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BOUSALAM, Issam and HAMZAOUI, Moustapha

Abdelmalek Essaädi University of Tangier

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Issam BOUSALAM*[a] and Moustapha HAMZAOUI[b]

[a,b]Department of economics, Faculty of law and economics, Abdelmalek Essaädi university of Tangier - Morocco
[a]boussalam.issam@gmail.com

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Abstract

Despite the increasing attention given to Islamic investment, there is still existing few empirical papers that examined the performance and volatility of Islamic Funds and indices in comparison to their conventional unscreened counterparts. These studies provide mixed evidence with regards to risk and returns of Islamic funds and indices. This paper aims to expand the literature on this subject by studying the Moroccan case considering the recent introduction of Islamic finance in the country towards the end of 2015. Since there is still no Shariah compliant indices in Morocco, we first applied four Shariah screening methodologies of some of the world leading equity index providers (i.e. Dow Jones, FTSE, S&P and MSCI) to screen the public listed companies in Casablanca Stock Exchange for Shariah compliance. Next, we constructed four Islamic float-weighted indexes for which we modeled the dynamic volatility using an extension of the AutoRegressive Conditional Heteroskedasticity models, namely EGARCH(1,1). The findings show that the screening process resulted in a well diversified universe of Shariah compliant stocks (25.6%) to invest in. Furthermore, it is found that constructed Islamic indices outperformed the broad-based Moroccan All Shares Index (MASI) during the considered period of analysis (January 2013 to December 2014) and their long run volatility is higher. This indicates that investors in Shariah-compliant stocks do not sacrifice financial performance for their risky investment. The estimates of the model show that volatility for the MASI is more persistent and takes longer time to die, and the leverage effect is positive for all indices meaning that volatility of indexes' returns is influenced more by good news than bad news, a result that is in contrast to other studies for developed countries.

JEL-Classification: C22, G11.

Keywords: Islamic Index, Shariah screening, EGARCH volatility model, Morocco.

*Address : BP. 1373 - Poste principale - Tanger / Maroc. Tel/Fax : (+212) 661 692 643/(+212) 536 501 245
For data request, please contact (boussalam.issam@gmail.com).

1 Introduction

Shaken by the Arab spring of 2011 and the global financial crisis of 2008, Morocco as one of the most promising emerging countries in the world has recently aligned its economic development strategy with the inclusion of Islamic finance to strength its economy and diversify its funding sources.

After the approval of an earlier Islamic finance bill by the Moroccan parliament in November 2014, Moroccan Ministry of Finance and Economy adopted in July 2015 a circular outlining the banking licensing process including for Shariah compliant units (TAN, 2015). The new banking law allows the establishment of Shariah (Islamic law) compliant banks and enables foreign lenders to set up Islamic units in Morocco as well.

The success of this new financial industry in Morocco is perceived to be mainly attributed to the Muslim-majority community representing more than 95% of the Moroccan population. In fact, the Islamic Finance Advisory and Assurance Services (IFAAS) conducted a study in Morocco in June 2012 and revealed that 94% of those polled were in favor of the practice of Islamic finance in the country. The introduction of Islamic finance will surely bolster domestic savings, draw foreign and domestic alternative investors into the country's financial sector and boost the commercial capital of Casablanca Finance City (CFC) as a regional financial hub. More importantly, it would grant a higher level of accessibility and attraction for investors from the Arab states of the Gulf region allowing the country to position itself as an Islamic financial hub for the Arab states and French-speaking portion of Africa as well.

In order to meet the needs of the wealthy investors desiring to fructify their capital and diversify their portfolios by holding "*halal*" assets, financial operators should urgently establish Shariah compliant equity funds to invest in and develop a set of indices that list Shariah compliant companies, and serve as benchmarks for Shariah compliant portfolios managers. Unfortunately, Moroccan stock market players did not yet create such indexes by which international Muslim investors could be tempted and could track the evolution of equity markets in a style that is consistent with their underlying ethical principles.

