented by S&P500. Their findings contradicted the assumption proposed and found that the returns vary across the days. Moreover, the results documented that the mean return of Monday is unusually low or even negative.

Rogalski (1984) extended previous work a bit further by touching upon an important issue. He defined Monday return as the return occurring on Monday itself, between its opening and close prices, while others defined it as the return between Monday's opening and Friday's close. He realised that the Monday effect was meant to be the weekend effect. He investigated DJIA and S&P500 for the periods from 1974 to 1984 and from 1979 to 1984 (respectively). The results documented that returns between Friday's close and Monday's (weekend effect) opening are significantly negative, while the return on Monday itself is insignificant.

Lakonishok and Shapiro (1986) were also the first to document the turn-of-the-month (TOM) effect in the US equity market. The TOM effect postulates that returns are higher around the turn of each month. McConnell and Xu (2008) confirmed the existence of the TOM effect in the US equity market for more than 100 years, plus in another 34 equity markets around the world. However, Hudson and Atanasova (2009) noticed that the data series used for the 34 markets are relatively short in contrast to that of US data. Therefore, they further investigated this topic by examining TOM in the Financial Times Industrial Ordinary Share Index, the oldest daily index available for the UK market, from 1935 through 2009. Remarkably, their results confirmed the existence of TOM similar to that found in the US equity market.

So far, all the studies mentioned above used simple econometric models with strong assumptions by applying the standard linear regression method to investigate seasonality in the stock markets. However, there are evidences that some of these assumptions have been actually violated in practice. Examples of these violations are the fact that the variance of the stock returns changes over time, which previous studies' methodologies did not take into account. Moreover, these empirical studies, using standard linear regression, usually assume that stock returns and error terms follow a normal distribution, but this seems not to be the case, as the error terms generated from stock returns regressions are certainly believed to be not normally distributed. Mandelbrot (1963) found evidence that the empirical distribution of stock price changes do not follow normal distribution. Fama (1965) concluded that real data employed in his research supports Mandelbrot's findings. Instead, three features have generally been observed in stock returns: skewness, leptokurtosis and volatility clustering.

Empirical studies realised that stock price changes exhibit volatility clustering and kurtosis. Thus, GARCH models introduced by Engle (1982), Bollerslev (1986) and Taylor (1986) are the ones that seem to be capable of dealing with these features of stock returns.

Connolly (1989) was from the earliest studies that took into consideration all these features. He firstly raised suspicions about the assumptions in previous methods, tackling DOWE, which is based on a simple market model. Then, he examined the sensitivity of inferences about the DOWE and the weekend effects to alternative estimation and testing procedures. The sample examined was the US stock market for the period from 1963 to 1983. In conclusion, he recommended GARCH models as useful methods enabling researchers to conduct such analysis while taking into account autocorrelation in returns, non-constant variance and fat-tailed error distributions.

An empirical study by de Jong et al. (1992), using GARCH models with t-distribution, emphasized that for actual data the assumptions of the simple market model are violated. The sample that they examined was from the Dutch stock market for the period from 1984 to 1987. They confirmed the fact that return distribution is not normal, nor is the variance of the error term or the risk parameter beta constant. Their conclusions confirmed the results of Connolly (1989). Furthermore, when comparing their results with those obtained under the simple market model assumptions, such as homoskedastic and normal distribution, they found that failing to take heteroscdasticity and fat tails into account when conducting such analysis can lead to spurious results. Finally, as a recommendation, they also suggested that as future work will also be subject to the same concerns, researchers should use techniques similar to theirs.

Subsequently, GARCH models gained popularity for their usefulness in a wide variety of stock market tests, including seasonality. Alexakis and Xanthakis (1995) investigated DOWE on the Greek equity market (taking into consideration the time varying variance) using GARCH-M model for the period 1988-1994. Their results provide evidence of high positive returns on Monday and negative returns for Tuesday, especially during the pre-1988 period, whereas during the post-1998 the results indicated positive returns on both Monday and Tuesday. This seems to contradict the results of previous studies in the US and other developed markets, where Monday exhibits low and negative returns.

GARCH models are also important because they allow one to examine the proposition that high return occurring on a day can be a reward for the high risk on that particular day. Hence, Clare et al. (1998) examined DOWE in addition to other calendar time anomalies, such as the holiday effect and monthly seasonality (January effect) for Kuala Lumpur Stock Exchange market (KLSE) for the period from 1983 to 1993. For DOWE, they employed the traditional analysis by regressing the returns of KLSE on five dummy variables representing Monday through to Friday. The results indicate that there is strong evidence of DOWE in KSLE. The lowest return occurred on Monday and the highest on Thursday, while slightly significant positive return was observed on Wednesday. Importantly, they then applied GARCH-M to investigate the proposition advanced above, namely whether DOWE in KSLE is due to seasonal variation in the risk of the equity market. The right model happened to be ARCH (4)-M. The findings indicated that the positive returns enjoyed on Wednesday and Thursday are due to the high equity market risk, but Monday seemed to represent a true market anomaly.

Choudhry (2000) examined the presence of DOWE using GACH model in international markets; India, Indonesia, Malaysia, Philippines, South Korea, Taiwan, and Thailand over the period from January 1990 to June 1995. His findings indicate that DOWE and the Monday effect are global phenomena in the international stock markets on both their returns and conditional variances. However, he cast doubt on the assertion that this could be accounted for by the possibility of spill-over from the Japanese stock market.

Al-Loughani and Chappell (2001), exploring the Kuwaiti Stock Exchange (KSE), documented that returns on Saturday (the first day of the week in KSE) are higher. This can be called the Saturday effect, corresponding to the Monday effect in markets opening on Monday. They applied a nonlinear GARCH model to examine the Kuwaiti market over the period January 1993 to December 1997.

Berument and Kiymaz (2001) aimed to examine DOWE and stock market volatility by applying GARCH model to the US market represented by S&P500 over the period from January 1973 to October 1997. This examination aimed to find out whether a high (low) variation in volatility of stock return can be associated with a high (low) stock return on a particular day. The results documented DOWE in the return and the conditional variance equations. The findings generally confirmed previous studies' results; Monday recorded the lowest returns, whereas Wednesday had the highest. In terms of volatility, modified GARCH model indicated that Friday and Wednesday recorded the highest and the lowest volatilities (respectively).

Berument and Kiymaz (2003), using a similar methodology to their previous one, investigated DOWE in volatility and volume of the major developed stock markets (Canada, Germany, Japan, the UK and the US) during the period from January 1988 to June 2002. It is believed that high volatility is associated with low trading volume; thus, they examined whether there is a link between volatility observed on various days and the trading volume. The study documented DOWE in the examined stock markets; it also found a link between high volatility and low trading volume, supporting the argument made by Foster and Viswanathan (1990), who suggested that high volatilities on various days are related to low trading volume, because liquidity traders are reluctant to trade when the volatility of prices is higher.

Gardeazable and Regulez (2004) examined seasonality in the Spanish stock market from 1998 to 2000 using daily returns. They employed three methods: Dummy Variable

Approach (DVA), which is commonly used; an extension version, which they named Extended Dummy Variable Approach (EDVA); and conditional variance analysis (the GARCH model). The first approach found weak seasonality in the market, while the other two confirmed each other by finding positive and significant Monday and Friday effects and negative and significant Wednesday and Thursday effects. In addition, the GARCH model uncovered more facts about this market by finding heavy daily seasonality in the conditional variances.

An empirical study by Yakob et al. (2005) using the GARCH and GARCH-M model investigated calendar anomalies such as DOWE, month-of-the-year and holiday effects in the Asia Pacific stock markets (Australia, China, Hong Kong, Japan, India, Indonesia, Malaysia, Singapore, South Korea and Taiwan) covering the period from January 2000 to March 2005. They aimed to find out whether seasonality exists in these stock markets, and to inspect the influence of conditional risk on returns seasonality. The results verified the existence of seasonality in the Asia Pacific stock markets, concluding that stock market seasonality is a global phenomenon. However, the conditional risk fails to explain the seasonality in most of the Asia Pacific stock markets. It is important to mention that the authors indicated that the presence of seasonality and regular significant shifts in return do not necessarily produce abnormal return, which can lead to a violation of EMH, because it must be empirically evident that seasonality can generate excess return that exceeds the transaction costs.

Al-Khazali et al. (2010) investigated the Saturday effect in three emerging stock markets (Bahrain, Kuwait and Saudi Arabia) by taking into account thin trading that typically characterises the Gulf markets. They used stochastic dominance (SD) approach, which is not distribution-dependent, to examine DOWE in the three major Gulf stock markets for the period from January 1994 to December 2006. They stated that it is the first study that uses SD approach to investigate seasonality. Their findings showed that DOWE is present in the market when using raw data; however, when the data is corrected for thin and infrequent data, the DOWE disappears.

It can be clearly understood after reviewing the literature that DOWE exists in stock markets and has important implications. The popular and more recent methodology used to investigate calendar anomalies is GARCH models. The literature lacks empirical studies on the new emerging ISMI, especially about DOWE from the Islamic calendar perspective.

The main contributions of this chapter to the literature are two: the first is to examine the effects of Friday, as a Muslim holy day, on ISMI for the first time; and the second is to record the differences between ISMI and CSMI in terms of DOWE.

4. Data

This section displays the data used in this study and their descriptive statistics. There are two tables; one presents the descriptive statistics of all the indices, the other focuses on the mean return and standard deviation of each day of the week of each index.

This study employs daily closing prices throughout the period from 2 Jan 1996 to 20 April 2009 for DJIA (IA) and DJIM US (IM) with its 10 sub-indices, namely Oil & Gas (OG), Technology (TE), Basic Materials (BM), Industrial (IN), Consumer Goods (CG), Health Care (HC), Consumer Service (CS), Telecommunication (TC), Utilities (UT) and Financials (FI).

