Does Faith Move Stock Markets? Evidence from Saudi Arabia *

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Abstract

This paper investigates the effects of religious beliefs on stock prices. Our findings support the viewpoint that the religious tenets have important bearing on portfolio choices of investors. It is found that Shariah-compliant stocks have higher return and volatility than their non-Shariah compliant counterparts.

Keywords: Islamic religion, stock returns, volatility, stochastic dominance, Saudi Arabia
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1 Introduction

The role of beliefs, social norms and values has not been widely studied in financial literature. Yet, it seems intuitive that individuals operating in different social environments would exhibit different behavior. In the end, markets do not make decisions, but people do and interactions among individual choices, corporate culture and social norms are unavoidable.

Prior research suggests links between individual religiosity and risk aversion. For example, Miller and Hoffmann (1995) report a negative correlation at individual level between religiosity and attitude towards risk. Similarly, Osoba (2003) uses individual panel data to show that risk-averse individuals attend churches more often than risk-seeking individuals. Hilary and Hui (2009) examine if religion affects corporate behavior in US. They find that firms located in counties with higher level of religiosity display lower degree of risk exposure. Extant literature also acknowledge that religiosity and social norms have some bearing on investment decisions of institutions such as pension plans and corporate-decision making in general. In this paper we endeavour to add to the existing body of knowledge by focusing on the relation between religion and financial markets. This study focuses specifically on Islamic religion and examines the market effects of ethical norms in the novel setting of stock markets.

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

To investigate the market effects (if any) of ethical norms we focus on a country where religion constitutes an integral part of society, namely Saudi Arabia. This country is an ideal setting in which to study this phenomenon, for several reasons. Firstly, Muslims constitute 97% of population. Also, Saudi Arabia is a conservative society that has adopted the most austerely puritanical form of Islam. The country also plays a central role in the international Muslim community as the host of the two holy cities of Makkah and Medina and this is a paramount to the country identity. Secondly, although Islamic finance services industry is expanding rapidly in the homeland of Islam, non Shariah-compliant stocks are available on the market and there is no legal obligation to invest in these securities. Portfolio selection is entirely left to market participants and any moral obligation depends on the ethical attitude of investors. Finally, as a result of its development and the peculiarity of the Saudi economy (Saudi economy is heavily dependent on oil revenue), the Saudi stock market has several characteristics that makes it unique among emerging-market bourses. Market capitalization and trading volume have multiplied by some orders of magnitude in the last few years, yet the large majority of investors are individuals rather than institutions. Also, foreign investment is very limited as GCC national[1] and other Arab residents account for a small proportion of buy and sell transactions,

[1] The countries in the Cooperation Council for the Arab States of the Gulf (GCC) are: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates.

whereas the non-Arab resident proportion is close to zero.

It is clear from the few highlights above that Islamic religion plays an integral part of everyday life in the country determining much of the interaction within the society. The prominent role of religion in the society together with recent developments of the Saudi stock market constitute a rare opportunity for a social scientist to observe a phenomenon in an almost lab-made experiment in which to test the effect of religious tenets on financial markets: starting from 2001 onward, *first-time local individual* investors (i.e. not institutional or professional mutual fund managers) entered a "conventional" (i.e. not only Islamic finance oriented) and relatively thin stock market in large number and started trading massively.

A natural question arises at this point: Is portfolio selection of market participants affected by social environment? In other words, is there any market effect that can be ascribed to religious prescriptions? Moreover, given the very large proportion of retail investors versus institutional investors in the market how this affects stock prices? Is there an interaction between religious tenets concerning financial investment and portfolio choice of retail investors? These are the issues addressed in this paper.

We begin our investigation by classifying stock returns according to their degree of compliance with Islamic finance principles. First, we hypothesize that shares of stocks which are less Shariah-compliant should be held in smaller proportions in the religious minded investor's optimal portfolio. We test this hypothesis by considering the stochastic dominance principle for portfolio selection of a risk averse investor. Consistent with our predictions, we find that stocks that are more Shariah-compliant have higher returns and are associated with higher relative risk. Next we investigate the effect of retail investors on the volatility of returns. Given the massive increase of retail investors in the market that occurred in the recent years we postulate that by increasing trade volume of stocks which are more Shariah-compliant, religious tenets affect the volatility of returns. According to behavioral finance literature noise traders acting on the base of noisy signal create additional sources of systemic risk in the market, therefore increasing volatility of the assets affected by the action of noise traders. Looking at the evolution of trade volume in different stock market sectors it is found that individual investors trade more actively in Shariah-compliant stocks. Given the strong relation between trade volume and volatility it appears that by pushing away stock prices from their fundamental values noise traders affect volatility of Shariah-compliant stocks. Finally, because individual investors tend to place small orders their actions have to be coordinated in order to make an impact on the market. Accordingly, in order to test this hypothesis tests for herding behavior in the stock market are conducted. Overall, our findings on the effect of religious tenets in the context of stock market strongly support the viewpoint that religious prescriptions can have important effect for market in the country under consideration.

The rest of the paper proceeds as follows. Section 2 provides some theoretical background. In Section 3 the results of the empirical investigation are reported and the methodology used is discussed. In Section 4, the relationship between price volatility and trade volume is investigated. In Section 5 a test for herd behavior is conducted along with a limited analysis on the US stock market which is taken as a benchmark. Finally, some concluding remarks are given in Section 6.

2 Background and Theoretical Motivation

Economists have long realised the importance of understanding individual portfolio choice. A rich theoretical literature demonstrates how portfolio decisions depend on factors such as risk aversion and investment opportunities. Early contributions analyse static models in which an investor selects the portfolio that maximizes expected utility function given total wealth and the risk-return patters of available assets (Tobin (1958)). More recent research has moved to a dynamic framework in which a portfolio is selected to maximize expected lifetime utility. The empirical literature on portfolio choice seeks to find observable variables that explain cross-sectional variations in portfolio behavior. Typically, covariates include resources available to the household (total wealth and income) as well as demographic characteristics (age, race, gender, marital status). The role of religion has received little attention, yet in many communities religious tenets play a role in shaping economic behavior and market outcomes, overriding at times the profit motive.

In this paper we aim at investigating if religion affects portfolio selection. From the theoretical point of view our paper relates to the literature of ethical investments where portfolio selection is realised on the basis of ethical principle along with the traditional mean-variance relation. Following this literature we postulate that investors' religious considerations restrict the set of securities available for portfolios selection to a subset of the available stocks in the market. Testing whether religion affects portfolio selection directly requires micro-level data on individual ownership. Ideally, one should analyse the link between the level of religiosity and risk attitude. Unfortunately, micro-level data are not available to us. Therefore, we adopt and indirect approach and analyse the return behavior in the Saudi stock market. Underneath this approach lays the idea that portfolio composition of a religion minded investor is affected by the degree of Shariah-compliant element of the assets.

In order to understand how religion may affect portfolio selection we need to look at the recent evolution of the Saudi stock a market. The Saudi bourse experienced an impressive increase in the number of market participants in the recent years. According to the Samba Report (2009) the number of market participants increased from 52,598 in 2001 to 1.5 million at the end of 2005. The overflow of investors associated with the limited number of shares offered in the market inflated asset prices and caused a surge in volatility[2]. The bubble eventually busted in February 2006 when the market collapsed.

Periods of boom followed by painful bust are common in financial markets, however like many emerging markets, the Saudi market is a thin market heavily dominated by retail investors. In 2008 individual investors accounted for 88% of buy transactions. Saudi corporations placed less than 10% of transaction orders and mutual funds registered only 1.5% (note that in the majority of large OECD[3] bourses institutional investors account for around 90% of transactions). Also, in the same year, foreign participation accounted for only approximately 0.1%, whereas GCC citizens accounted for less than 2%. As foreign participation is extremely limited in the stock market it is logical

[2] Between 2003 and its peak in February 2006 the TASI gained an impressive 700%, with market capitalisation soaring at more than twice the country GDP. During this period the Saudi bourse was one of the largest stock market in the world by value traded, this despite having only 78 listed stocks (many of which with a limited free float).

[3] Note: OECD stands for "Organisation for Economic Co-operation and Development"

to infer that at least during the period of price run-up the most active participants were first-time local investors attracted into the stock market in large number by returns which were well above the stock fundamental values.