As for Shariah compliant investment, the economic literature argued that, mostly, screened investments funds such as the Islamic Mutual Funds bring lower expected returns than unscreened investments (Langbein and Posner, 1980; Rudd, 1981; Temper, 1991; Johnson and Neave, 1996) and the low diversification of screened investments results in a higher portfolio risk. Furthermore, screened investments are also perceived to incur high monitoring and administration costs. As consequence, a persistent challenge for Morocco goes with enabling domestic and foreign investors to pursue equity investment in conformity to their religious beliefs without sacrificing financial performance.

In this paper, we aim to verify whether the Shariah screening process of companies listed in Casablanca Stock Exchange (CSE) results in a riskier universe of stocks to invest in and whether Shariah compliant stocks underperform (outperform eventually) their conventional counterpart or not. For this, we first apply four Shariah screening methodologies set by some of the world leading equity index providers (*i.e., Dow Jones Islamic Market World Index; S&P Global BMI Shariah Index; MSCI ACWI Islamic; FTSE Shariah All-World Index*) to the 74 companies listed in CSE to filter out the Shariah compliant stocks. Next, we construct four float-weighted Islamic indexes for which we compare returns against the broad-based Moroccan All Shares Index (MASI)[1]. Finally, we model the dynamic volatility of all indexes including the MASI using an extension of the AutoRegressive Conditional Heteroskedasticity models, namely EGARCH(1,1) model.

The remaining of this paper is as follow. The first part gives a brief history of Shariah compliant investment and a literature review of studies that examined features and characteristics of this particular investment. The second part presents the four Shariah screening methodologies we used in this study, the method of construction of Islamic indexes and the theoretical framework of the exponential GARCH (EGARCH) model employed to estimate the long run volatility of all indices. The third part presents and discusses the results. The last part serves to conclude.

1.1 Literature review

The first Islamic equity fund was launched in 1986 but the Islamic jurisprudence did not allowed Muslim investors to invest in until the early 90s. This decision has contributed to a proliferation of the number of Shariah compliant funds during the last twenty years. For instance, the number of Islamic Mutual Funds increased from 29 funds in 1994 holding $800 million of assets under management to approximately 940 funds by the end of 2014 holding more than $53.2 billion of assets. This growth is explained by the advent of several events such as the 9/11 attacks, the internet bubble, the increase in Crude Oil prices, cyclical financial scandals, the subprimes crisis and the emergence of a Muslim middle class in India and Pakistan.

Shariah compliant investment makes a significant part of ethical finance for which the purpose is to satisfy the current needs without compromising the capacity of future generations to meet theirs. Shariah compliant funds on their side continuously seek to gain ground among non-Muslim investors worldwide which is very interesting for this emerging industry when we know that $1 of 9 is placed in a socially responsible portfolio in USA.

As a new constrained financial industry, the debate about performance and volatility of Shariah compliant investment continue to flourish among researchers, especially when considering the thesis of Temper (1991) and Hall (1986), inter alia, that assesses the negative effects of constrained investment on returns, volatility and portfolio's diversification.

In respect to the financial performance of Islamic funds and Islamic indices, the few empirical papers on ethical investing provide mixed evidence on the performance of Islamic indices/funds compared to their unscreened counterparts. A first pool of empirical studies show that ethical indices/funds do not outperform or underperform their conventional counterparts. Elfakhani et al. (2005) studied 46 funds for the period going from January 1997 to August 2002 and found that there is no statistical significance between performance of Shariah compliant funds and their respective indices of reference. Hayat (2006) and Abderrezak (2008) also found that yield gaps between Islamic indices and their counterparts have no statistical significance. On the other hand, when comparing Malaysian Islamic funds to their conventional counterparts between 1995 and 2001, Abdullah et al. (2007) found that performance of Shariah compliant funds is much lower due to their lack of diversification.