Each index return is calculated as the first difference of the log of the respective market index using the following equation:

$$R_t = \ln\left(P_t / P_{t-1}\right) \tag{2}$$

Table 1 presents the basic descriptive statistics of the return series from all indices. Descriptive statistics present quantitative descriptions to define basic features of the data to help condense lots of data into a simpler summary. They refer to properties of distributions, such as central tendency, dispersion of variability, and shape of distributions. They are mainly used to get a general overview of the data, and hence lay the foundation for further statistical analysis. Thus, the columns in table 1 report the mean, standard deviation, skewness, Kurtosis, and the Jarque-Bera test for Normality.

Table 1 illustrates that all average daily returns are positive except for TC and UT. In general, IM seems to be more risky than IA according to the standard deviation, but with higher mean return. Across all indices, OG and CG recorded the highest mean returns among the indices; while the UT experienced the lowest mean return by recording the most negative value. In terms of dispersion, describing the scatter or spread of the data, TE and UT both had the largest standard deviation among all indices, which gives the impression that these two sectors are more volatile than others. CG index appeared to be less risky than others, as it records the lowest standard deviation (even lower than IA).

Shape statistics, such as skewness and kurtosis, provide information about the shape of the distribution. Skewness describes the amount of asymmetry, while Kurtosis measures the concentration of the data around the peak and in the tails versus the concentration in the flanks. Table 1 shows that almost all of the indices are negatively skewed or left-skewed, with the exception for TE, TC and FI, which are found to be right-skewed. This generally indicates the presence of asymmetry in the data, yet the skewness statistics are not too large. The data also revealed high levels of excess kurtosis, with values larger than 3, indicating that the series tends to have fatter tails and higher peaks than the normal distribution. These statistics indicate a significant departure from normality for both general indices IA and IM, as well as the other sub-indices; therefore, all the series are not expected to be normally distributed. Jarque-Bera tests for normality, presented in the last column, confirmed that by rejecting the normality hypothesis of the data. In summary, this table shows that the daily returns do not follow normal distribution; instead they are leptokurtic and skewed.

Table 1: Descriptive statistics of the return series

	Mean	SD	Skewness	Kurtosis	Normality
IA	0.0124%	0.012592	-0.097768	10.55874	7973.226 a
IM	0.0167%	0.013602	-0.073658	9.433873	5988.125 a
OG	0.03%	0.017684	-0.2136	12.67416	11920.69 a
TE	0.018%	0.021333	0.206017	6.808047	1801.548 a
BM	0.007%	0.017892	-0.30761	10.81781	7776.845 a
IN	0.007%	0.014492	-0.20572	8.701445	4089.197 a
CG	0.013%	0.011475	-0.10935	12.41252	11259.25 a
HC	0.02%	0.013045	-0.15328	8.461815	3738.699 a
CS	0.033%	0.014973	-0.0548	7.941853	3038.966 a
TC	-0.001%	0.01687	0.088434	8.059245	3190.149 a
UT	-0.015%	0.020308	-1.49741	32.10423	110477.2 a
FI	0.007%	0.019122	0.27512	19.04534	33053.16 a

In the first row, the term “SD” stands for its standard deviation. In the first column, “IA” stand for Dow Jones Industrial Average, “IM” stands for Dow Jones Islamic Market, “OG” stands for Oil & Gas, “TE” for Technology, “BM” stands for Basic Materials, “IN” stands for Industrial, “CG” stands for Consumer Goods, “HC” stands for Health Care, “CS” stands for Consumer Service, “TC” stands for Telecommunications, “UT” stands for Utilities and “FI” stands for Financials. The sign “a” indicates the significance at the 99% level of confidence.

Table 2 reports only the mean and standard deviation of the return for each trading day of the week. The table illustrates that the mean return is negative on Mondays across indices except for IA, CG and TC. In previous empirical studies, returns on Monday, the start of the week, have mostly been lower than returns on other days. The majority of returns on other days are positive, while only a few negative returns were observed on various individual trading days across a few indices. The highest return observed across indices is 0.02% which occurred on three days: Tuesday for FI index, Wednesday for TE and CS indices, and Friday for BM index.

It can be seen that returns on Friday are positive and higher than those on Monday. Also, the lowest return, the most negative, is -0.02%, which is observed on Monday for FI, and on Wednesday for UT.

Table 2 also shows that CG constantly records the lowest standard deviation (0.5%) in all five individual trading days across indices, indicating that this index is less volatile than any other index. HC index comes next recording low standard deviation, but slightly higher than CG. On the other hand, TE and UT record the highest standard deviations in almost every case except on Tuesday, where FI was more volatile than UT. The highest standard deviation was 1.09%, observed in UT on Wednesday. The standard deviation in TE and UT was floating around 0.9 and 1%, well above some other bars such as IN, CG, HC, CS and US. In summary, it seems that TE and UT are more risky than any other index, while CG and HC appear to be the safest ones.

Table 2: Descriptive statistics for each trading days of the week

	Monday		Tuesday		Wednesday		Thursday		Friday	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
IA	0.009%	0.00612	0.016%	0.0058	-0.002%	0.0054	-0.005%	0.0056	-0.006%	0.0051
IM	-0.004%	0.006381	0.008%	0.00642	0.007%	0.00598	0.005%	0.006	0.0004%	0.0056
OG	-0.01%	0.008	0.01%	0.008	0.01%	0.0084	-0.01%	0.008	0.01%	0.007
TE	-0.01%	0.0092	0.01%	0.0101	0.02%	0.0099	0.01%	0.0095	-0.01%	0.0088
BM	-0.001%	0.009	0.01%	0.008	-0.004%	0.0081	-0.01%	0.008	0.02%	0.007
IN	-0.01%	0.007	0.01%	0.007	-0.001%	0.006	0.01%	0.007	0.01%	0.006
CG	0.003%	0.005	0.01%	0.006	0.01%	0.005	-0.002%	0.005	-0.01%	0.005
HC	-0.004%	0.0062	0.01%	0.006	0.01%	0.0057	0.003%	0.0059	-0.001%	0.005
CS	-0.01%	0.007	0.014%	0.007	0.02%	0.0064	0.011%	0.007	-0.002%	0.006
TC	0.011%	0.0081	-0.005%	0.008	-0.014%	0.0077	0.005%	0.0072	0.003%	0.007
UT	-0.001%	0.0092	-0.011%	0.009	-0.02%	0.0109	0.01%	0.0086	0.01%	0.008
FI	-0.02%	0.0087	0.02%	0.0096	0.001%	0.0079	0.002%	0.0085	0.012%	0.0079

In the second row, the term “SD” stands for standard deviation. In the first column, “IA” stand for Dow Jones Industrial Average, “IM” stands for Dow Jones Islamic Market, “OG” stands for Oil & Gas, “TE” for Technology, “BM” stands for Basic Materials, “IN” stands for Industrial, “CG” stands for Consumer Goods, “HC” stands for Health Care, “CS” stands for Consumer Service, “TC” stands for Telecommunications, “UT” stands for Utilities and “FI” stands for Financials.

5. Methodology

A distinguishing feature of many financial data is their time varying volatility or heteroscdasticity (Harris and Sollis 2003). Data is said to suffer from heteroscdasticity if the variances of the error terms are not equal, and the error terms may reasonably be expected to be larger for some points of the data than for others. In response, the ARCH model was introduced by Engle (1982).

It is more sensible to initially conduct a simple testing methodology using OLS model to test for seasonality by simply regressing the index return on constant, lag of return and the daily dummy variables. This will allow investigating the presence of ARCH effects in the employed data using ARCH-LM[48] test suggested by Engle (1982). If ARCH effect is present in the data, then ARCH and GARCH models are appropriate. The following is the employed standard model:

$$R_t = \alpha_0 + \beta\, R_{t-1} + \gamma_1 M_t + \gamma_2 T_t + \gamma_3 H_t + \gamma_4 F_t + \varepsilon_t \qquad (3)$$

Where R_t is the return on the investigated index on time *t*. The terms M, T, H and F are the dummy variables, representing Monday, Tuesday, Thursday and Friday respectively. Wednesday dummy variable was removed from the model to avoid the dummy variable trap. Despite the presence of heteroscdasticity, the regression coefficients for an ordinary least squares regression are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of accuracy. Instead of considering this as a problem to be corrected, ARCH and GARCH models treat heteroscdasticity as a variance to be modelled.

Due to the fact that the data suffers from ARCH effects[49], this study employs GARCH and Modified GARCH (*p, q*) models, as introduced by Bollerslev (1986) and Taylor (1986), to investigate DOWE in the selected stock indices. These models help to avoid two weaknesses of the use of the standard OLS methodology used by previous studies to run the regression of the returns on the five daily dummy variables (Kiymaz and Berument 2003). The first one is to avoid the problem of autocorrelations in the error terms. The second is to overcome the problem of assuming that the variance is constant;

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[48] ARCH-LM is Lagrange Multiplier Autoregressive Conditional Heteroscedastic test.
[49] Results of ARCH-LM are presented later in the results section.

instead, GARCH model allows the conditional variance to vary over time and to be a function of its own lags, as well as the squared lagged values of the error terms.

This study uses different types of GARCH models to investigate DOWE more thoroughly. The first adopted model specifies the mean equation, similar to model 3, as follows:

$$R_{\mathrm{t}} = \alpha_0 + \sum_{i=1}^{n} \beta_i R_{t-i} + \gamma_1 M_t + \gamma_2 T_t + \gamma_3 H_t + \gamma_4 F_t + \varepsilon_t \quad (4)$$

Where

$$\varepsilon_t^2 | \Omega_{\mathrm{t}-1} \sim N(0, h_t)$$

The conditional variance equation is specified as follows:

$$h_t = \varphi_t + \delta_{1t}\varepsilon_{t-1}^2 + \delta_{2t} h_{t-1} \quad (5)$$

The term h_t represents the conditional variance. The small *n* is the lag order; the small t is the time period and $\boldsymbol{\varepsilon}$ is the error term. The term is the constant, whereas β and γ are estimated parameters for the lag of the return and the dummy variables, respectively. The term is the conditional variance at time *t*. The terms φ and δ are estimated parameters that capture the presence of heteroscdasticity in the series.