In behavioral finance literature individual investors are often viewed as noise-traders (see for example Black (1986) or Kyle (1985)). Several studies confirm that noise-traders (also called uninformed investors) acting on non-fundamental information affect the level of asset prices by trading when markets are unusually bullish or bearish. Noise traders acting in concert on non-fundamental signals can introduce a systematic risk which should manifest itself as added price volatility of assets affected by the actions of noise traders. In the literature an example of profitable destabilizing effects of uninformed investors is given in the seminal article by De Long *et al.* (1990) where it is shown that in a perfectly competitive economy with risk-averse agents, retails traders bearing a larger amount of risk relative to rational investors, may earn higher than expected returns. The case of imperfectly competitive markets is considered in Palonimo (1996) were it is shown that noise traders earn higher returns than rational investors. Palonimo argues that if speculation based on irrational beliefs breeds imitation, noise traders are not driven out of the market and influence prices. The thinner the market, the larger the relative share of uninformed investors. As a result noise traders risks and the rewards stemming from the lack of competition are larger. In general, Palonimo shows that the lower the level of competition in the economy, the higher the impact of individual agent trade on price and so the larger the difference in quantity traded between a perfectly competitive economy and an imperfectly competitive one.

Against this background, we postulate individual investors act as noise traders in the market under consideration. Building on Palonimo we suggest that in the thin Saudi stock market, dominated by retail investors, and surrounded by a heavily religious-oriented social environment, higher trade volume of Shariah-compliant stocks increases volatility of these assets. Shariah-compliant stock holders, bearing a larger amount of risk relative to other market participants, should therefore obtain higher expected returns.

In order to investigate the price effect of religion on the stock market we begin our analysis by investigating the risk-return characteristics of Shariah-compliant stocks. Consistent with the model in Palonimo (1996), if religious tenets are binding we should see that Shariah-compliant stocks are more volatile with respect to other stocks.

Investigating the risk-return characteristic of a given portfolio is usually undertaken by estimating some asset pricing-type models (see for example the seminal article by Jensen (1968)). However, capital asset pricing models rely on the assumption that risk-free interest rate is readily available. This assumption is often problematic in Islamic oriented markets where a risk free rate is not available. For this reason we use a non-parametric approach based on stochastic dominance. Since stochastic dominance is non-parametric, statistical inference based on stochastic dominance tests does not depend on any specific model. Therefore it overcomes the problem of a risk-free benchmark incurred when estimating capital pricing asset models.

Before describing the empirical analysis we briefly review some basic principles of Islamic finance. One of the main pillars in Islamic finance is the prohibition of collection or payment of interest (*riba*). In general, any interest or predetermined payment over the principle is not allowed according to Islamic religion. Other forms of restrictions

Muslims face are the prohibition of gambling, investing in businesses that are considered sinful or socially irresponsible such as companies that produce alcohol or weapons. Also, many practices associated with stock trading such as margin trading (i.e. borrowing to invest) or short selling are not allowed in Islamic finance. Other important considerations relates to derivative products, such as futures and options which are in general considered invalid instruments in Islamic finance.

Islamic investors have, however, a range of choices when constructing their financial portfolio. These include among others interest free bank deposits, investment in Islamic unit trusts and investments in stock markets. The literature on Islamic finance is large and it would not be possible to review it here. For an extensive survey on principles and methods of Islamic finance see for example Gait and Worthington (2007).

3 Stock Market and Islamic Law: a Stochastic Dominance Approach

In this section we test the hypothesis that there is a relation between stock market returns and Islamic law. A battery of methodologies has been used in order to test this hypothesis. As a first approach some descriptive statistics are reported. We then go a step further and investigate the hypothesis that return volatility is higher for Shariah-compliant stocks by using the stochastic dominance approach.

3.1 The Empirical Investigation

The data under consideration consists of daily closing prices for Saudi stock market general index (TASI) and the sector indexes. The period considered in this study covers from January 1^{st} 2002 to April 1^{st} 2008. There are 6 sectors in the stock market. Namely, the sectors are: Banking, Industry, Cement, Agriculture, Services, and Telecommunications. However, we do not include Telecommunication in the study as it consists of one company only and few data are available for this sector.

In order to investigate if Shariah law affects the stock returns the five sectors were classified according to the degree of compliance with Islamic finance principles. Unlike other countries with high proportion of Muslim population Saudi stock market does not offer a Shariah compliant index such as the Malaysian SI index for example. However, Al-Osaimi provides a highly regarded list where companies offering securities on the market are classified by authoritative religious experts. In the Al-Osaimi list financial services that provide interest (*riba*), or publicly traded companies involved in producing alcohol, tobacco and gaming are considered not suitable to a devoted Muslim and classified as "*haram*". On the other side, Shariah-compliant companies enjoy the status of "*halal*" and can be considered by investors seeking to make their investment based on Islamic jurisprudence. Finally, companies whose business activities are Shariah-compliant, but sources of funds for some activities are not compliant are considered “mixed”. Investment in this kind of stock is considered halal, but investors have to relinquish a proportion of their dividends in order to "purify" their profits for the non Shariah-compliant part of their revenues. In principle, the higher this proportion, the less Shariah-compliant is the company and therefore the less suitable the stock is for a pious Muslim investor. Therefore, by considering the distinction between haram, halal and mixed type of securities it is possible to rank each of the five sectors according to the degree of Shariah-compliant.

In order to rank sectors according to the degree of Shariah-compliance the Al-Osaimi list was considered for the period 2005-2008[4]. In the top panel of Table 1 the proportion of stocks in each category by sector is reported. From Table 1 it appears that the Banking sector is the less compatible with Islamic principles as approximately 90% of the stocks are classified as haram. This classification reflects the fact that for the period under consideration most of the publicly traded financial institutions were conventional banks. On the other side, the Agriculture includes only Shariah-complaint stocks and therefore all equities in this sector are suitable to a religious minded investor. As far as the other sectors are concerned, the Service with approximately 65% of halal companies is the sector with the highest number of halal stocks after the Agriculture sector. The remaining two sectors have either only a small proportion of halal companies (Industrial) or none (Cement). Most of the stocks in the Industrial sector are instead classified as belonging to the mixed type. Mixed type of stocks are also present in the Services sector, but in a smaller proportion.

In the bottom panel of Table 1 some descriptive statistics for proportion of dividends that has to be alienated in order to "purify" the revenues from a financial investment is reported for each sector. Note that this proportion was calculated by considering for each stock the arithmetic average of the percentage to be cleansed over the period 2005-2008. In order to construct an index for the Shariah-compliant element, the average proportion of dividends to be cleansed in each sector was then calculated from the average amount of each stock in the given sector.

From Table 1 it appears that, for the mixed category, the most Shariah-compliant sector is the Service, where the average proportion of dividends to be cleansed is approximately only 8% of the dividends. For a religious minded investor the less attractive stocks are those in the Cement sector where the proportion raises to approximately 12%.

Overall, looking at the proportion of stock type in each sector, the Agriculture sector is the most Shariah compliant sector. The the Service appears to be the second best, with Industrial, Cement and Bank ranked the third, forth and fifth, respectively.

[4]Note: The Al-Osaimi list is published annually.

Table1. Ranking of Shariah-compliant stocks by sector.

Sector	Stock Category		
	Halal	Mixed	Haram
Bank	11	0	89
Cement	0	100	0
Industrial	10	90	0
Services	65	35	0
Agriculture	100	0	0

Mixed Stock Descriptive Statistics

	Size	Mean	Std. Dev.	Min	Max
Bank	0	-	-	-	-
Cement	8	12.21	12.00	3	23.3
Industrial	22	8.27	12.25	0.4	53.6
Services	8	7.16	6.53	0.4	29
Agriculture	0	-	-	-	-

Note: a) In the top panel the proportion of halal, haram and mixed stocks in each sector is reported as percentage of the total number of stocks in the sector. b) In the bottom panel the number of mixed companies in each sector and some descriptive statistics are reported. Note that descriptive statistics are of percentages. Also, descriptive statistics for Agriculture and Bank sectors are not reported as there are no mixed type companies in these sectors.

Prior to presenting the empirical results a possible limitation of this work is discussed. In our study industry-level data are used to investigate the effect of Shariah-Law on the stock market. Alternatively, company-level data could have used to construct portfolios with stocks of similar characteristic (i.e. Shariah-compliant elements in the portfolio) and then compare the risk-return characteristics of these portfolios. Unfortunately, company-level data were not available to us. However, from the description of the industry-level data above it is clear that there a natural ranking among the sectors under consideration. Starting from the Agriculture sector, where all companies are Shariah-compliant to the Bank sector where all but one companies are non-Shariah compliant, the other sectors can be ranked easily according an ordinal criterion using the proportion of Shariah-compliant elements in each sector. We therefore believe that the natural ranking of these sectors provides a good ground for our investigation.

3.2 A First Look at the Data

We now consider the returns for the five sectors and investigate if there is a relation between the ranking of sectors reported in Table 1 and the distribution of returns. For the empirical investigation daily returns for each sector and the general market index (called Tadawull All share index or TASI) were calculated as:

$$R_t = \ln(P_t/P_{t-1})$$

where P_t and P_{t-1} are the closing prices on day t and $t-1$, respectively. The Dickey-Fuller test for stationarity was also calculated and the null hypothesis that the data contained a unit root was rejected in each of the continuously compounded series of returns. In the interest of brevity, these the unit root test results are not reported here. However, results are available upon request.