Beyond the financial performance of Islamic funds, these studies also outlined some specific characteristics of the latter. It is found that Shariah compliant funds outperform in both periods of crisis

[1]The Moroccan All Shares Index (MASI) is the principal stock index of the Casablanca Stock Exchange located at Casablanca, Morocco and tracks the performance of all companies listed on the Moroccan stock market.

and economic growth (Elfakhani et al., 2005; Hayat, 2006). Furthermore, Elfakhani et al. (2005) demonstrated that performance of Islamic funds is positively correlated with the experience of their managers and their educational background. Finally, Abderrezak (2008) noted that Islamic funds have a particular preference for small cap companies and growth stocks.

As for financial performance of Islamic indices, the results are similarly mixed compared to those of Shariah compliant funds (Hakim and Rashidian, 2002; Hakim et al., 2004; Hussein, 2004; Guyot, 2008; Albaity et al., 2008; Abdul Rahman et al., 2010). To sum up, the Muslim investor does not seem to be penalized when investing in accordance to its religious convictions and Shariah compliant investment has a unique risk-return profile.

With respect to volatility, while the studies on conventional stocks and indices are proliferating recently, less attention is being given to their Islamic counterparts. For instance, in a global context, Hakim and Rashidian (2002) explored the volatility and return of the Dow Jones Islamic Market Index (DJIMI) and its conventional counterpart Wilshire 5000 Index (W5000). The findings show that the DJIMI presents unique risk-returns characteristics compared to those of W5000. In a Malaysian context, Muhammad (2002) investigated the performance of three indices, the KLSE Composite index, the KLSE Syariah index and the RHBI index for the period between 1992 and 2000. The results of his study suggest that both Islamic and conventional indices behaved in the same way during the period of analysis. Yusof and Majid (2006) used a GARCH-M approach to compare the risks and returns of the Islamic and conventional stock market volatilities in Malaysia for the period covering 1992 to 2000. They found that there is no evidence of significant time varying risk premium for both conventional and Islamic stock returns.

In the light of the above reviewed studies, mitigated results prevail with regards to which stock market indexes/funds are more volatile and which one of these outperform the other. Most of these studies contribute to our understanding of the econometric characteristics of volatility and risk-adjusted returns. However, it is still very instructive to study the Moroccan case especially when we know that there is still no existence of Shariah compliant funds and indices. The present study is the first of its kind in Morocco to construct Islamic indices using Shariah screening methodologies for which the volatility is modeled.

2 Materials and Methods

2.1 Shariah Screening Methodologies

Since 1987, when a team of leading Shariah scholars came up with criteria that would allow Muslim investors to own shares of Shariah compliant listed companies (Mian, 2008), a variety of Shariah screening methodologies have been developed around the world. The world major equity index providers climbed the bandwagon and published their proper methodologies of Shariah screening that filter stocks for Shariah compliance worldwide.

The screening process for Shariah compliance of stocks outlined by funds and these index providers generally undergoes a two-level scrutiny process. The first one consists of a qualitative screening which is followed by a second quantitative screening (Khatkhatay and Nisar, 2007; Derigs and Marzban, 2008; Abdul Rahman et al., 2010). According to Khatkhatay and Nisar (2007), this qualitative screening looks at (1) the structure of the transaction in terms of whether there is any element that is prohibited in Islam such as interest (*riba*), uncertainty (*gharar*), etc; and (2) the nature of the counter-party's (company's) business. It is worth mentioning here that the majority of Shariah boards, generally, acknowledged the same qualitative screening criteria. Derigs and Marzban (2008) gave an excellent summary of the qualitative criteria used by three prominent international Shariah equity index providers (*i.e., Dow Jones, FTSE and S&P*). Table 1 below presents an overall comparison of qualitative criteria for these three Islamic indices in addition to those of the MSCI we added. These four methodologies are those we used in this study.