It is also possible to have an augmented GARCH (p, q) specification, because the nature of these models allows exogenous variables to enter the specification of the conditional variance. Karolyi (1995), investigating S&P500 and TSE 300 (Toronto Stock Exchange market), included the volatility of the international stock market's returns in the conditional variance equation of the home country stock market return in order to capture the effect of the international markets on the stability of the home country market. Hsieh (1988) reported the DOWE in volatility for a number of international currencies in terms of the US dollars. Asteriou and Price (2001) used the modified GARCH to capture the effects of socio-political instability in UK GDP.

Similar to these studies, the second adopted model of this study allows the trading days of the weeks to enter the conditional variance equation using the modified GARCH (*p*, *q*). The model includes DOWE in the conditional variance equation as follows:

$$h_t = \varphi_t + \theta_1 M_t + \theta_2 T_t + \theta_3 H_t + \theta_4 F_t + \delta_{1t}\varepsilon_{t-1}^2 + \delta_{2t} h_{t-1} \quad (6)$$

The existence of DOWE implies that the return distribution on particular days in a stock market significantly differ from others by causing regular higher (or lower) returns and volatilities than on other days. CAPM proposes that the linear relationship between risk and expected return is positive. The implication of this proposition is that it is possible for a significant positive return observed in a portfolio to be considered as a reward to the investors for bearing higher risk. Thus, regularities in the returns can possibly be attributed to the market variation rather than being a true anomaly.

Similar to the empirical investigation of Clare et al. (1998), the third specification investigates the possibility that the stock market is inherently more risky on particular days, and hence higher return is required on those days as a compensation. Investigating this hypothesis can confirm whether any detected DOWE in the market are true anomalies or can be accounted for by the market variation.

Therefore, the third adopted model is GARCH-M (*p, q*), introduced by Engle et al. (1987), which allows the coefficient of the conditional variance to enter the mean equation to be directly examined against the expected return. Modified GARCH-M allows the investigation of the possibility that the market is more risky on particular days, and thus higher risk requires higher return for compensation on those particular days. In this specification, GARCH-M is applied to determine whether the presence of DOWE in the examined samples can be justified by the market risk.

Thus, while the variance equation remains the same as in the second model, the mean equation changes to be as follows:

$$R_t = \alpha_0 + \sum_{i=1}^{n} \beta_i R_{t-i} + \gamma_1 M_t + \gamma_2 T_t + \gamma_3 H_t + \gamma_4 F_t + \lambda \sqrt{h_{t-1}} + \varepsilon_t \qquad (7)$$

In summary, this study applies three types of specifications of the return and the variance equations using GARCH (1, 1). The first one examines the days of the week only in the mean equation. The second examines the days of the week in both the mean and variance equations. The last one incorporates the conditional variance coefficient in the mean equation of the second specification. According the descriptive statistics of the employed data shown in table 1, where the data exhibit excess positive kurtosis, the error distribution used in this study is the t-distribution, as suggested by Bollerslev (1987), Hsieh (1988), Baillie and Bollerslev (1989), Hamilton and Susmel (1994) and Wilhelmsson (2006).

6. Results

This section presents the actual results of the study organised in 5 tables. The first one is table 3, which displays the results of the basic OLS model. Table 4 presents the three proposed specifications all together of only the two general indices DJIA and DJIM US. The rest of the tables concentrate only on the 10 sub-indices of DJIM US, so table 5 displays the results of the first specification applied on the sub-indices, whereas tables 6 and 7 show the results of the second and the third specifications respectively.

Table 3 reports the results from OLS estimation to investigate seasonality in the employed data. The model is also estimated for testing the presence of ARCH effects. The presence of conditional heteroscdasticity suggests that variations in daily returns cannot be accounted for by the normal linear model. Instead, GARCH models can provide a better explanation. ARCH-LM tests are appropriate for testing ARCH effects.

Table 3: DJIA and DJIM US results using basic model

	DJIA	DJIM US
	Panel A: Mean equation	
Con	-4.78E-05 (0.9207)	0.000376 (0.4665)
R t-1	-0.058927 (0.0007) a	-0.062358 (0.0002) a
M	0.000527 (0.4474)	-0.000553 (0.4486)
T	0.000862 (0.2045)	5.02E-06 (0.9945)
H	-0.000231 (0.7348)	-0.000105 (0.8852)
F	-0.000254 (0.7102)	-0.000338 (0.6428)
	Panel B: ARCH-LM	
R-squared	0.004648	0.004130
F-statistic	3.119328 (0.008194) a	2.872104 (0.0000) a
N*R^2	848.1678 (0.0000) a	824.6529 (0.0000) a

The results of the estimated model in this table is to test the presence of ARCH effect in DJIA and DJIM US. The term "Con" stands for constant and "Rt-1" represents the lag of the return, "M" refers to Monday, "T" refers to Tuesday, "H" refers to Thursday and "F" refers to Friday. Panel A shows the results of the mean equation and Panel B show the result of ARCH-LM test (Lagrange Multiplier Autoregressive Conditional Heteroscedastic test) for the presence of ARCH effect. "N*R^2" refers to the number of Observation * R-squared which is the LM test statistic for the null hypothesis of no serial correlation. The letters "a", "b" and "c" indicate that the estimated coefficient is statistically significant at the 1%, 5% and 10% level respectively.

Table 4 presents the results of GRACH models conducted on DJIA and DJIM US. The table contains the results of all three specifications together. The results in this table make two main contributions to the literature: to record the differences between ISMI and CSMI in terms of DOWE; and to investigate the Friday effect as a Muslim holiday on DJIM US for the first time.

The results of the two main indices are exhibited together in table 4 for comparison purposes. The results of the sub-indices to be presented in the following tables are separated because they have a different aim, which is to further explore DOWE (and the Friday effect in particular) on the Islamic indices.

Table 4: DJIA and DJIM US results

	DJIA	DJIM US	DJIA	DJIM US	DJIA	DJIM US
	Panel A: Mean equation					
$\sqrt{h_{t-1}}$	----	----	----	----	0.042562 (0.3835)	0.050846 (0.3023)
Con	0.000779 (0.0163)a	0.001207 (0.0013)a	0.000787 (0.015)a	0.00122 (0.0011)a	0.000428 (0.4141)	0.000739 (0.2152)
R t-1	-0.02719 (0.1453)	-0.02876 (0.123)	-0.026785 (0.1505)	-0.026845 (0.1498)	-0.026811 (0.1514)	-0.02697 (0.1502)
M	0.000274 (0.568)	-0.00054 (0.3203)	0.000219 (0.6356)	-0.000604 (0.2521)	0.000236 (0.611)	-0.00057 (0.275)
T	2.37E-05 (0.9582)	-0.00064 (0.2201)	2.04E-05 (0.9653)	-0.00064 (0.2391)	7.47E-07 (0.9987)	-0.00067 (0.2166)
H	-0.00064 (0.1575)	-0.00064 (0.2237)	-0.000649 (0.1544)	-0.000641 (0.2202)	-0.000645 (0.1561)	-0.00063 (0.2252)
F	-0.00066 (0.1481)	-0.00087 (0.1002)c	-0.000679 (0.1351)	-0.000912 (0.0818)c	-0.000672 (0.138)	-0.00091 (0.0827)c
	Panel B: Variance equation					
Con	8.21E-07 (0.0025)a	1.07E-06 (0.0025)a	-4.24E-06 (0.4288)	-7.36E-06 (0.2716)	-4.20E-06 (0.4338)	-7.33E-06 (0.2732)
ε_{t-1}^2	0.071909 (0.000)a	0.072478 (0.000)a	0.071119 (0.000)a	0.073115 (0.000)a	0.071745 (0.000)a	0.073906 (0.000)a
h_{t-1}	0.92477 (0.000)a	0.923227 (0.000)a	0.926005 (0.000)a	0.923069 (0.000)a	0.925311 (0.000)a	0.922194 (0.000)a
M	----	----	6.45E-07 (0.9253)	1.59E-06 (0.8572)	7.09E-07 (0.9178)	1.58E-06 (0.8581)
T	----	----	1.45E-05 (0.1032)c	2.37E-05 (0.032)b	1.46E-05 (0.1015)c	2.40E-05 (0.0304)b
H	----	----	4.85E-06 (0.5438)	8.03E-06 (0.4123)	4.69E-06 (0.5579)	7.90E-06 (0.4204)
F	----	----	4.72E-06 (0.5278)	8.00E-06 (0.3839)	4.56E-06 (0.5419)	7.86E-06 (0.3923)
	Panel C: Autocorrelation (Q statistics) and ARCH-LM test					
5	4.945 (0.423)	7.4411 (0.19)	4.7821 (0.443)	7.2424 (0.203)	4.5853 (0.469)	6.8099 (0.235)
10	9.8152 (0.457)	10.952 (0.361)	9.2363 (0.51)	10.334 (0.412)	9.2046 (0.513)	10.033 (0.438)
15	23.027 (0.084)c	23.824 (0.068)c	22.475 (0.096)c	23.512 (0.074)c	22.201 (0.103)c	23.367 (0.077)c
20	24.384 (0.226)	27.498 (0.122)	24.004 (0.242)	27.255 (0.128)	23.824 (0.25)	27.128 (0.132)
$N{*}R^2$	17.77610 (0.8517)	15.36306 (0.9325)	18.88120 (0.8028)	17.09906 (0.8782)	19.07132 (0.7937)	17.44098 (0.8652)

This table presents the results of GARCH models for DJIA and DJIM US. In the first column, the term "$\sqrt{h_{t-1}}$" is the lag of the square root of the conditional varaince, "Con" stands for constant and "Rt-1" represents the lag of the return, "M" refers to Monday, "T" refers to Tuesday, "H" refers to Thursday, "F" refers to Friday, and "$\boldsymbol{\varepsilon_{t-1}^2}$" is the lag of the squared error term. Panel A shows the results of the mean equation of GARCH model, Panel B shows the results of the variance equation of GARCH model, and Panel C presents the results of Ljung-Box test (Q-test) for autocorrelation where the numbers "5", "10", "15" and "20" represent the number of lags. "$N{*}R^2$" refers to the number of Observation * R-squared which is the LM test statistic for the null hypothesis of no serial correlation. The letters "a", "b" and "c" indicate that the estimated coefficient is statistically significant at the 1%, 5% and 10% level respectively.