Together with the returns, the return volatility is a key input in portfolio allocation decision making. One problem in evaluating the volatility of returns is that the underlying volatility process is not observed. In the literature a common way of overcoming this problem is to calculate the squared return as a proxy for the unobserved volatility process. Following Corradi and Awartani (1996), for each sector index and the TASI the series of volatilities were calculated as

$$\sigma_t = \left(R_t - (1/T) \sum_{j=1}^{T} R_j \right)^2 . \tag{1}$$

In equation (1), the volatility series is calculated by subtracting the mean and then taking the square of the standardized returns. For each index, for any t, we therefore obtained $N = 1, ..., T$ estimated volatilities, where N indicates the sample size.

Recently, other proxies for volatility have been suggested. A well known example is realised volatility where volatility is estimated using intraday observations of daily stock prices. Assuming that the log of the series of stock prices are continuos semimartingale processes, realised volatility also is a consistent estimator of the true underlying volatility process (see Andersen, Bollerslev, Diebold and Labys (2003) or Barndorff-Nielsen and Shephard (2001)). However, we did not have access to intraday stock prices. Thus, given that square returns provide a unbiased estimator of the true unobservable volatility the former were used as a proxy of volatility.

Table 2 reports some basic univariate statistics for the Saudi returns throughout the sample. The mean, minimum, maximum, standard deviations, skewness and kurtosis indices are reported. The mean returns for the 5 sectors are positive, ranging from a maximum of 0.096 for Industrial to a minimum 0.055 for the Cement sector. The positive sign reflects high growth in Saudi stock market during the period under consideration. From Table 2 it is of interest to note that the Banking sector which is the least Sharia-compliant sector and the Cement sector which is ranked second in Table 1 have the lowest standard deviation. On the other side, Agriculture is the most volatile sector followed by Service and Industrial.

Table 2. Summary statistics of the daily returns for the five sectors in the Saudi stock market.

Sector	Mean	Std. Dev.	Skewness	Kurtosis
Bank	0.055	1.150	-0.640	10.653
Industrial	0.096	2.930	-0.451	6.621
Cement	0.056	1.688	-0.609	10.600
Service	0.053	2.153	-0.909	6.382
Agriculture	0.083	2.788	-0.457	3.670
Tasi	0.064	1.507	-1.027	9.929

From Table 2 it also appears that stock returns in each of the sectors are negatively skewed and leptokurtic, as the skewness and kurtosis indices are higher than zero and three, respectively. Excess kurtosis in stock returns has been well documented in many equity market studies in both developed and emerging markets.

The preliminary investigation in Table 2 suggests that the magnitude of the standard deviation of returns is a good match with Table 1, where the ranking of the sectors according to the degree of Shariah-compliance is reported. In order to further investigate this issue, below we use the stochastic dominance method to compare the returns in different sectors of the Saudi stock market. The theory of stochastic dominance provides a systematic framework for comparing relationship between two distributions. With respect to the simple mean-variance approach it has the advantage of exploiting the information embedded in the entire distribution of stock market returns instead of a finite set of statistics.

3.3 The Stochastic Dominance Analysis

Before presenting the results of the empirical investigation we briefly define the criteria of stochastic dominance. Define X and Y be two stochastic processes for the returns of any two sectors. Let U_1 denote the class of all von Neumann-Morgestern type of utility functions, u, such that $u' \geq 0$, also let U_2 denote the class of all utility functions in U_1 for which $u'' \leq 0$, and U_3 denote a subset of U_j for which $u''' \leq 0$. Let $X_1, ..., X_p$ be p observation of X and $Y_1, ..., Y_m$ denote the m observation in Y and let $F_1(x)$ and $F_2(x)$ be the cumulative distribution functions of X and Y respectively, then we define

Definition 1. X first order stochastically dominates (FSD) Y if and only if either:
i) $E[u(X)] \geq E[u(Y)]$ for all $u \in \mathcal{U}_1$
ii) $F_1(x) \leq F_2(x) \quad \forall\, x$ with strict inequality for some x.

According to Definition 1 investors prefer higher returns to lower returns, which implies that a utility function has a non-negative first derivative. First order stochastic dominance is a very strong result, for it implies that all non-satiated investors will prefer X to Y, regardless of whether they are risk neutral, risk-averse or risk loving. Second order stochastically dominance (SSD) also takes risk aversion into account, but it posits a negative second derivative (which implies diminishing marginal utility) of the investor's utility function. This is sufficient for risk aversion. More formally, the definition of SSD is as follows:

Definition 2. X second order stochastic dominates Y if and only if either:
i) $E[u(X)] \geq E[u(Y)]$
ii) $\int_{-\infty}^{x} F_1(t)\,dt \leq \int_{-\infty}^{x} F_2(t)\,dt \;\forall\, x$ with strict inequality for some x.

Whitmore (1970) introduced third-order SD by adding the condition that utility functions have non-negative third derivative. This assumes the empirically attractive feature of decreasing absolute risk aversion. It is clear that higher order efficient sets are subsets of the lower efficient sets. Therefore, stochastic dominance results imply hierarchy.

An attractive feature of stochastic dominance is that being a non-parametric analysis statistical inference based on stochastic dominance tests does not depend on any asset pricing model or require returns to be normally distributed. If there is stochastic dominance, then the expected utility of an investor is always higher under the dominant asset than under the dominated asset. This implies, that the dominated asset would not be chosen by any non-satiated investor.

Testing for stochastic dominance can be based on comparing (functions of) the cumulate distributions of the five sectors. Of course, the true cumulated distribution functions (CDFs) are not known in practice. Therefore, stochastic dominance relies on the empirical distribution functions. In the literature several procedures have been proposed to test for stochastic dominance. An early work by McFadden (1989) proposed a generalization of the Kolmogorov–Smirnov test of first and second order stochastic dominance among a number of prospects (distributions) based on i.i.d. observations and independent prospects. Later works by Klecan *et al.* (1991) and Barrett and Donald (2003) extended these tests allowing for dependence in observations, and replacing independence with a general exchangeability amongst the competing prospects. An important breakthrough in this literature is given in Linton, Maasoumi and Whang (2005) where consistent critical values for testing stochastic dominance are obtained for serially dependent observations. The procedure also accommodates for general dependence amongst the prospects which are to be ranked. Since stock market returns are well known to have fat-tail distributions[5] in this paper the inference procedure suggested by Linton *et al.* (2005) is adopted.

3.3.1 *Hypotheses of Interest and Test Procedure*

Let Ξ denote the support of $\{X_k : \ k = 1, ..., 6\}$ where k includes the five stock market sectors as well as the all share index TASI. Also, let $s = 1, 2$ represents the order of stochastic dominance. Under the null hypothesis returns in sector $X_i \succeq_s Y_j$, for $i, j \in k$ ("$\succeq_s$" indicate stochastic dominance at the s order). For each k and $x \in \Xi$, let $D_i^s(x)$ and $D_j^s(x)$ the empirical distribution function of sector i and j. To test the null hypothesis, $H_0^1 : X_i \succeq_s X_j$, we test that

$$D_i^s(x; F_i) \leq D_j^s(x; F_j) \qquad \forall\, x \in \mathbb{R},\ s = 1, 2.$$

The alternative hypothesis is the negation of the null, that is

$$D_i^s(x; F_i) > D_j^s(x; F_j) \qquad \forall\, x \in \mathbb{R},\ s = 1, 2.$$

[5] See for example the seminal article by Cont and Bouchaud (2000) among others.