Table 1: Overall Comparison of Qualitative Criteria for Shariah-Compliance Screening Methodologies

Qualitative Criteria (Prohibited sectors)	**Dow Jones**	**FTSE**	**S&P**	**MSCI***
Alcohol	a.i.	c.b.	a.i.	a.i.
Broadcasting & entertaining	a.i.	c.b.	a.i.	a.i.
Conventional financial services	a.i.	c.b.	a.i.	a.i.
Gambling	a.i.	c.b.	a.i.	a.i.
Hotels	a.i.	c.b.	a.i.	a.i.
Insurance	a.i.	c.b.	a.i.	a.i.
Media (except newspapers)	a.i.	-	a.i.	a.i.
Pork-related products	a.i.	c.b.	a.i.	a.i.
Restaurants & bars	a.i.	c.b.	a.i.	a.i.
Tobacco	a.i.	c.b.	a.i.	a.i.
Trading of gold & silver	-	-	a.i.	-
Weapon & defense	a.i.	c.b.	-	a.i.

* Based on the latest published version of MSCI Islamic Index Series Methodology of September 2015 available at: www.msci.com [Retrieved on December 3, 2015]

a.i. = any involvement; c.b. = core business.

Source: Extracted from (Derigs and Marzban, 2008) and extended by the authors.

These sector screens are general prescriptions through which operating or involved companies (at a certain degree) in specific types of Shariah non-compliant business activities are excluded from investment decisions. However, equity index providers do not unanimously agree the same degree of involvement. While Dow Jones, S&P and MSCI do not tolerate a total income from the aforementioned impure sources exceeding 5% of revenue (a.i.), the FTSE excludes companies from its Islamic indexes only when the Shariah non-compliant business activity is the core business (c.b.) of the company. This is one of the reasons why the screening methodologies might result in a different compliant stock universe to invest in.

The qualitative screening process might be performed whether in an automated or a researched way. The process of automated screening uses automated data feeds to decide whether an equity is Shariah-compliant or not. By using broad industry classifiers such as Industry Classification Benchmark (ICB)[2] or Global Industry Classification Standard (GICS)[3], each company is attributed a single industry classifier based on the majority of its revenue. If this industry classifier is related to a non-compliant or suspicious industry the company is deemed non-compliant.

[2]The Industry Classification Benchmark (ICB) is an industry classification taxonomy launched by Dow Jones and FTSE in 2005 and now owned solely by FTSE International. It is used to segregate markets into sectors within the macroeconomy. The ICB uses a system of 10 industries, partitioned into 19 supersectors, which are further divided into 41 sectors, which then contain 114 subsectors. [Retrieved on December 4, 2015 from www.icbenchmark.com]

[3]GICS is a common global classification standard developpped in 1999 by MSCI and Standard & Poor's, it is a four-tiered, hierarchical industry classification system which comprises 10 sectors, 24 industry groups, 67 industries and 156 sub-industries. Each company is assigned a single GICS classification at the sub-industry level according to its principal business activity based on the majority of its revenue. [www.msci.com/gics; Accessed on December 4, 2015]

As for the researched screening, it refers to the process of using researched data so that non-compliant income activities are clearly discerned rather than depending on a broad sector classification. This second type of qualitative screening process has the advantage to ensure that Shariah screening is done according to the intended Shariah requirements defined by the governing Shariah boards. Conversely, the automated screening may result in compliance credibility issues. This occurs, for example but not exclusively, when a company is given different sector classification depending on the adopted taxonomy.

Table 2 below resumes the industry screens for each one of the methodologies we used in our automated screening to scan for Shariah compliance of Casablanca Stock Exchange listed companies.