Table 5 displays the results of GARCH models conducted on the 10 subindices of DJIM US applying only the first specification. The reason only the subindices of DJIM US are examined is the fact that DJIA has no subindices, in addition to the fact that DOWE has no effects on DJIA, as shown in table 4. This specification includes the dummy variables of the days of the week only in the mean equation. The contriobution of this specification is to examine firstly the DOWE on the expected returns of ISMI before including the dummies in the variance equation. This allows the study to check the effects of including the dummies after the first specification estaimate are already obtained.

Table 5: DOWE in the mean equation

	DJ_OG*	DJ_TE	DJ_BM	DJ_IN	DJ_CG	DJ_HC*	DJ_CS*	DJ_TC*	DJ_UT	DJ_FI
	Panel A: Mean Equation									
Con	0.001223	0.001919	8.02E-05	0.000936	0.000864	0.000897	0.001339	-2.98E-05	0.000176	0.000512
	(0.0138)a	(0.0005)a	(0.8647)	(0.0155)a	(0.0043)a	(0.0128)a	(0.0026)a	(0.9483)	(0.6477)	(0.2103)
R t-1	-0.01335	-0.008877	0.002078	0.028456	-0.031542	-0.00609	0.022262	-0.020937	0.032319	0.01617
	(0.4498)	(0.6283)	(0.906)	(0.1292)	(0.0803)c	(0.7295)	(0.2199)	(0.2344)	(0.0658)c	(0.3654)
M	-0.000578	-0.00113	0.000723	-0.00033	-0.000491	-0.00073	-0.00097	0.00091	0.000981	1.90E-05
	(0.4165)	(0.1663)	(0.2853)	(0.5546)	(0.272)	(0.1631)	(0.118)	(0.1831)	(0.0814)c	(0.9743)
T	-0.000413	-0.001305	0.000692	-0.00043	-0.000209	-0.00036	-0.00049	0.000127	0.000498	-0.00027
	(0.5469)	(0.0924)c	(0.2925)	(0.4183)	(0.6251)	(0.487)	(0.4095)	(0.8473)	(0.3675)	(0.631)
H	-0.000913	-0.001562	2.89E-05	-0.00032	-0.000598	-0.00029	-0.00026	0.0002	0.000422	-0.00019
	(0.2217)	(0.0414)b	(0.9658)	(0.5481)	(0.1658)	(0.5700)	(0.6771)	(0.762)	(0.4471)	(0.7485)
F	0.000088	-0.002203	0.000986	-0.00033	-0.000781	-0.00087	-0.00116	0.000794	-5.45E-05	8.93E-05
	(0.8725)	(0.0047)a	(0.1478)	(0.5464)	(0.0714)c	(0.0904)c	(0.0615)c	(0.2426)	(0.9233)	(0.8766)
	Panel B: Variance Equation									
Con	0.000003	1.01E-06	1.34E-06	1.40E-06	6.69E-07	1.18E-06	1.45E-06	1.19E-06	1.69E-06	3.11E-06
	(0.0014)a	(0.0218)b	(0.0072)a	(0.001)a	(0.0041)a	(0.0013)a	(0.002)a	(0.0124)a	(0.0004)a	(0.0001)a
ε_{t-1}^2	0.0654	0.0616	0.057778	0.078808	0.067317	0.075207	0.066606	0.05711	0.098192	0.102983
	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a
h_{t-1}	0.9243	0.937779	0.939124	0.916166	0.929506	0.920342	0.928439	0.940365	0.901469	0.888143
	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a	(0.0000)a
	Panel C: Autocorrelation (Q statistics) and ARCH-LM test									
5	4.9338	2.4956	4.6285	3.1512	4.2822	1.4521	1.3042	2.0304	5.4317	5.7979
	(0.424)	(0.777)	(0.463)	(0.677)	(0.51)	(0.919)	(0.934)	(0.845)	(0.365)	(0.326)
1	13.187	5.6118	5.3661	6.3943	10.689	5.1047	3.463	14.733	8.8596	11.67
	(0.213)	(0.847)	(0.865)	(0.781)	(0.382)	(0.884)	(0.968)	(0.142)	(0.545)	(0.308)
15	15.741	17.592	9.7736	19.526	21.09	21.104	19.167	20.234	11.286	20.935
	(0.399)	(0.285)	(0.834)	(0.191)	(0.134)	(0.134)	(0.206)	(0.163)	(0.732)	(0.139)
20	23.210	20.276	12.798	26.29	24.166	22.935	22.238	27.086	18.32	23.39
	(0.279)	(0.441)	(0.886)	(0.156)	(0.235)	(0.292)	(0.328)	(0.133)	(0.566)	(0.27)
$N*R^2$	16.819	28.76188	19.46410	21.88204	10.59726	15.31706	13.38006	17.38453	29.57238	30.61206
	(0.8883)	(0.2740)	(0.7743)	(0.6425)	(0.9947)	(0.9337)	(0.9715)	(0.8674)	(0.2407)	(0.2022)

This table presents the results of GARCH models for teh subindices of DJIM US. In first row, “DJ” refers to a sub-index of DJIM US to be identified by the following two letters so that “OG” stands for Oil & Gas, “TE” for Technology, “BM” stands for Basic Materials, “IN” stands for Industrial, “CG” stands for Consumer Goods, “HC” stands for Health Care, “CS” stands for Consumer Service, “TC” stands for Telecommunications, “UT” stands for Utilities and “FI” stands for Financials. The star “*” attached to some of the sub-indices is to indicate that different number of lags of returns are used as suggested by Q-statistics and the orders of return for OG, HC, CS and TC are 4, 5, 8 and 3, respectively. In the first column, The term $\sqrt{h_{t-1}}$ is the lag of the square root of the conditional varaince, “Con” stands for constant and “Rt-1” represents the lag of the return, “M” refers to Monday, “T” refers to Tuesday, “H” refers to Thursday, “F” refers to Friday, and “$\boldsymbol{\varepsilon_{t-1}^{2}}$” is the lag of the squared error term. Panel A shows the results of the mean equation of GARCH model, Panel B shows the results of the variance equation of GARCH model, and Panel C presents the results of Ljung-Box test (Q-test) for autocorrelation where the numbers “5”, “10”, “15” and “20” represent the number of lags. “N*R^2” refers to the number of Observation * R-squared which is the LM test statistic for the null hypothesis of no serial correlation. The letters “a”, “b” and “c” indicate that the estimated coefficient is statistically significant at the 1%, 5% and 10% level respectively.

The results presented in table 6 explain the DOWE in the mean and variance equations in the context of the 10 sub-indices of DJIM US. This specification allows the variance equation to depend on the dummy variables of the days of the week. It shows whether volatility of the market is seasonally affected or not. One day can be more risky than another if there is a positive relationship between that particular day and the index volatility. If there is a negative relationship, it will mean this particular day is less risky than others. The contribution of these results is to further explore the effects of DOWE (and the Friday effect in particular as a Muslim holy day) on the DJIM US through examining its sub-indices.

Table 6: DOWE in the mean and variance equations

	DJ_OG	DJ_TE	DJ_BM	DJ_IN	DJ_CG	DJ_HC*	DJ_CS*	DJ_TC*	DJ_UT	DJ_FI
	Panel A: Mean equation									
Con	0.001253	0.001948	9.28E-05	0.000947	0.00084	0.000899	0.001415	-3.20E-05	0.000198	0.000492
	(-0.0204)b	(0.0008)a	(0.8483)	(0.0137)a	(0.0074)a	(0.0123)a	(0.0005)a	(0.9469)	(0.6257)	(0.2063)
Rt-1	-0.012266	-0.007968	0.003108	0.028315	-0.031088	-0.00502	0.023247	-0.01994	0.032042	0.016387
	(0.488)	(0.6638)	(0.8599)	(0.1321)	(0.0858)c	(0.7755)	(0.1986)	(0.2584)	(0.068)c	(0.358)
M	-0.000636	-0.00126	0.000692	-0.00036	-0.000472	-0.00075	-0.00106	0.000895	0.000989	4.96E-05
	(0.41)	(0.1149)	(0.3073)	(0.5145)	(0.281)	(0.1407)	(0.0736)c	(0.1896)	(0.0845)c	(0.9299)
T	-0.000427	-0.001364	0.000698	-0.00045	-0.000181	-0.00037	-0.0005	0.000125	0.000499	-0.00026
	(0.5739)	(0.0921)c	(0.3142)	(0.4111)	(0.6866)	(0.4731)	(0.4054)	(0.8544)	(0.3812)	(0.6479)
H	-0.000936	-0.001606	1.30E-05	-0.00032	-0.000571	-0.00029	-0.00033	0.000211	0.000393	-0.00015
	(0.2092)	(0.0429)b	(0.9845)	(0.5567)	(0.191)	(0.5769)	(0.5752)	(0.7568)	(0.4965)	(0.7872)
F	8.95E-05	-0.002243	0.001011	-0.00036	-0.00076	-0.00088	-0.00131	0.00081	-7.53E-05	9.92E-05
	(0.9044)	(0.0053)a	(0.1317)	(0.5104)	(0.0844)c	(0.0856)c	(0.0257)b	(0.2329)	(0.8929)	(0.8615)
	Panel B: Variance equation									
Con	2.07E-05	3.95E-06	-6.82E-06	-1.24E-06	7.51E-07	1.05E-06	-2.03E-05	6.28E-06	5.55E-06	-7.19E-06
	(0.0846)c	(0.7497)	(0.5097)	(0.8588)	(0.8728)	(0.8677)	(0.0153)a	(0.5512)	(0.48)	(0.4074)
$\boldsymbol{\varepsilon^2_{t-1}}$	0.06729	0.060791	0.059205	0.078228	0.068502	0.072996	0.064951	0.058473	0.096468	0.099827
	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)	(0.000)	(0.000)	(0.000)a	(0.000)a
$\boldsymbol{h_{t-1}}$	0.921965	0.939141	0.93812	0.916907	0.928436	0.923307	0.930321	0.93927	0.902775	0.89157
	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a
M	-6.32E-06	-2.13E-05	1.26E-05	1.05E-06	-4.48E-06	-4.19E-06	2.42E-05	-6.00E-06	-6.08E-07	2.58E-06
	(0.6946)	(0.1733)	(0.3514)	(0.909)	(0.468)	(0.6249)	(0.0227)b	(0.6438)	(0.9532)	(0.8364)
T	-1.89E-05	1.75E-05	2.47E-05	7.35E-06	6.97E-06	3.66E-06	3.78E-05	3.73E-06	-6.00E-08	1.86E-05
	(0.3466)	(0.3598)	(0.1612)	(0.5286)	(0.3525)	(0.7228)	(0.0093)a	(0.8333)	(0.9963)	(0.2232)
H	-4.29E-05	-6.63E-06	-3.14E-06	7.26E-06	-3.52E-06	5.67E-06	3.31E-05	-9.98E-06	-5.29E-06	1.87E-05
	(0.0359)b	(0.7225)	(0.8535)	(0.4842)	(0.6345)	(0.5709)	(0.0088)a	(0.5526)	(0.6811)	(0.1548)
F	-1.90E-05	-6.79E-06	6.38E-06	-2.78E-06	1.97E-07	-5.44E-06	1.36E-05	-1.36E-05	-1.33E-05	1.07E-05
	(0.2712)	(0.7012)	(0.6568)	(0.7832)	(0.9757)	(0.5541)	(0.2522)	(0.3678)	(0.2301)	(0.3882)