Linton *et al.* (2005) consider the Kolmogorov-Smirnov distance between functional of the empirical distribution functions of the returns and define the test statistic as

$$\hat{\Lambda} = \min \sup_{x \in \mathbb{R}} \sqrt{N} \left[\hat{D}_i^s \left(x; \hat{F}_i \right) - \hat{D}_j^s \left(x; \hat{F}_j \right) \right]. \tag{2}$$

where $t = 1, ..., N$ and

$$\hat{D}_i^s \left(x; \hat{F}_i \right) = \frac{1}{N(s-1)!} \sum_{t=1}^{T} 1(X_{it} \leq x) \left(x - X_{it} \right)^{s-1} \tag{3}$$

and $\hat{D}_j^s$ is similarly defined. Under suitable regularity conditions Linton *et al.* (2005) show that $\hat{\Lambda}$ converges to a functional of a Gaussian process. However, the asymptotic null distribution of $\hat{\Lambda}$ depends on the unknown population distributions, therefore in order to estimate the asymptotic p-values of the test we use the overlapping moving block bootstrap method. Let B be the number of bootstrap replications and b the size of the block. The bootstrap procedure involves calculating the test statistics in $\hat{\Lambda}$ using the original sample and then generating the subsamples by sampling the $N - b + 1$ overlapping data blocks. Once that the bootstrap subsample is obtained one can calculate the bootstrap analogue of $\hat{\Lambda}$. Defining the bootstrap analogue of (2) as

$$\hat{\Lambda}^* = \min \sup_{x \in \mathbb{R}} \sqrt{N} \left[\hat{D}_j^{s*} \left(x; \hat{F}_i \right) - \hat{D}_j^{s*} \left(x; \hat{F}_j \right) \right], \tag{4}$$

where

$$\left(\hat{D}^* (x, \hat{F}_k \right) = \frac{1}{N \left(s-1 \right)!} \sum_{i=1}^{N} \{ 1 \left(X_{2i}^* \leq x \right) \left(x - X_{2i}^* \right)^{s-1} - \omega(i, b, N) 1 \left(X_{2i} \leq x \right) \left(x - X_{2i} \right)^{s-1} \},$$

and

$$\omega(i, b, N) = \left\{ \begin{array}{cl} i/b & \text{if } i \in [1, b-1] \\ 1 & \text{if } i \in [1, N-b+1] \\ \left(N - i + 1 \right)/b & \text{if } i \in [N-b+2, N] \end{array} \right\}.$$

The estimated bootstrap p-value function is defined as the quantity

$$p^* \left(\hat{\Lambda} \right) = \frac{1}{N - b + 1} \sum_{i=1}^{N-b+1} 1 \left(\Lambda^* \geq \hat{\Lambda} \right).$$

Under the assumption that the stochastic processes X_k are strictly stationary and α-mixing with $\alpha \left(j \right) = O \left(j^{-\delta} \right)$, for some $\delta > 1$, when $B \to \infty$ the expression in (4) converges to (2). Also, asymptotic theory requires that $b \to \infty$ and $b/N \to 0$ as $N \to \infty$.

3.3.2 *Stochastic Dominance Results*

As a preliminary analysis to establish the stochastic dominance relation a graphical representation of the empirical CDFs can be used as a tool to visually compare of two or more distributions.

In order to investigate if Shariah Law affects stock returns we compare the distribution of returns in the Agriculture sector where all companies are Shariah-compliant with other sectors. Figures 1-2 plot the empirical cumulate distribution functions for the agriculture sector against the other sectors and the TASI. Figures 1 a)-f) show the empirical CDFs of the daily returns over the sample period, whereas the CDFs of the volatility are plotted in Figure 2.

In general, the function $\hat{D}_i^s$ can be evaluated, for a given argument, as the area beneath the empirical CDF using the usual interpretation of the Riemann integral. Looking at Figure 1 a) it appears that the returns in the Agriculture sector dominate at second order the returns in the Banking and services sectors. According to Definition 2 second order stochastic dominance allows the CDFs to cross by small amount as long as the area under the CDF of the dominating distribution is always less than the area under the CDF of dominated distribution. In Figure 1a) although the empirical CDFs cross, the area between the distributions is such that the condition for second order dominance is satisfied. From Figures 1, b), c) and e) we see that the CDF of Agriculture is shifted to the right and does not intersect with the CDFs of Industrial, Cement and the TASI general index. This satisfies the condition in Definition 1 indicating that returns in the Agriculture sector first order stochastically dominate these sectors. Figure 1 f) plots the empirical CDFs of all sectors and the TASI and gives an overview of the empirical distributions of returns across different sectors. We can see that the CDF of the Banking sector is shifted to the left and intersects with the CDFs of the Industrial, Cement sectors and the TASI. This clearly rules out first order stochastic dominance of the Banking sector over the other sectors.

Turning to the analysis of volatility, Definition 2 implies that if returns in $X_i \succeq_{SSD} X_j$, then X_i is more risky than X_j. However, the distributions in Figures 1 a)-f) do not give information on the magnitude of the risk differential. For the purpose of this paper it is of interest to analyse the magnitude of the volatility differential in order to detect any effect of Shariah law on stock market. From Figure 2, f) it appears that volatility in Shariah compliant agriculture sector first-order dominate all the other sectors. Note that in this case first or second order stochastic dominance indicate that volatility of returns is higher for stocks in the Agriculture sector than in for stocks in other sectors.

The magnitude of the volatility differential is indicated by the position of the quantile on the vertical axis. For example, the volatility of the median portfolio containing Shariah-compliant stocks in the Agriculture sector is approximately 1% greater than the volatility of a portfolio containing stocks in the bank sector in the same quantile. Volatility differential is greater in the upper part of the distribution, that is for greater returns. In the upper quartile of the distribution the volatility of returns in the Agriculture sector is approximately 8% greater than volatility in the Banking sector. The volatility of returns for the Service sector is approximately 6% lower than that of the Agriculture with the other sectors falling in between these two boundaries.

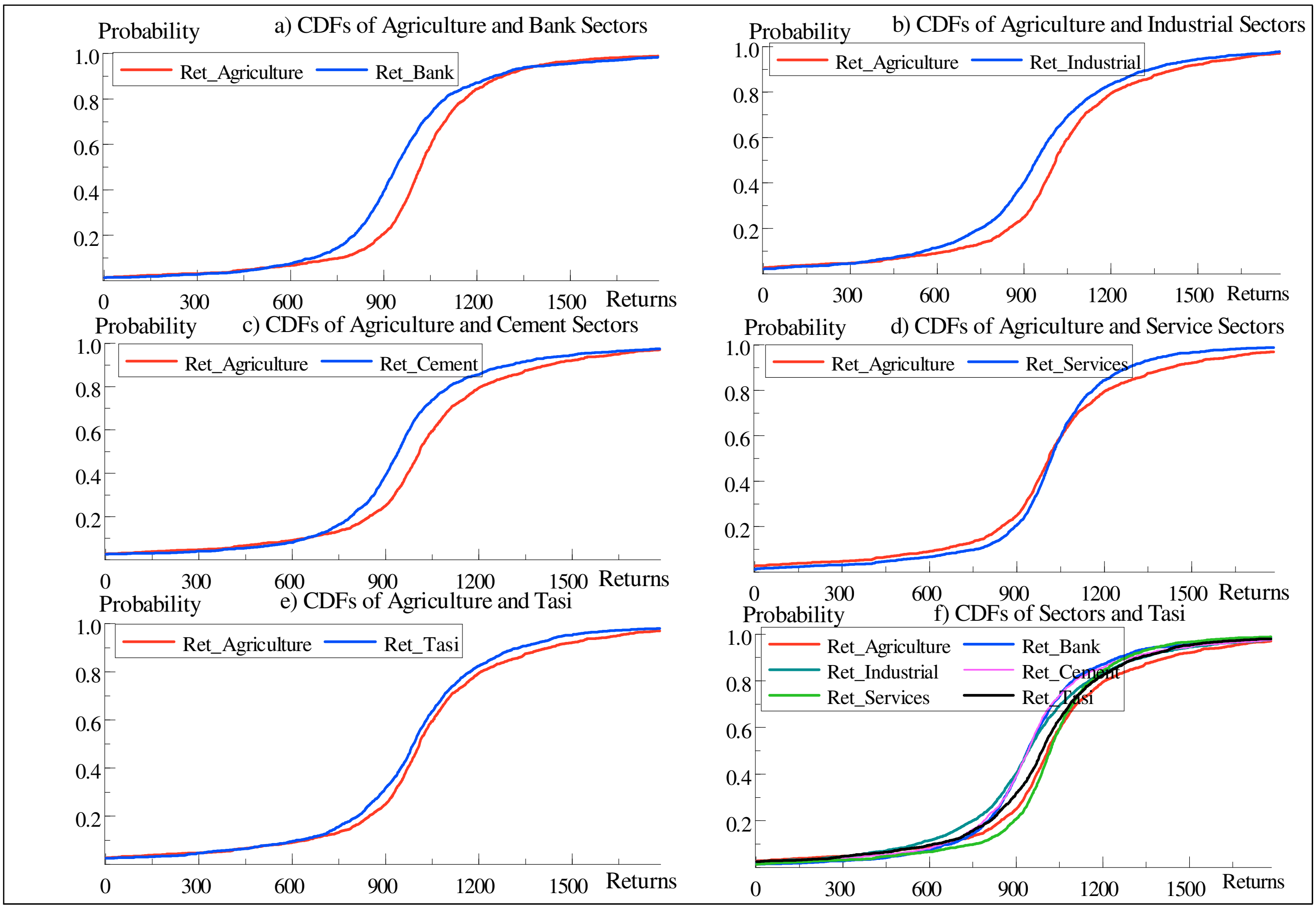

Figure 1: CDFs for the returns for different sectors and the TASI general index. Note: Ret_Tasi indicates the CDF of the returns. The CDFs of the sector indexes are defined in a similar fashion.