Table 2: Industry Screens for the Used Shariah-Compliance Screening Methodologies

Dow Jones and FTSE (ICB Sectors)		**S&P* and MSCI**** (GICS Sub-industries)	
3533 Brewers	3535 Distillers & Vintners	30201010 Brewers	30201020 Distillers & Vintners
5757 Restaurants & Bars	3785 Tobacco	25301040 Restaurants	40201040 Specialized Finance
3577 Food Products	5337 Food Retailers & Wholesalers	40101010 Diversified Banks	40201010 Consumer Finance
8355 Banks	8532 Full Line Insurance	40101015 Regional Banks	40102010 Thrifts & Mortgage Finance
8534 Insurance Brokers	8536 Property & Casualty Insurance	30203010 Tobacco	25301020 Hotels, Resorts & Cruise Lines
8538 Reinsurance	8575 Life Insurance	25401025 Cable & Satellite	25401030 Movies & Entertainment
8773 Consumer Finance	8775 Specialty Finance	25401020 Broadcasting	40201030 Multi-Sector Holdings
8777 Investment Services	8779 Mortgage Finance	25301010 Casinos & Gaming	40201020 Other Diversified Financial Services
2717 Defense	5752 Gambling	40301050 Reinsurance	40301020 Life & Health Insurance
5753 Hotels	3745 Recreational Products	40301030 Multi-line Insurance	40203020 Investment Banking & Brokerage
5555 Media Agencies	5553 Broadcasting & Entertainment	40301010 Insurance Brokers	40301040 Property & Casualty Insurance
5755 Recreational Services		40203030 Diversified Capital Markets	40203010 Asset Management & Custody Banks

* S&P adopts additional sector screens related to business activities of Cloning and Trading of gold and silver.
** MSCI has one more sector screen related to aerospace and defense (20101010 Aerospace & Defense) in addition to those mentioned on the table.

Source: Extracted from "Methodology Map: Islamic Indexes" published by Dow Jones Indexes Analytics & Research on December 31, 2011, Accessed : December 5, 2015 at www.djindexes.com.

The GICS and the ICB classification standards are the most used by Shariah screens providers compared to their competitors (*e.g. Thomson Reuters Business Classification (TRBC)*). While the differences between these competing schemes still minor, the GICS has the advantage to give a precise definition to Shariah non-compliant sectors and exceeds its counterparts in terms of classification granularity, naming 154 different sub-industries, 30 more than the TRBC and 40 more than the ICB.

The second stage of Shariah compliance screening is the quantitative process that inspects: (1) the indebtedness level of the company; (2) the interests and other illicit earnings of the company; and (3) the expanse of cash and receivables of the company. This by calculating financial ratios to compare with rejection thresholds set by the equity index providers.

Similarly to the first sector screening process, there is no consensus among equity index providers about this quantitative filters. In fact, the financial ratios employed by Shariah screening methodologies use different nominators and denominators, and additionally, even when it is about the same formula of the financial ratio, the rejection thresholds might differ from a methodology to another. Furthermore, S&P and MSCI adopt a fourth ratio that measures the revenue share from non-compliant activities. In general, a stock is considered Shariah compliant when all financial ratios are less than their respective rejection thresholds.

The following table 3 details the screens for acceptable financial ratios used by each one of the methodologies we used in this study.

In this paper, the proceeding we performed to scan for Shariah compliance of the 74 companies listed on Casablanca Stock Exchange consisted in: (1) the identification of the ICB and the GICS industry classifiers of each company; and (2) the calculation of the financial ratios mentioned above

Table 3: Summary of Screens for Acceptable Financial Ratios

		Dow Jones	FTSE	S&P	MSCI
Leverage Compliance	R_1	$\frac{TD_i(t)}{MC_{24i}(t)} < 33\%$	$\frac{TD_i(t)}{TAi(t)} < 33\%$	$\frac{TD_i(t)}{MVE_{36i}(t)} < 33\%$	$\frac{TD_i(t)}{TAi(t)} < 33\%$
Cash Compliance	R_2	$\frac{C_i(t)+IbS_i(t)}{MC_{24i}(t)} < 33\%$	$\frac{C_i(t)+IbS_i(t)}{TA_i(t)} < 33\%$	$\frac{C_i(t)+IbS_i(t)}{MVE_{36i}(t)} < 33\%$	$\frac{C_i(t)+IbS_i(t)}{TA_i(t)} < 33\%$
	R_3	$\frac{AR_i(t)}{MC_{24i}(t)} < 33\%$	$\frac{AR_i(t)+C_i(t)}{TA_i(t)} < 50\%$	$\frac{AR_i(t)}{MVE_{36i}(t)} < 49\%$	$\frac{AR_i(t)+C_i(t)}{TA_i(t)} < 33\%$
Revenue Share from Non-Compliant Activities	R_4	N/A	$\frac{NPI_i(t)+II_i(t)}{R_i(t)} < 5\%$	$\frac{NPI_i(t)}{R_i(t)} < 5\%$	N/A