Table 6 to be continued in the following page containg Panel C

Table 6 continues

	Panel C: Autocorrelation (Q statistics) and ARCH-LM test									
5	4.5495	2.1676	4.4397	3.0704	4.1838	1.3664	1.3104	2.1216	5.5551	5.6229
	(0.473)	(0.825)	(0.488)	(0.689)	(0.523)	(0.928)	(0.934)	(0.832)	(0.352)	(0.345)
10	12.77	5.2895	5.2096	6.1985	10.292	4.985	3.5434	14.595	8.8632	11.164
	(0.237)	(0.871)	(0.877)	(0.798)	(0.415)	(0.892)	(0.966)	(0.148)	(0.545)	(0.345)
15	15.433	17.482	9.8447	18.949	20.682	21.546	18.826	20.325	11.091	19.982
	(0.421)	(0.291)	(0.829)	(0.216)	(0.147)	(0.12)	(0.222)	(0.16)	(0.746)	(0.173)
20	22.789	20.384	12.971	25.818	24.14	23.424	21.85	27.442	18.41	22.545
	(0.299)	(0.434)	(0.879)	(0.172)	(0.236)	(0.268)	(0.349)	(0.123)	(0.56)	(0.312)
$N{*}R^2$	15.51599	29.75397	18.95618	22.27701	12.24678	15.09295	13.6515	17.03073	30.11293	29.69276
	(0.985)	(0.2336)	(0.7992)	(0.6197)	(0.9845)	(0.9392)	(0.9653)	(0.8807)	(0.2201)	(0.236)

This table presents the results of GARCH models for teh subindices of DJIM US. In first row, “DJ” refers to a sub-index of DJIM US to be identified by the following two letters so that “OG” stands for Oil & Gas, “TE” for Technology, “BM” stands for Basic Materials, “IN” stands for Industrial, “CG” stands for Consumer Goods, “HC” stands for Health Care, “CS” stands for Consumer Service, “TC” stands for Telecommunications, “UT” stands for Utilities and “FI” stands for Financials. The star “*” attached to some of the sub-indices is to indicate that different number of lags of returns are used as suggested by Q-statistics and the orders of return for HC, CS and TC are 5, 8 and 3, respectively. In the first column, The term$\sqrt{h_{t-1}}$ is the lag of the square root of the conditional varaince, “Con” stands for constant and “Rt-1” represents the lag of the return, “M” refers to Monday, “T” refers to Tuesday, “H” refers to Thursday, “F” refers to Friday, and “$\boldsymbol{\varepsilon}_{t-1}^{2}$” is the lag of the squared error term. Panel A shows the results of the mean equation of GARCH model, Panel B shows the results of the variance equation of GARCH model, and Panel C presents the results of Ljung-Box test (Q-test) for autocorrelation where the numbers “5”, “10”, “15” and “20” represent the number of lags. “$N{*}R^2$” refers to the number of Observation * R-squared which is the LM test statistic for the null hypothesis of no serial correlation. The letters “a”, “b” and “c” indicate that the estimated coefficient is statistically significant at the 1%, 5% and 10% level respectively.

The results of the third specification applied to the 10 sub-indices are presented in table 7. These results add more information to that shown in table 6 (which is about the risk-return relationship). The contribution of the third specification is to incorporate the risk coefficient in the mean equation to detect the risk-return trade-off in DJIM US, whereas the risk is allowed to be explained by the dummy variables of the days of the week.

Table 7: DOWE in the mean and variance equations using GARCH-M

	DJ_OG	DJ_TE	DJ_BM	DJ_IN	DJ_CG	DJ_HC*	DJ_CS*	DJ_TC*	DJ_UT	DJ_FI
	Panel A: Mean equation									
$\sqrt{h_{t-1}}$	-0.039164	0.029624	-0.03945	0.021149	0.018403	0.114063	0.058517	-0.041973	-0.6442	-0.06177
	(0.5556)	(0.468)	(0.43)	(0.6587)	(0.7151)	(0.0237)b	(0.2553)	(0.4069)	(0.4942)	(0.1639)
Con	0.001827	0.001531	0.000594	0.00074	0.00069	-0.00019	0.000801	0.000508	0.000287	0.001143
	(0.0992)c	(0.0597)c	(0.4542)	(0.2222)	(0.1832)	(0.7568)	(0.2324)	(0.5248)	(0.5015)	(0.0585)c
Rt-1	-0.012395	-0.008056	0.002934	0.028406	-0.031082	-0.00673	0.022622	-0.020074	0.031691	0.015824
	(0.486)	(0.6611)	(0.8677)	(0.1318)	(0.0866)c	(0.7033)	(0.2129)	(0.2546)	(0.0719)c	(0.3742)
M	-0.000668	-0.001214	0.000656	-0.00035	-0.000462	-0.00071	-0.001077	0.000856	0.00098	6.60E-05
	(0.39)	(0.1277)	(0.3344)	(0.5194)	(0.2923)	(0.1621)	(0.0689)c	(0.2095)	(0.0877)c	(0.9069)
T	-0.000465	-0.001355	0.000707	-0.00045	-0.000182	-0.00037	-0.000589	0.00011	0.000493	-0.00022
	(0.5423)	(0.0935)c	(0.3106)	(0.4071)	(0.6844)	(0.4682)	(0.3309)	(0.8716)	(0.3873)	(0.7037)
H	-0.000992	-0.001592	-2.25E-05	-0.00032	-0.000567	-0.00034	-0.000368	0.000191	0.00039	-0.00011
	(0.1858)	(0.0444)b	(0.9733)	(0.5513)	(0.1941)	(0.5111)	(0.5368)	(0.7789)	(0.5013)	(0.8453)
F	3.37E-05	-0.002227	0.000972	-0.00036	-0.000752	-0.00086	-0.00131	0.000776	-8.65E-05	0.000136
	(0.9643)	(0.0055)a	(0.1489)	(0.5116)	(0.0877)c	(0.0936)c	(0.0252)b	(0.2532)	(0.8773)	(0.8116)
	Panel B: Variance equation									
Con	2.09E-05	3.80E-06	-6.51E-06	-1.25E-06	8.20E-07	1.62E-06	-1.98E-05	6.15E-06	5.77E-06	-7.22E-06
	(0.0809)c	(0.7581)	(0.5312)	(0.858)	(0.8612)	(0.7971)	(0.0182)a	(0.558)	(0.4622)	(0.4068)
$\boldsymbol{\varepsilon_{t-1}^2}$	0.067248	0.061273	0.058622	0.078363	0.06887	0.074754	0.066461	0.05776	0.095956	0.098404
	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a
$\boldsymbol{h_{t-1}}$	0.922114	0.938678	0.938792	0.916748	0.928027	0.921248	0.928698	0.939987	0.903281	0.893023
	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a	(0.000)a
M	-6.20E-06	-2.14E-05	1.22E-05	1.09E-06	-4.55E-06	-4.41E-06	2.32E-05	-5.50E-06	-9.01E-07	2.51E-06
	(0.6997)	(0.1713)	(0.3693)	(0.9059)	(0.4627)	(0.6021)	(0.0287)b	(0.6688)	(0.9306)	(0.8414)
T	-1.93E-05	1.76E-05	2.46E-05	7.34E-06	6.92E-06	3.36E-06	3.75E-05	3.49E-06	-2.87E-07	1.90E-05
	(0.3345)	(0.3564)	(0.1654)	(0.5298)	(0.3566)	(0.7435)	(0.0099)a	(0.8435)	(0.9823)	(0.2118)
h	-4.36E-05	-6.09E-06	-3.77E-06	7.29E-06	-3.67E-06	4.59E-06	3.22E-05	-9.55E-06	-5.65E-06	1.88E-05
	(0.033)b	(0.7435)	(0.8248)	(0.4817)	(0.6211)	(0.6489)	(0.0114)a	(0.5688)	(0.6604)	(0.1536)
F	-1.92E-05	-6.57E-06	5.85E-06	-2.79E-06	1.37E-07	-6.35E-06	1.32E-05	-1.37E-05	-1.36E-05	1.02E-05
	(0.2638)	(0.7102)	(0.6841)	(0.783)	(0.9832)	(0.492)	(0.2685)	(0.3635)	(0.2201)	(0.4132)