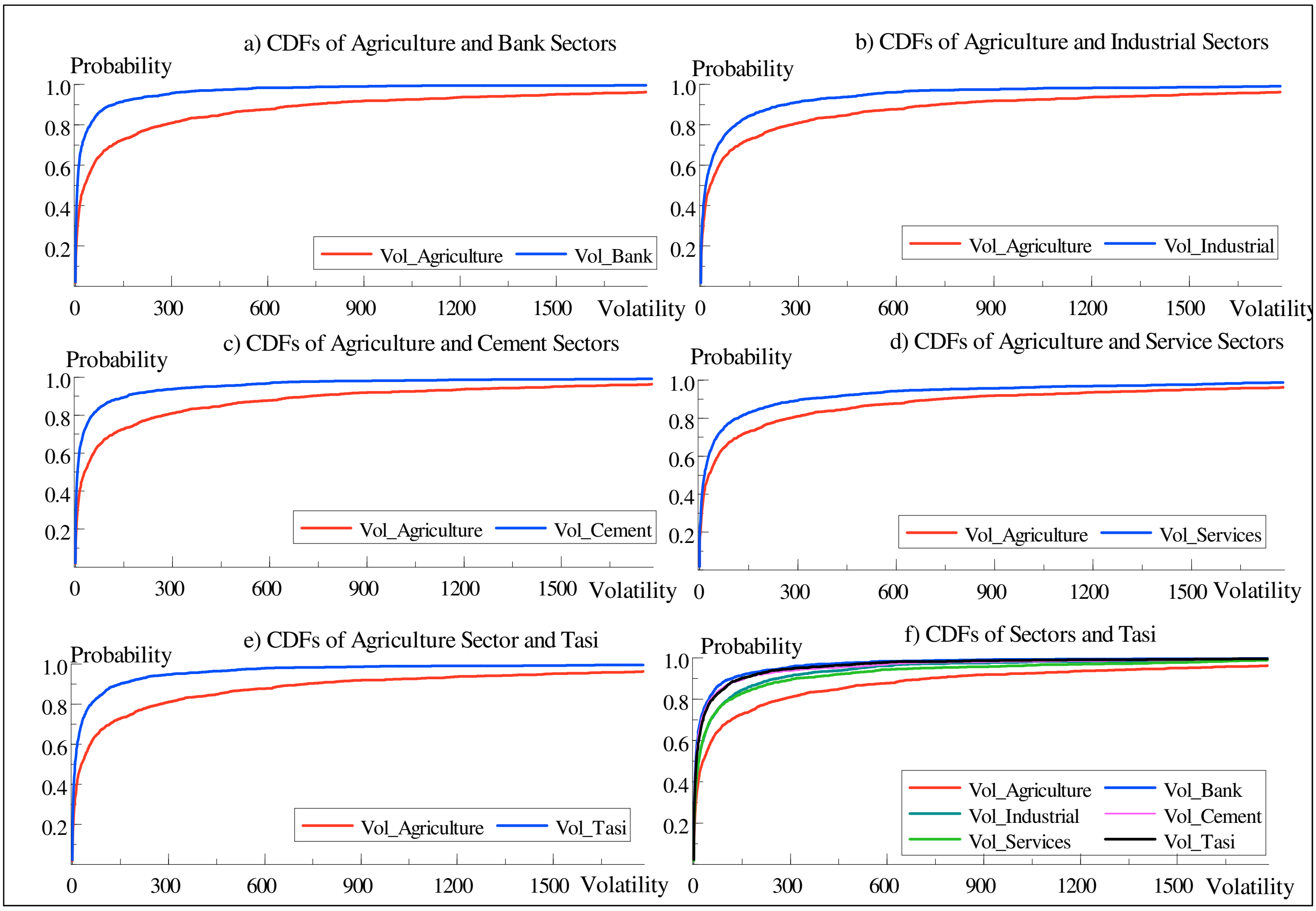

Figure 2: CDFs for return volatility for different sectors and the TASI general index. Note: Vol_Tasi indicate the CDF of the volatility. The CDFs of the sector indexes are defined in a similar fashion.

We next present the results based on the calculation of the test statistics in equation (4). The stochastic dominance tests are conducted for each sector in pairs. Suppose that returns in X_1 dominate X_2 in the s order. In order to establish the direction of the stochastic dominance two null hypothesis are tested. The first hypothesis is that $H_0^1 : X_1 \succeq_s X_2$ in the s order and the second null hypothesis is the converse: $H_0^2 : X_2 \succeq_s X_1$. We infer that X_1 dominates X_2 if we accept H_0^1 and reject H_0^2. In cases where H_0^1 and H_0^2 are both not rejected the test for stochastic dominance is inconclusive. Therefore, we can't infer that one distribution of returns stochastically dominates the other. Table 3a-b and Table 4a-b report the p-values of the FSD and SSD tests for the returns and volatilities, respectively. The p-values were obtained using the bootstrap algorithm described above with $B = 1000$ replications. To investigate the effect of the stock market crash in February 2006 the analysis was conducted firstly by dividing the sample in two sub-periods (i.e. pre and post February 2006) and then repeated considering the whole period.

In the top panel in Table 3a we test that returns in bank sector stochastically dominate returns in each of the other sectors. From the p-values in Table 3a appears that the null hypothesis that the returns in the banking sector stochastically dominate the returns in each of the other sectors is strongly rejected for both the sub-periods.

With regard to the middle panel returns in Industrial sector SSD returns in the Banking and Cement sectors in all periods under consideration, whereas the null hypotheses is rejected for the other sectors and the TASI. In the bottom panel the null hypothesis that Cement SSD Bank is not rejected. However, looking at the top panel the hypothesis that Bank stochastically dominates Cement when the whole period is considered is also not rejected. Therefore, in this case the test for stochastic dominance is inconclusive.

Turning now our attention to Table 3b, the Service sector is SSD by Agriculture, but SSD each of the others sectors. There is also evidence of FSD of Agriculture on Industrial, Cement and the TASI. Finally, the general index FSD Cement and SSD Bank and Industrial, whereas the null hypothesis of SSD of Agriculture is rejected.

Turning to the volatility, from the top panel of Table 4a it is clear that the null hypothesis that the Banking sector stochastically dominates the other sectors is strongly rejected: for all sectors, no matter the sub-period considered, the null is rejected in favour of the alternative hypothesis. It is of interest to note that the null hypothesis is also rejected for the Tasi.

In the middle panel of Table 4a, when the period 2002-2008 is considered, Industrial is first order stochastically dominated by Services and Agriculture, but first order stochastically dominates Banking and Cement. This is in agreement with the ranking of sectors according to the degree of Shariah-compliance given in Table 1. Results for the two sub-periods follow a similar pattern. The bottom panel of Table 4a reports the p-values for the hypothesis that the Cement sector stochastically dominates the other sectors. Looking at the 2002-2008 period, it is clear that the null hypothesis of FSD is rejected for all but the Banking sector.

Before concluding the section a caveat regarding the interpretation of the test results in Tables 3-4 is discussed. It is of interest to note that in most cases the result that returns in sector X_i SSD returns in X_j in Table 3 corresponds to SSD of volatility for the same sector in Table 4. For example in Table 3 returns in Shariah-compliant Agriculture sector FSD returns in Cement and Industrial sectors. This corresponds to FSD of the volatility in Table 4. Also, FSD of the volatility of returns in Agriculture over the banking sector in Table 4 implies, according to the definition of stochastic dominance, that the condition for SSD is also satisfied. Therefore, this result is consistent with the fact that returns in Agriculture SSD returns in Bank sector.

There is however, a case where the findings in Table 3 and Table 4 are inconsistent. This is for the Bank and Cement sectors where the test in Table 3 is inconclusive, but the empirical p-values in Table 4 indicate FSD of Agriculture over the Bank sector. However, looking at Figure 2 f) it is clear that the empirical CDF for Cement is everywhere below the empirical CDF of Banks (note that the definition of FSD allows distributions to overlap). The p-value in Table 4 and the analysis of the empirical CDFs suggest that the conclusion that volatility in Cement is higher than volatility in the Bank sector is reasonable. Therefore, for a given return of a portfolio in each of these sectors, volatility is greater in the former sector than the latter.

Table 3a. P-values for the test for first and second order stochastic dominance (returns) by sector.