Table 7 to be continued in the following page containing Pane C

Table 7 continues

	Panel C: Autocorrelation (Q statistics) and ARCH-LM test									
5	4.6631	2.1002	4.5359	3.0159	4.1634	1.6459	1.4354	2.1726	5.5869	5.6121
	(0.458)	(0.835)	(0.475)	(0.698)	(0.526)	(0.896)	(0.92)	(0.825)	(0.349)	(0.346)
10	12.777	5.1722	5.4074	6.0902	10.356	5.3193	3.5986	14.895	8.9081	11.364
	(0.236)	(0.879)	(0.862)	(0.808)	(0.41)	(0.869)	(0.964)	(0.136)	(0.541)	(0.33)
15	15.621	17.514	10.195	18.947	20.645	21.511	18.956	20.84	11.065	20.355
	(0.408)	(0.289)	(0.807)	(0.216)	(0.149)	(0.121)	(0.216)	(0.142)	(0.748)	(0.159)
20	23.104	20.446	13.228	25.709	24.17	23.525	22.479	27.67	18.097	23.022
	(0.284)	(0.43)	(0.867)	(0.176)	(0.235)	(0.264)	(0.315)	(0.117)	(0.581)	(0.288)
N*R^2	15.53637	30.102	19.10774	22.38093	12.208	14.4208	13.65151	17.03839	29.77527	29.5842
	(0.9279)	(0.2205)	(0.7919)	(0.6137)	(0.9848)	(0.9539)	(0.9675)	(0.8804)	(0.2328)	(0.2402)

This table presents the results of GARCH models for teh subindices of DJIM US. In first row, “DJ” refers to a sub-index of DJIM US to be identified by the following two letters so that “OG” stands for Oil & Gas, “TE” for Technology, “BM” stands for Basic Materials, “IN” stands for Industrial, “CG” stands for Consumer Goods, “HC” stands for Health Care, “CS” stands for Consumer Service, “TC” stands for Telecommunications, “UT” stands for Utilities and “FI” stands for Financials. The star “*” attached to some of the sub-indices is to indicate that different number of lags of returns are used as suggested by Q-statistics and the orders of return for HC, CS and TC are 5, 8 and 3, respectively. In the first column, The term $\sqrt{h_{t-1}}$ is the lag of the square root of the conditional varaince, “Con” stands for constant and “Rt-1” represents the lag of the return, “M” refers to Monday, “T” refers to Tuesday, “H” refers to Thursday, “F” refers to Friday, and “$\boldsymbol{\varepsilon}_{t-1}^{2}$” is the lag of the squared error term. Panel A shows the results of the mean equation of GARCH model, Panel B shows the results of the variance equation of GARCH model, and Panel C presents the results of Ljung-Box test (Q-test) for autocorrelation where the numbers “5”, “10”, “15” and “20” represent the number of lags. “N*R^2” refers to the number of Observation * R-squared which is the LM test statistic for the null hypothesis of no serial correlation. The letters “a”, “b” and “c” indicate that the estimated coefficient is statistically significant at the 1%, 5% and 10% level respectively.

7. Analysis and Discussion

This section discusses and analyses the actual results of the study that are presented in section 6. In parallel, this section attempts to briefly go through the methodology in some detail to explain its application, and look at whether the methodology conditions have been satisfied or not. The importance of this study lies in the fact that only limited studies focused on seasonality in ISMI, and none have thus far investigated DOWE in ISMI from an Islamic perspective, especially the effect of Friday, the Muslim holy day. Therefore, this study is conducted to detect the existence of DOWE in the mean and the volatility of DIJA and the DJIM US and its 10 sub-indices.

This section explains the reported results of the performed tests. The methodology used for the tests is GARCH models. Three specifications were applied to run the tests.

The first specification includes the days of the week in the mean equation to detect DOWE only in the conditional mean of GARCH. Then, the second specification allows the conditional variance of the return to change every trading day by modelling a modified GARCH. This specification includes the days of the week in the conditional variance equation to investigate the presence of DOWE in volatility. In other words, the modified GARCH examines the DOWE in both the mean return and the conditional variance. The days employed in the tests are Monday, Tuesday, Thursday and Friday. Wednesday dummy variable is excluded in order to avoid dummy variable trap. The third specification is the modified GARCH-M, utilised to check whether the high return for a given day is actually a reward for the high volatility by including the coefficient of the conditional variance (or risk) in the conditional mean equation. If the regular seasonal shift in the returns cannot be explained by the market risk, then it can be considered as a true anomaly.

In GARCH models, different combinations of p and q were applied. Results based on Akaike information criterion (AIC), Schwarz criterion (SC) and Hannan-Quinn criterion (HQC) indicated that p=q=1 is the appropriate lag length in all cases. The mean equation includes one lag as the first choice; however, a different number of lags of the return were also attempted in some indices when necessary to avoid significant lags, or autocorrelation, in the Q-test.

The study started by applying the standard model to investigate the seasonality in the data. Table 3 shows the results of the basic linear model for DJIA and DJIM US displayed in two panels, A and B. Panel A displays the estimated coefficients of the independent variables. Panel B presents the R-squared values, F-statistics and ARCH-LM test results. However, OLS results should be interpreted with caution, since the description statistics and ARCH-LM tests shown in tables 1 and 3 (respectively) indicate that the OLS assumptions are violated and that GARCH models are the appropriate models to adopt.

The other four tables 4, 5, 6 and 7, present the results of GARCH (1, 1) models for all examined indices. The estimated models allow the varying conditional variance to follow GARCH (1, 1) specification. Each table consists of three panels A, B and C. Panel A in each table displays the results of the mean equation; while, the results of the variance equations are shown in Panel B of each table. Panel C presents the results of Ljung-Box test (Q-test) and ARCH-LM, the tests that have important implications for the mean and variance equations.

Ljung-Box test (introduced by Ljung and Box (1979) is a test for randomness that examines the overall randomness on a number of lags under the null hypothesis that the data are random. In other words, it is applied as a test of whether the series is white noise. It is commonly used for to check the quality of fit of the time series model. Q-test is performed with 20 lags to test the existence of autocorrelation in the data.

ARCH-LM test is performed by regressing the squared residuals on its own lags and calculating its value to detect the presence of ARCH components. The null hypothesis is that in the absence of ARCH effects, all the estimated coefficients of the lag residuals must be equal to zero. On the other hand, the presence of the ARCH effect exists when at least one estimated coefficient is significant. Hence, in a sample of "N" residuals under the null hypothesis of no ARCH effect, the test statistic N^*, following distribution with q degrees of freedom, investigates whether the null hypothesis can be rejected or not.

The first empirical test estimated in this study was a basic testing methodology. The results of the basic model (presented in table 3) indicate that there is no sign of DOWE in both indices. The first lag of return is the only significant estimated coefficient in both indices, at the 99% level of confidence. The values of R-squared in both indices are low but close to each other, recording 0.46% for DJIA and 0.41% for DJIM US. The F-statistics are also significant.

However, ARCH-LM test indicates that ARCH effect exists in the two series. The presence of ARCH effect is a clear indication that the generated results of the basic linear model are not accurate for both indices. The presence of ARCH effect implies that the data exhibit wide volatility, suggesting the variance of the data changes over time. Therefore, GARCH models are appropriate for properly modelling the variances and more accurately testing seasonality in the employed data.

Therefore, GARCH models were applied to investigate the presence of DOWE in the examined indices. Table 4 contains the results of the starting point of the GARCH models' investigations. The table shows the results of all three test specifications performed on DJIM US and DJIA. It is designed to initially compare between the two indices before investigating the sub-indices.

In this table, the sum of coefficients of the GARCH equation is less than one in all cases. The signs of all coefficients are always positive, except the one for the constant, which turns to negative only when days of the week are included in the variance equations; however, all the negative estimated coefficients are insignificantly different from zero. This suggests that the conditional variance is always positive and non-explosive in the examined samples. Panel C indicates that the coefficients of the normalised residuals are statistically insignificant, except for the lag 15, which is significant at the 90% level of confidence. Interestingly, the lag 15 is the only significant lag in both indices, indicating that there might be some information related to the specific lag 15 which is equal to 2 weeks of time. ARCH-LM test documented that there is no ARCH effect in the samples by simply failing to reject the null hypothesis of homoscdasticity, or the squared residuals are not auto-correlated. In the meantime, the null hypothesis was rejected in the OLS model, hence ARCH effects are present.

Panel A reveals the estimates of the return equations for DJIA and DJIM US. The signs of the estimated coefficients on Monday and Tuesday are positive for DJIA and negative for DJIM US, but all of them are insignificantly different from zero. It is very clear that there is no sign of DOWE being present in DJIA. In contrast, there is evidence that Friday exhibits different characteristic in DJIM US by exerting significant negative effects on the mean returns; its estimated coefficient is significantly different from zero at the 90% level of confidence. This finding could be explained by the fact that Friday is a day where all Muslims, including investors, tend to be occupied with religious and social activities. In turn, this could result in having less investors trading in the Islamic market, making less liquidity available, which consequently force prices to decline (Amihud and Mendelson 1991). Furthermore, decrease in liquidity can actually make it more risky to hold assets on Friday, because lower liquidity may force investors to accept lower prices when having to sell stocks on Friday.