Sector	Period	SD	Bank	Industrial	Cement	Services	Agriculture	Tasi
Bank	2002-	2nd	-	0.000	0.008	0.000	0.000	0.003
	2006	1st	-	0.009	0.005	0.005	0.000	0.001
	2006	2nd	-	0.004	0.002	0.000	0.009	0.005
	2008	1st	-	0.009	0.009	0.009	0.000	0.002
	2002-	2nd	-	0.000	0.245	0.013	0.000	0.005
	2008	1st		0.006	0.019	0.008	0.004	0.009
Industrial	2002-	2nd	0.549	-	0.480	0.040	0.000	0.000
	2006	1st	0.015	-	0.009	0.009	0.009	0.012
	2006-	2nd	0.768	-	0.795	0.004	0.000	0.013
	2008	1st	0.005	-	0.009	0.019	0.031	0.014
	2002-	2nd	0.966	-	0.677	0.036	0.000	0.000
	2008	1st	0.012	-	0.011	0.007	0.009	0.010
Cement	2002-	2nd	0.036	0.000	-	0.000	0.000	0.045
	2006	1st	0.000	0.009	-	0.000	0.007	0.037
	2006-	2nd	0.542	0.064	-	0.000	0.000	0.010
	2008	1st	0.012	0.019	-	0.015	0.009	0.008
	2002-	2nd	0.245	0.001	-	0.000	0.000	0.001
	2008	1st	0.001	0.024	-	0.000	0.006	0.002

Table 3b. Continue.

Sector	Period	SD	Bank	Industrial	Cement	Services	Agriculture	Tasi
Services	2002-	2nd	0.583	0.880	0.999	-	0.089	0.876
	2006	1st	0.449	0.000	0.002	-	0.000	0.999
	2006-	2nd	0.432	0.795	0.284	-	0.010	0.995
	2008	1st	0.762	0.003	0.000	-	0.056	0.271
	2002-	2nd	0.519	0.697	0.792	-	0.031	0.999
	2008	1st	0.681	0.006	0.007	-	0.004	0.638
Agriculture	2002-	2nd	0.882	0.825	0.999	0.835	-	0.999
	2006	1st	0.022	0.992	0.999	0.029	-	0.887
	2006	2nd	0.253	0.679	0.999	0.673	-	0.999
	2008	1st	0.019	0.999	0.142	0.019	-	0.526
	2002-	2nd	0.763	0.312	0.835	0.792	-	0.999
	2008	1st	0.024	0.999	0.999	0.011	-	0.762
Tasi	2002-	2nd	0.851	0.636	0.876	0.000	0.000	-
	2006	1st	0.295	0.039	0.995	0.028	0.000	-
	2006-	2nd	0.607	0.622	0.278	0.000	0.000	-
	2008	1st	0.008	0.018	0.999	0.034	0.005	-
	2002-	2nd	0.832	0.743	0.638	0.003	0.000	-
	2008	1st	0.025	0.011	0.995	0.019	0.009	-

Note: The p-values are obtained using the bootstrap algorithm described in Section 3 with $B = 1000$ replications.

Table 4a. P-values for the test for first and second order stochastic dominance (volatility) by sector.

Sector	Period	SD	Bank	Industrial	Cement	Services	Agriculture	Tasi
Bank	2002-	2nd	-	0.000	0.000	0.036	0.041	0.036
	2006	1st	-	0.002	0.001	0.027	0.041	0.033
	2006-	2nd	-	0.000	0.000	0.019	0.023	0.020
	2008	1st	-	0.007	0.018	0.020	0.024	0.019
	2002-	2nd	-	0.017	0.037	0.035	0.021	0.022
	2008	1st		0.015	0.005	0.005	0.034	0.014
Industrial	2002-	2nd	0.890	-	0.200	0.020	0.037	0.405
	2006	1st	0.899	-	0.280	0.037	0.028	0.451
	2006-	2nd	0.215	-	0.993	0.000	0.048	0.795
	2008	1st	0.216	-	0.699	0.000	0.014	0.820
	2002-	2nd	0.986	-	0.774	0.008	0.000	0.999
	2008	1st	0.999	-	0.494	0.007	0.022	0.995
Cement	2002-	2nd	0.938	0.000	-	0.000	0.062	0.419
	2006	1st	0.932	0.000	-	0.000	0.052	0.038
	2006-	2nd	0.967	0.000	-	0.000	0.011	0.154
	2008	1st	0.844	0.028	-	0.028	0.013	0.168
	2002-	2nd	0.975	0.026	-	0.032	0.018	0.012
	2008	1st	0.873	0.000	-	0.021	0.004	0.000

Table 4b. Continue

Sector	Period	SD	Bank	Industrial	Cement	Services	Agriculture	Tasi
Services	2002-	2nd	0.999	0.968	0.999	-	0.010	0.964
	2006	1st	0.954	0.556	0.976	-	0.010	0.763
	2006-	2nd	0.999	0.720	0.976	-	0.024	0.940
	2008	1st	0.930	0.337	0.835	-	0.020	0.738
	2002-	2nd	0.999	0.973	0.999	-	0.009	0.912
	2008	1st	0.974	0.802	0.971	-	0.015	0.613
Agriculture	2002-	2nd	0.998	0.995	0.999	0.995	-	0.999
	2006	1st	0.972	0.955	0.989	0.663	-	0.950
	2006-	2nd	0.999	0.999	0.999	0.999	-	0.999
	2008	1st	0.988	0.990	0.989	0.930	-	0.956
	2006-	2nd	0.999	0.998	0.867	0.999	-	0.974
	2008	1st	0.975	0.911	0.729	0.932	-	0.780
Tasi	2002-	2nd	0.541	0.000	0.514	0.000	0.038	-
	2005	1st	0.620	0.000	0.032	0.009	0.019	-
	2006	2nd	0.856	0.008	0.008	0.006	0.027	-
	2008	1st	0.909	0.009	0.209	0.005	0.010	-
	2002-	2nd	0.763	0.018	0.137	0.012	0.011	-
	2008	1st	0.536	0.006	0.022	0.013	0.002	-

Note: The p-values are obtained using the bootstrap algorithm described in Section 3 with $B = 1000$ replications.

To summarise our results, the stochastic dominance analysis reveals that portfolios of stocks containing Shariah-compliant assets are more volatile than stocks in other sectors. It appears that the volatility of a portfolio is closely related to the degree of Sharah-compliant element contained. Moreover, the higher volatility of Shariah-compliant stocks is rewarded with greater returns. However, the stochastic dominance analysis does not provide an explanation of why returns and unconditional volatility of returns in particular are higher for Shariah-compliant stocks. To get further insights on this issue we consider the recent evolution of the stock market and in particular the relation between trade volume and conditional volatility.

4 Retail Investors, Volatility and Religious Tenets

The literature on the causes of stock market volatility is vast, but there is now widespread consensus that changes in price volatility are affected by investor behavior other than by the fundamentals. This is especially true during periods of financial turmoil. Shiller (2000) for example analysed the dramatic rise in stock prices that occurred during the 1990s in the US and suggested that the run-up in stock price volatility was driven by sociological and psychological factors and not justified on the base of changes in the fundamentals. In Section 2 it is postulated that by increasing trade volume for Shariah-compliant stocks religious tenets affect the volatility of returns. In order to test this hypothesis we now investigate to what extent volatility in a given sector is affected by changes in trade volume. If religious prescriptions are binding, then investors should select Shariah-compliant stocks. As individual investors mainly place small orders, we should see that the rate of change in the trade volume should affect volatility more in Shariah-compliant sectors. As a proxy of trade volume we use the number of shares traded in each sector in each given day. From Figure 3 it appears that trade volume is higher in the Industrial and Service sector. This is probably due to the large number of companies in these sectors (note that together stocks in the Industrial and Service sectors constitute 70% of all shares traded, a large number of shares traded in these sectors is therefore to be expected). It is interesting however, that trade volume in Agriculture is high with respect to the size of the sector. There are 8 companies in this sector and more or less the same number in the Banking sector. However, the number of shares traded in Agriculture is significantly higher than the number of shares traded in the Banking sector. Interestingly enough trade volume growth in Agriculture is in correspondence with the exponential expansion of market participation that occurred in recent years. In order to further investigate this phenomenon we look at the relation between trade volume and stock market volatility.

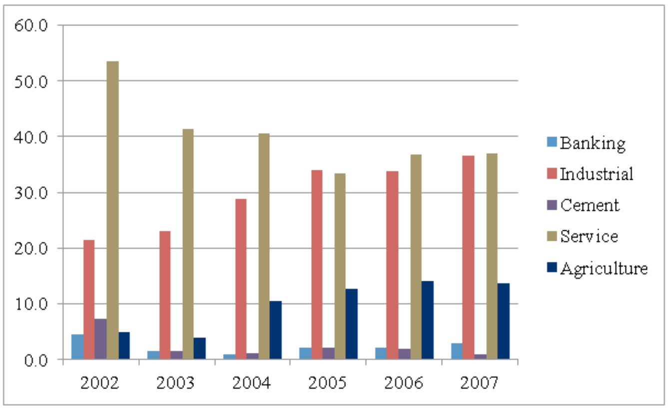

Figure 3 : Trade volume by sector as a percentage of the number of shares trated.