As expected, Friday exhibited different characteristics from what was reported in the literature (that positive return is a characteristic of Friday in the conventional markets). The increase in CSMI's returns on Friday can be accounted for by the increase in liquidity. Singal (2004) explained by indicating that speculative short sellers are to some extent responsible for the increase in prices on Friday, because they tend to close their positions at the end of the week. He also explained that non-trading hours add special risk to short sellers. The special risk lays in the fact that the short sellers will not be able to trade if prices go up for any unforeseen reasons during the non-trading hours in the weekend. Therefore, short sellers tend to close their positions by buying back all their stocks before the market close which, in turn, drive the prices up. However, in the Islamic finance, short selling is a prohibited investment activity (according to Islamic law; hence, such effects should not be expected to occur in ISMI on the part of Muslim investors).[50]

With respect to the estimates of the variance equations, Panel B reveals the relevant results, indicating that Tuesday is a key day that influences volatility in both indices. However, it is more significant in DJIM US than in DJIA (with 95% and 90% level of confidence respectively). Both indices experience higher volatility on Tuesday, which means that it is more risky than other week days.

The estimated coefficient of the market risk in the mean equation is insignificant in both indices. Friday remains significant in the mean equation of DJIM US after the inclusion of the conditional variance coefficient, and this can indicate that the seasonality observed on Friday cannot be justified by a seasonal variation in the market risk. Hence, Friday seems to represent a true anomaly in the examined Islamic market.

Two inferences can be drawn here. Firstly, the results can possibly be a challenge for the previous findings in the literature, which commonly document that returns on Friday are positive and higher than those on Monday in the US equity market. So, in the

[50] Islamic law prohibits Muslims from selling anything they do not actually own, and short selling is a form of this prohibited transaction.

context of ISMI the case can be different. Secondly, the existence of the negative effect of Friday dummy variable in DJIM US shows that a religious day can be a source of seasonality in a market.

In order to run a more thorough investigation to assure the presence of DOWE in DJIM US sub-indices, the three test specifications were estimated for the 10 sub-indices of DJIM US. A similar practice was not followed in the context of DJIA for two simple reasons: DJIA basically has no sub-indices to be investigated; and the results of the comparison between DJIA and DJIM US did not encourage further digging into CSMI, because DOWE is not present in DJIA mean returns.

Table 5 reports the results of the first specification investigating DOWE in the mean equation of the 10 sub-indices. The Q-statistic suggested that the order of return is one for all sub-indices except OG, HC, CS and TC. This exception is because of the significance of some lags of the residuals, yet altering the number of lags of the returns in the mean equation of these indices caused the autocorrelation to disappear. After the disappearance of the autocorrelation in residuals, the significance of the GARCH specifications estimated coefficients remain unchanged. The orders of return for OG, HC, CS and TC are 4, 5, 8 and 3, respectively. For simplicity, the results are not included in the tables due to the fact that the increase of number of lags changes nothing in the significance of all the other estimated coefficients.

Panel A displays that the estimated coefficient of the first day of the week Monday is negative across most of the sub-indices, but is not significantly different from zero except in the case of UT, in which Monday coefficient (0.0981%) is significant at the 90% level of confidence, with a positive sign. On the other hand, the estimated coefficient of the end of the week (Friday) is (interestingly) significantly different from zero, and negative across many indices; TE, CG, HC, and CS (all at the 90% level of confidence except TE, which is at the 99% level). This finding stresses the presence of the seasonal pattern on Friday in DJIM US. Tuesday and Thursday seem not to be of importance to the market, as their estimated coefficients are insignificantly different from zero in all indices except TE in which Tuesday (-0.13%) and Thursday (-0.15%) are significant at 90% and 95% level of confidence, respectively, with negative effects on the mean return.

The highest return occurred on Monday in UT (0.098%), while the lowest returns are observed on Friday in TE (-0.22%). Moreover, TE records the lowest return in every day with statistical significance except Monday, which is not significantly different from zero. In summary, it can be noticed that Monday and Friday exhibit the highest and the lowest returns (respectively).

The results also document that most of the returns of the trading days of the week in the samples are negative; however, the mean return represented by the constant coefficient is positive and statistically significant at 99% level of confidence in six indices (OG, TE, IN, CG, HC and CS).

Table 6 presents the results of the second specification. Firstly, Panel A reports the mean equation results. Similar inferences to the previous table were found in this specification in regard to the mean equation. The estimated coefficients of Monday dummy variable remain significant at the 90% level of confidence in both UT (0.0989%) and in CS (-0.106%), but with different signs. This finding differs from those in table 5 in that the Monday coefficient is significant in the results presented in table 6 after including the days' dummy variables in the conditional variance equation. Friday remains negative in the TE, CG, HC and CS, while Tuesday and Thursday exhibit similar results to those previously exhibited in the first specification.

Secondly, Panel B reports the results with respect to the conditional variance equation. The GARCH coefficients are positive and their sum is less than unity, indicating that the variance is positive and the data is not explosive. However, some constant terms appear to be associated with negative sign, yet they are insignificantly different from zero except the one in CS. This could be accounted for by over-parameterisation, because the negative sign actually appeared only after including DOWE in the variance equation, while the signs of the constant terms were positive across all indices beforehand. Therefore, this can cast some doubt upon the significance of Monday dummy variable in the mean equation of CS.

Panel B, in table 6, also documents that there is almost no DOWE in the conditional variance in the examined sub-indices except OG and CS. The coefficient of Thursday dummy variable (-0.00429%) is significantly affecting the volatility in OG at the 95% level of confidence. Monday, Tuesday and Thursday coefficients are also significant in CS at the 95%, 99% and 99% level of confidence, respectively. However, there is some doubt about that due to the negativity of the constant in the conditional variance equation. Friday exerts no significant effect on the volatility of the market at all.

The results of the third specification applied on the 10 sub-indices are displayed in table 7, which aims to investigate the possibility that the detected DOWE in the market can be accounted for by market variation, as hypothesised in the empirical investigation conducted by Clare et al. (1998). In terms of the presence of DOWE, the significance of the dummy variables in the mean and the variance equations remain unchanged, as shown previously in table 6, but table 7 contains more information about DOWE.

The results in table 7 present that the market risk estimated coefficients are all insignificantly different from zero except for HC, which is significant at the 95% level of confidence. However, the seasonality presence in the mean and the variance equations remains the same as before the inclusion of the conditional variance in the mean equation. In addition to the fact that Friday dummy variable remains significant in HC after the inclusion, it can be clearly understood that seasonality in this sub-index seems not to be attributed to the market risk. This can imply that the regular shifts in returns observed in this study represent true anomalies especially the Friday effects on the DJIM US. As expected, Friday, as a religious day, can be a source of anomaly in the return distribution of the Islamic market.

8. Conclusion

DOWE is an area of interest for many researchers in the literature of finance. This type of anomaly has been documented previously in equity markets in both developed and developing markets. Having the seasonal component present in a market can allow investors to set up trading strategies to make profits or avoid losses out of these regular shifts in the market by predicting these shifts in the return and volatility.

The existence of seasonality can be considered as informational inefficiency in the market, which violates EMH. Therefore, investors, observing these regularities in the market, are expected to exploit this inefficiency to generate abnormal return by buying on the day where return is significantly lower and sell on the day where return is significantly higher. However, French (1980) confirmed that this trading strategy is often not as profitable as expected, due to the transaction costs. Instead, he stated that investors who are planning to purchase can at least increase their expected returns by delaying purchases to be exercised on the day that has significant negative return and delaying sell transaction to be executed on the day associated with the significant positive return.

A major advantage of a study investigating seasonality in the stock market can be to ensure an understanding of these anomalies so that investors can avoid unprofitable situations or marginally alter their trading patterns in beneficial ways (Singal 2004).

This chapter offers two main contributions: to have investigated the DOWE, especially the Muslim Friday effects, in the context of the ISMI for the first time; and to have recorded the difference between the ISMI and CSMI in terms of DOWE.

Therefore, the main question to be answered in this empirical study is whether DOWE exists in DJIM US and its sub-indices or not. Besides, the same question is posed in the context of DJIA with the intention of exploring the differences between ISMI and CSMI. As far as the expected returns are concerned, the findings clearly report that DOWE exists only in DJIM US, whereas DOWE is found to be significantly present in the variance equation of both DJIM US and DJIA.

The main conclusion to be drawn is that a religious day such as Friday can be a source of seasonality in ISMI, because the results revealed that Friday exhibits a true anomaly dominating the DOWE in DJIM US. So, Friday is not only the last day of the week, but also a Muslims holy day which seems to be offering Friday more characteristics than the conventional expectation.

Friday’s association with negative returns in DJIM US could be a result of the fact that it is a less active trading day. In other words, Friday may suffer from less liquidity and low trading volume. This consequence happens because Muslim investors tend to be occupied with religious and social activities such as attending the Friday congregations in mosques among other things. The overlap between trading activities and religious rituals may result in preventing Muslim investors from fully trading on Friday. The significance of the Friday dummy variable in DJIM US is confirmed when investigating its sub-indices.

It can be recommended that investors should try to avoid or postpone selling stocks on Friday. This is because holding assets seems to be more risky on Friday, as liquidity is expected to be lower. When liquidity is lower, investors who plan to sell on Friday, before the markets close for the weekend, may be pushed to accept lower prices as less investors are present in the market.

Another important day is Tuesday, which appeared to be a high-risk day in both markets, because the relationship between the volatility and Tuesday dummy variable is significantly positive. However, this finding is not confirmed when examined by the 10 sub-indices of DJIM US. Another inference that can be drawn from this study is that the presence of DOWE is not due to the seasonal variation in market risk; instead it represents a true anomaly in the market.

In light of these inferences, it appears that the Islamic market exhibits different characteristics from its conventional counterpart in terms of seasonality. The implications understood from this study can be beneficial to investors in DJIM US, who should be able to take advantage of the observed regular shifts in return and volatility in the examined indices. It is expected to be highly advisable for investors in DJIM US to delay their purchases until Friday, when stocks are expected to be cheaper. Also, investors should try avoiding trading on Tuesday, due to the expected higher risk on that day in comparison to other trading days. Finally, this study helps to fill the gap in the literature of finance with respect to the emerging ISMI.