To model volatility we consider a generalized autoregressive conditional heteroskedastic (GARCH) type model. Since the seminal papers by Engle (1982) and Bollerslev (1986), GARCH models have been successfully used to study the behavior over time of financial market volatility. Following Glosten, Jagannathan and Runkle (1993) (GJR) we specifically model the "leverage effect"[6] in the Saudi stock market. In particular, we model the behavior of the

[6] The leverage effect is the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude (see Glosten *et al.* for more details).

returns as

$$
\begin{aligned}
R_{kt} &= \delta + u_{kt} \\
\sigma^2_{kt} &= \omega + \alpha u^2_{kt-1} + \gamma u^2_{kt-1} I_{kt-1} + \beta \sigma^2_{kt-1} + \kappa DVOL_{kt}
\end{aligned}
\tag{5}
$$

where R_{kt} are the realised returns in a given sector and the TASI and $u_{kt} \sim IID(0, \sigma^2_{kt})$. The conditional variance is specified as a function of the mean volatility ω, u^2_{kt-1} which is the lag of the squared innovation from the mean equation and which provides information about volatility clustering, σ^2_{kt-1}which is the last period's forecast variance (the GARCH) term, $DVOL_t$ is the first difference in (log) volume at period t, and finally $I_{kt-1} = 1$ if $u_{kt-1} > 0$ and $I_{kt-1} = 0$ otherwise. Finally, the γ coefficient is meant to capture the asymmetric effect of news on volatility. If bad news has greater impact on volatility than good news, a leverage effect exists, and we expect $\gamma > 0$. The impact of good news is given by α, while bad news have an impact given the $(\alpha + \gamma)$.

The model in (5) was estimated separately for each sector and the general index. The estimated parameters as well as the tests for asymmetry in volatility are reported in Table 5. Columns 2-6 in the top panel of Table 5 report the estimated parameters for the five sectors, whereas in the last column the estimation results for the general index TASI are given. Robust standard errors are given in parenthesis. Also, due to the non-normality of the innovations, the distribution of the $\{u_t\}$ process was approximated by a Student-t distribution. Finally, the p-values for the sign bias test, the negative size bias test and the positive bias test proposed by Engle and NG (1993) are reported at the bottom of Table 5. These tests are useful to assess whether asymmetry is a significant feature of the data. Under the null hypothesis there is no asymmetry. In each test rejection of the null hypothesis leads to the conclusion that the leverage effect is binding.

The estimated parameters tell an interesting story. Trade volume affects the conditional variance of returns as the parameter κ is significant in all the estimated models. As expected, all the estimated signs of $DVOL$ are positive, meaning that an increase in trade volume positively affects volatility. Looking at the magnitude of the estimated coefficient, the Agriculture sector has the highest estimated parameter followed by Industrial and Services, whereas Cement and Banking sectors have the lowest estimated coefficients.

Looking at the ω parameter, it appears that the estimated mean volatility is the highest in the Agriculture sector and the lowest for stocks in the Cement sector, with the estimated mean parameters of the other sectors falling in between the two. This result is in agreement with the findings of the stochastic analysis reported in Section 3 where it was found that the unconditional volatility of the Agriculture sector stochastically dominates the other sectors. Coming to the α parameter, once again volatility clustering is much higher for stocks in the Agriculture sector. The Industrial, Cement and Service sectors show a similar estimated coefficient, but the magnitude of the estimated α parameter for the Banking sector is about one third with respect to its counterpart in Agriculture. As the sign of γ is positive a leverage effect exists in all sectors, but the effect of bad news on volatility is much higher for the Agriculture sector. Finally, volatility persistence (given by β) is relatively high in all sectors as well as the general index TASI.

Coming to the asymmetry tests, the results in Table 5 illustrate that for these data there is evidence against the null of symmetry from the all the test statistics considered. Therefore, the models in Table 5 are correctly specified.

Table 5. Estimated GJR(1,1) model for sectors and all share index.

	Sectors					TASI
Coeff.	Bank	Industrial	Cement	Services	Agriculture	
δ	0.035*** (0.023)	0.116* (0.028)	0.002 (0.051)	0.115* (0.025)	0.031 (0.033)	0.135* (0.020)
ω	0.067* (0.015)	0.119* (0.038)	0.031* (0.010)	0.086** (0.037)	0.327* (0.076)	0.064* (0.018)
α	0.109* (0.019)	0.172* (0.042)	0.214* (0.049)	0.201* (0.058)	0.325* (0.055)	0.191* (0.039)
γ	0.153* (0.041)	0.150* (0.051)	0.116* (0.049)	0.122* (0.053)	0.162* (0.061)	0.138* (0.048)
β	0.798* (0.018)	0.784* (0.041)	0.779* (0.034)	0.794* (0.044)	0.623* (0.045)	0.748* (0.033)
κ	0.286* (0.038)	0.439* (0.088)	0.114** (0.015)	0.450* (0.090)	0.711* (0.071)	0.301* (0.038)
Asymmetry Tests						
Sign Bias t-Test	0.009	0.034	0.018	0.022	0.026	0.007
Neg. Size Bias t-Test	0.013	0.048	0.062	0.023	0.033	0.003
Pos. Size bias t-Test	0.021	0.033	0.031	0.021	0.037	0.034

Note: Table 5 reports the estimated coefficients of model

$$
\begin{aligned}
R_{kt} &= \delta + u_{kt} \\
\sigma^2_{kt} &= \omega + \alpha u^2_{kt-1} + \gamma u^2_{kt-1} I_{kt-1} + \beta \sigma^2_{kt-1} + \kappa DVOL_{kt}
\end{aligned}
$$

where R_{kt} are the realised returns in a given sector and the TASI, δ, ω, α, γ, β, κ are the estimated parameters and $I_{kt-1} = 1$ if $u_{kt-1} > 0$ and $I_{kt-1} = 0$ otherwise. *, **, *** indicate significance at 1% and 5% and 10%,respectively. Standard errors are reported in brackets. Note that the conditional distribution of returns was estimated assuming a Student-t distribution of the innovations.

To summarise our findings, looking at the evolution of trade volume in different stock market sectors from Figure 2, it appears that individual investors trade more actively in Shariah-compliant stocks. Given the strong relation between trade volume and volatility it is evident that individual investors, acting as noise traders, push away stock prices from their fundamental values thus affecting volatility of Shariah-compliant stocks. These results are in agreement with the model in Palonimo (1996) where noise traders acting in concert affect stock prices in a systematic way. According to this model noise traders acting on the base of noisy signals create an additional source of systemic risk in the market. This additional risk manifests itself as added volatility of the assets affected by the action of noise traders. Once that the extra-risk is priced by the market, the returns of these assets increases.

5 Robustness Checks

5.1 Herd Behavior and the Equity Market

From Table 5 it is clear that trade volume affects the conditional volatility of returns. Since this is particularly true for Shariah-compliant stocks we infer that religious minded investors trade more actively in these stocks. However, given that individual investors tend to place small orders their actions have to be coordinated if they are to make an impact on the market. To check the validity of this assumption we test for herd behavior in the stock market. Following Chang, Cheng and Khorana (2000) we specify a non linear model that allows us to control for an asymmetric relationship between the cross-sectional absolute deviation of returns (CSDA) and market returns. The model is specified as follows

$$CSDA_{kt}^{up} = \mathring{\beta} + \mathring{\gamma}_{1t}^{up} \left|R_{mt}^{up}\right| + \mathring{\gamma}_{2t}^{up} \left(R_{mt}^{up}\right)^2 + \varepsilon_t, \tag{6}$$

where

$$CSDA_{kt}^{up} = \frac{1}{N}\sum_{i=1}^{N} \left|R_{kt} - R_{mt}\right|,$$

and R_{mt}^{up} is the absolute value of the equally-weighted realized return portfolio of all available securities in a given sector (market for the TASI) during periods when the market is up. Similarly, the following equation is meant to capture herd behavior during periods when the market is down

$$CSDA_{kt}^{down} = \mathring{\beta} + \mathring{\gamma}_{1t}^{down} \left|R_{mt}^{Down}\right| + \mathring{\gamma}_{2t}^{down} \left(R_{mt}^{down}\right)^2 + \varepsilon_t. \tag{7}$$

The intuition behind the model in (6)-(7) is that according to the capital asset pricing model the relationship between market return and equity return dispersion should be positive and linear. This is because individual securities have different reactions to the market return to reflect the different investors' beliefs in the rational market. On the other side, if during periods of relatively large price movements market participants herd around indicators such as the average consensus of all market constituents, a non-linear behavior between $CSAD_{kt}$ and the average market returns should result. In particular, if investors conform to the market consensus, deviations of the individual securities return from $CSDA_{kt}$ should increase at decreasing rate or decrease as average price movement increases. Therefore a significantly different coefficient γ_2 in (6)-(7) implies the presence of herding.

Table 6. Regression results of the daily cross-sectional absolute deviation (asymmetric model).

Model A: $CSDA_{kt}^{up} = \mathring{\beta} + \mathring{\gamma}_{1t}^{up}\left\|R_{mt}^{up}\right\| + \mathring{\gamma}_{2t}^{up}\left(R_{mt}^{up}\right)^2 + \varepsilon_t$				
	$\mathring{\beta}$	$\mathring{\gamma}_{1t}^{up}$	$\mathring{\gamma}_{2t}^{up}$	$\bar{R}_2$
Bank	0.003 * (0.0002)	1.509* (0.084)	−9.611* (2.088)	0.66
Industrial	0.005* (0.0004)	1.544* (0.076)	−8.296* (1.114)	0.55
Cement	0.002* (0.0002)	1.495* (0.028)	−6.642* (1.0185)	0.73
Service	0.002* (0.0001)	1.083* (0.028)	−1.759* (0.478)	0.88
Agriculture	0.004* (0.0004)	1.621* (0.058)	−7.352* (0.749)	0.74
Tasi	0.001* (0.0002)	1.651* (0.109)	−8.123* (1.975)	0.66
Model B: $CSDA_{kt}^{down} = \mathring{\beta} + \mathring{\gamma}_{1t}^{down}\left\|R_{mt}^{Down}\right\| + \mathring{\gamma}_{2t}^{down}\left(R_{mt}^{down}\right)^2 + \varepsilon_t$				
	$\mathring{\beta}$	$\mathring{\gamma}_{1t}^{down}$	$\mathring{\gamma}_{2t}^{down}$	$\bar{R}_2$
Bank	0.003* (0.0002)	1.473* (0.066)	−7.120* (1.098)	0.69
Industrial	0.003* (0.0003)	1.532* (0.075)	−6.519* (1.436)	0.69
Cement	0.002* (0.0002)	1.476* (0.086)	−5.478* (1.134)	0.73
Service	0.002* (0.0001)	1.035* (0.043)	−0.517 (0.563)	0.93
Agriculture	0.004* (0.0003)	1.593* (0.062)	−8.135* (0.892)	0.79
Tasi	0.003* (0.0003)	1.428* (0.092)	−8.421* (2.356)	0.48

Note: a) This table reports the estimated coefficient of model A and model B above. R_{mt}^{up}, R_{mt}^{down} is the absolute value of the equally-weighted realized during periods when the market is up and down, respectively. b) *, **, *** indicate significance at 1% and 5% and 10%,respectively. Heteroskedasticity consistent standard errors are reported in brackets.

Table 6 reports the estimated coefficients of equations (6)-(7). In Table 6, Model A refers to the herding behavior during periods of a rising market, whereas Model B in the bottom panel is intended to capture the behavior when the market is down. Once again the model was estimated separately for each sector and the TASI. The estimated robust standard errors are reported in brackets, whereas the adjusted $\bar{R}^2$-coefficients are shown in the last column.

From Table 6 it appears that all coefficients on the linear term $|R_{m,t}|$ are significant and positive. These results strongly confirm that $CSAD_t$ increases with $|R_{m,t}|$. Both in the up and down markets the rate of increase is highest for the Agriculture sector. Furthermore, in most sectors, the rate of increase in the up market is higher than that of the down market. These results are consistent with the model in (5) where it is assumed that stock prices react quickly to negative macroeconomics news, but small stocks adjust to positive news with some delay.

We now turn our attention to the coefficients γ_2^{up} and γ_2^{down}. From Table 6 it appears that, with the exception of γ_2^{down} for the Service sector, the all estimated coefficients are negative and statistically significant. This suggests that as the average market return becomes large in absolute term, the cross sectional return dispersion increases at decreasing rate. The result in Table 6 are consistent with the intuition that during periods of extreme market movements individuals suppress their own beliefs in favor of the market consensus and confirm the validity of our assumption that noise traders in the market act in concert.

5.2 Religion and Stock Market in the United States

In this paper it suggested that social environment affects affect portfolio selection. Following the literature on ethical investments it was argued that portfolio selection is realised on the basis of ethical considerations along with the traditional mean-variance approach. However, there may be other potential reasons that affect the distribution of returns other than ethical concerns. As a robusteness check, it is therefore of interest to consider a benchmark market where the Shariah-compliant effect is not supposed to be binding and see if the the distribution of returns have similar characterictic to the ones of the Saudi stock-market.

With this issue in mind the stochastic analysis in Section 3 was replicated for the same period and the same sectors using the FTSE index for the U.S. market. Foreign participation is large in the U.S. market and institutional investors constitute the vast majority of market participants. Also, religious believes are highly heterogeneous in the country. Therefore, if the Sahriah-compliant effect is reflected in the distribution of returns one should not expect the same ranking of the sectors for the U.S. market.

Table 7 reports the estimated p-values for the returns obtained using the bootstrap algorithm in Section 3. From Table 7 it appears that the returns in Agriculture are first order stochastically dominated by Bank, Industrial, Cement and Services. Whereas the returns in the Cement sector first order stochastically dominate returns in Banks and Agriculture and second order dominate returns in the Industrial and Service sectors. It is clear that the ranking of returns by sector in the benchmark market is different from the distribution of the returns in the Saudi market [7].

[7] Note that the stochastic dominance analysis for the volatility displayed a similar result. In the interest of brevity the p-values are not reported, but available upon request.

Table 7. P-values for the test for first and second order stochastic dominance (returns) for the FTSE index.

Sector	SD	Bank	Industrial	Cement	Services	Agriculture	FTSE
Bank	2nd	-	0.999	0.009	0.000	0.678	0.001
	1st	-	0.725	0.001	0.005	0.622	0.005
Industrial	2nd	0.725	-	0.013	0.004	0.999	0.002
	1st	0.544	-	0.000	0.000	0.608	0.004
Cement	2nd	0.999	0.589	-	0.556	0.995	0.648
	1st	0.588	0.019	-	0.017	0.557	0.521
Services	2nd	0.725	0.550	0.010	-	0.999	0.514
	1st	0.544	0.000	0.006	-	0.514	0.888
Agriculture	2nd	0.000	0.009	0.000	0.004	-	0.000
	1st	0.006	0.008	0.001	0.005	-	0.000
FTSE	2nd	0.999	0.999	0.000	0.999	0.514	-
	1st	0.567	0.543	0.526	0.512	0.536	-

Note: The p-values are obtained using the bootstrap algorithm described in Section 3 with $B = 1000$ replications.

To summarise our results, from the comparison between the Saudi market and the U.S. market it appears the there is no Shariah-compliant effect in the sectors considered in the U.S. stock market. On the other side, the joint effect of market structure and social norms appears to have an important role in Saudi Arabia. However, the Saudi stock market is quite unique among the emerging market bourses. Although significant progress has been made to boost the partecipation of foreign entities, the Saudi market is still heavily dominated by national investors. National investors are more likely to be affected by "domestic" social norms. It would be of interest to extend this investigation to other GCC countries to see if the Shariah-compliant effect is still relevant. Hence, an important agenda for future research is to see if the Shariah-compliant effect is a general phenomenon or a peculiarity of the market under consideration.

6 Conclusion

In this paper we investigate the effect of Islamic tenets on the Saudi stock market and we show that religious norms have a significant effect on stock prices. We show that Shariah-compliant stocks have higher returns and volatility then their non-Shariah compliant counterparts. In particular, we found a close match between return volatility and the degree of compliance with religious tenets. These results have important implications for both corporations seeking to raise capital in the stock market and investors.

Looking at the relation between trade volume and volatility, our findings suggest that individual investors do act as noise traders in the market under consideration. In this sense our findings are in agreement with the model in Palonimo (1996) where it is suggested that in an economy with risk averse agents noise traders bearing a larger amount of risk relative to informed traders earn higher expected returns. According to Palonimo psychological biases and sentiment cause individual investors to trade systematically as a group. From our results it appears that speculation based on sentiment is profitable when trading in Shariah-compliant stocks, given that noise traders are not driven out of the market and therefore able to influence prices.

Overall, from our empirical analysis it is evident that the level of volatility of the Saudi stock market cannot be explained with any variant of the efficient market model in which stock prices are formed by looking at the present discounted value of future returns. In this sense behavioral finance models are more helpful. However, there is still something to desired from these models as they fail to consider the interaction between individual choices (rational or not) and environmental factors. From our results it appears that the combination of market structure (i.e. retail versus institutional investors) and ethical norms can have a substantial role in shaping stock market volatility and ultimately the financial stability of a country.

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