However, stock market anomalies are changeable over time, so investors are encouraged to keep themselves updated about the latest evidence of such anomalies. Furthermore, Hudson et al. (2002) warned investors not to make future investment decisions based only on the results of academic analysis. They argued that investors should be cautious in regard to stock market anomalies because the objectives of finance academics and investors are different. Therefore, investors should only be concerned with the implications of the results of the academic based analysis on future returns, and not only the degree of the statistical significance of these results.

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Chapter 5. Summary and Conclusion

1. Summary

The rapid expansion of Islamic financial services has led to the establishment of ISMI that tracks the performance of Shari'aah-compliant companies and serves as a benchmark with which to examine the performance of the Islamic funds. The emergence of the ISMI attracts the attention of the researchers in the literature of finance. A number of empirical studies have already investigated the performance of the ISMI and compared them to their counterpart CSMI (Hakim and Rashidian 2002; Hakim and Rashidian 2004; Hussein 2004; Abdullah, Taufiq et al. 2007). The overall conclusion of these studies indicated that investors actually lose nothing by restricting themselves to invest only in the Shari'aah-complaint stocks. Therefore, this thesis has approached the subject from a different perspective (other than appraising performance). The focus of the thesis is to conduct different empirical essays to investigate different exogenous variables' effects mainly on the Islamic stocks. Hence, DJIM US has been empirically investigated on certain subjects that are believed to be relevant to the stock markets in general. The accomplished results from DJIM US have then been compared to those of its counterpart CSMI.

Chapter 2, presenting the first empirical essay, employs a variant of the technique of Fama and MacBeth (1973) to estimate CAPM, APT, FF models on DJIM US and S&P500, in order to empirically investigate the effects of the systematic risk factors and the market portfolio on the Islamic and the conventional portfolios and explore their differences. The findings generally pointed out that some differences truly exist, and that the default-related risk factors are only significant in explaining the returns of the conventional portfolios. The results are encouraging for further investigations, particularly for identifying other risk factors that can be responsible for driving the Islamic compliant stocks. There are two main contributions offered by this empirical study to the literature of finance about the Islamic finance. The first contribution is to have examined the sensitivity of Islamic portfolios towards the systematic risk factors for the first time. The second is to have recorded the differences between the Islamic and conventional portfolios in terms of sensitivities towards the unanticipated macroeconomic variables.

In chapter 3, the reaction of the Islamic stocks towards the boost in the oil market is examined and compared to the reaction of the conventional stocks using GARCH models. This chapter empirically examined the link between oil price changes and the expected return and volatility of three stock markets indices: TASI, S&P500, and DJIM US. The first and the second indices incorporate the conventional stocks from oil-producing and consuming countries respectively, whereas the last one comprises the Islamic stocks. The main finding indicated that the oil returns only exerted significant effects on the conventional stocks. This chapter offers three contributions to the literature. The first contribution is to have examined the effects of crude oil prices on the ISMI for the first time. The second is to have recorded the differences between ISMI and CSMI in terms of their reaction to the oil price changes for the first time. The third is to have examined the effect of oil prices on the conventional stocks in both oil-exporting and importing countries. However, due to the limited availability of ISMIs, only DIMI US was examined in this study.

Chapter 4 focuses on DOWE, one of the most common calendar anomalies. The overlap between Islamic rituals and trade activities on Friday is the main motive of this empirical investigation. Therefore, GARCH models were employed to investigate DOWE in DJIM US alongside its 10 sub-indices and DJIA. The latter is utilised to explore the differences between the Islamic and conventional stocks in the context of DOWE. The main finding showed that ISMI exhibit different characteristics from its conventional counterpart in terms of seasonality and that Friday can be a true source of seasonality in ISMI. In this chapter, there are two main contributions to the literature of finance. The first contribution is to have examined the effects of Friday, as a Muslim holy day, on ISMI for the first time. The second is to have recorded the differences between the ISMI and CSMI in terms of DOWE for the first time.

2. Conclusion

This thesis is mainly about conducting three different empirical essays on ISMI. DJIM US was determined to be the best available candidate to represent ISMI throughout the thesis. In each empirical essay the same test was also applied on a compatible counterpart CSMI for comparison purposes. The focus of the thesis is on the effects of the exogenous variables that usually influence stock markets, and whether any such effects exerted on CSMI will be any different in the context of the emerging ISMI.

The first empirical essay, presented in the second chapter, found that the Islamic and conventional portfolios responded differently to the same systematic risk factors. The findings of this chapter confirm that the default-related risk factors are only significant in explaining the returns of the conventional portfolios; hence, Islamic portfolios are empirically considered less risky to default. Having investors restricted to the Islamic portfolios indicates that they are exposed to higher risk; however, the employed risk premiums fail to compensate for that. It is possible that other unknown risk factors are more important and hence are priced in the stocks that are Shari'aah-compliant. The results generally indicate that variables related to the economy as a whole, such as DEI (change in expected inflation) and MP (monthly industrial production growth rate), are more important and significant for the stock market during the crisis than other firms' specific risk factors.

The second empirical essay, presented in the third chapter, using GARCH models, also indicated that ISMI can react differently to the oil price changes in a way unlike the other examined CSMIs. Oil price changes managed to have an influence only on TASI and S&P500 in a way that is explainable by the state of the economy of each index. Saudi Arabia has a massive dependence on its oil revenue; hence, increased oil returns stimulate the expected return of TASI and reduce risk. The opposite happened with S&P500, because USA is the largest oil importer; therefore, high oil prices increase the cost of production, which in turn depresses earnings as well as share prices. In conclusion, portfolios investing in DJIM US seemed to be immunised against the oil market turbulences. This can be explained by the fact that the tendency of important Islamic investors from GCC to invest in Islamic funds can cancel out the negative effect of high oil prices on the U.S. companies in DJIM US.

The last empirical essay, presented in the fourth chapter, highlighted another important aspect in the financial market. It concluded that the emergence of ISMI in the West can bring about another calendar anomaly or change its effect direction. In the literature of finance, the documented Friday effect on expected returns of stocks is positive, and the return on Friday tends to be higher than other days (French 1980; Agrawal and Tandon 1994; Mills and Coutts 1995). A logical reason for this increase on Friday was offered by Singal (2004), who indicated that short sellers tend to reduce their trading risk by closing their positions before the weekend, as prices may rise higher during the weekend due to any unexpected news. However, the overlap between Islamic religious rituals and trading activities is not without cost. The Friday effect turned out to be different and negative on ISMI according to the results of chapter 4. Although, there is no clear evidence to say why this has happened, it can be supposed that less liquidity is highly expected on Friday, when a large proportion of Muslim investors are expected to be distracted from trading by religious rituals and social activities. Moreover, short selling is not allowed by the Islamic rulings on finance. In effect, this significant negative impact of Friday on expected returns should be taken into account, as well as the fact that this day can exhibit different characteristics in the context of ISMI.

In light of the findings achieved by the three main chapters, there seem to be variations between ISMI and CSMI in the way they react towards the same exogenous variables. This conclusion is drawn despite the fact that previous studies failed to find significant differences between them in terms of performance, concluding that investors lose nothing by restricting themselves to ISMI.

Although this research clearly proved the indifference of ISMI towards the risk factors that usually affect CSMI, this conclusion cannot be simply justified by the Islamic identity of the index. Providing valid justifications for this indifference from DJIM US was impeded by the lack of proper evidences. This can be easily comprehended because it requires another separate task and investigation to look into this particular issue, which can be the subject of future research. However, the logical available explanation can be that ISMI might have been driven by other hiding factors. A useful suggestion for future research can be to examine the financial ratios introduced by the board of scholars restricting the components of ISMI. These ratios can possibly serve as risk factors that are rewarded in the Islamic stocks' returns. It is not impossible that the indifference of ISMI can be accounted for by the fact that these financial ratios replaced the traditional risk factors mentioned in the literature of finance, and hence can provide better information.

The financial ratios are generally about the level of interest-based debt. The Islamic ruling's intention is to keep this debt level as low as possible. Obviously, this Islamic criterion can result in making the Shari'aah-compliant companies less likely to default. The low level of interest-based debt reduces the risk of bankruptcy, and this may have contributed in shaping ISMI on the way it is. Hence, the stocks with low risk to default may tend to exhibit different characteristics. Hence, interested researchers are advised to expand on this thesis's topic by working on identifying other sources of risk that could be priced in the returns and volatility of ISMI.

Investors and fund managers in general, not only Muslim investors, can benefit when they learn from this thesis that ISMI exhibits different characteristics from CSMI towards systematic risk factors, oil price changes and DOWE. In addition, ISMI can be considered unique in their low risk to default. These findings indicate that ISIM can offer these investors and fund managers a wider selection of stocks that can improve the performance as well as reduce the risk of their portfolios.

This thesis can also provide useful information to concerned policymakers about the fact that the existence of such a stock market index in the economy can enhance diversity features, which may also help to lower the risk of the respective economy. It is to the advantage of an economy to contain different stock market indices which can respond to the same crisis differently. An example of that is the collapse of the Tyco, Enron and WorldCom companies between 2001 and 2002[51]. The Islamic portfolios managed to come out unscathed from the bankruptcy of these three companies because these companies had already been ejected from DJIM before they collapsed due to violating financial ratios. As a result, Islamic fund managers saved their ordinary investors millions of dollars. Furthermore, the existence of ISMI in the Western market manages to attract Islamic capital from abroad, as well ensuring that local Islamic capital is locally accommodated.

[51] According to R. Siddiqui, Global Director of the DJII- Dow Jones Islamic Indexes http://tyo.ca/islambank.community/modules.php?op=modload&name=News&file=article&sid=1418. Also,http://www.islamic-banking.com/resources/7/NewHorizon%20Previouse%20Issues/NewHorizon_JanMar09.pdf.

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