Notes: $TD_i(t)$ refers to Total Debt of company i at time t, $MC_{24i}(t)$ refers to average Market Capitalization for last 24 months of company i at time t, $MVE_{36i}(t)$ refers to average Market Value of Equity for last 36 months of company i at time t, $TA_i(t)$ refers to Total Assets of company i at time t, $C_i(t)$ refers to Cash of company i at time t, $IbS_i(t)$ refers to Interest Bearing Securities of company i at time t, $AR_i(t)$ refers to Accounts Receivables of company i at time t, $NPI_i(t)$ refers to Non-Permissible Incomes of company i at time t, $R_i(t)$ refers to Revenue of company i at time t and $II_i(t)$ refers to Interest Incomes of company i at time t.

Source: Extracted from "Methodology Map: Islamic Indexes" published by Dow Jones Indexes Analytics & Research on December 31, 2011, Accessed : December 6, 2015 at www.djindexes.com.

based on the financial statements and reports of each company. As mentioned on the Shariah screening methodologies documentation, the calculation of the financial ratios relies on the last published financial statements of the companies. For this, we used those of the year 2014 (and those of 2013 and 2012 for the calculation of the 36 month average market value of equity). The companies that were found to be Shariah compliant served next for the construction of the Islamic indices.

2.2 Construction of the Islamic indices

Stock indexes are mathematical constructs that measure the value of a section of stock market and there exist different methods of their calculation. The three commonly used methods are *price-weighting*, *capitalization-weighting* and *equal-weighting*. Market cap or value-weighting is currently the most popular of these three methods.

One of the advantages of market cap weighted stock indexes is that companies are represented according to their market capitalization, which is a good indicator of importance in the stock market and in the economy. But the downside of this method is that sometimes companies typically having a big market capitalization are favored and dominate the index. To workaround this problem, many of the leading equity indexes turned into the float-adjusted weighting method, this by considering only shares readily available on the market (the float) instead of using all outstanding shares.

Casablanca Stock Exchange climbed the bandwagon since December 2004 and adopted the floating-weighted capitalization for its principal, underlying and sector indices. Since, the broad-based Moroccan All Shares Index (MASI) becomes the MASI$^{\text{®float}}$ and is calculated according to the following formula[4]:

$$I_t = 1000 \frac{\sum_{i=1}^{n} ff_{it} \cdot Cf_{it} \cdot TNS_{it} \cdot SP_{it}}{BC \cdot K_t} \tag{1}$$

Where

[4]Casablanca Stock Exchange. *Nouveaux Indices MASI*$^{®Flottant}$ *et MADEX*$^{®Flottant}$. December 2004. Retrieved from www.casablanca-bourse.com on December 7, 2015.

$$
\begin{array}{rcl}
I_t & : & \text{price of the index at time } t \text{ in basis points ;} \\
ff_{it} & : & \text{floating factor of share } i \text{ at time } t \text{ ;} \\
Cf_{it} & : & \text{capping factor of share } i \text{ at time } t \text{ ;} \\
TNS_{it} & : & \text{total number of shares } i \text{ at time } t \text{ ;} \\
SP_{it} & : & \text{price of share } i \text{ at time } t \text{ ;} \\
BC & : & \text{base capitalization on December 31, 1991 ;} \\
K_t & : & \text{the adjustment coefficient of the base cap at time } t.
\end{array}
$$

In order to compare the constructed Moroccan Islamic indices with the MASI®float in term of volatility, these should be elaborated following the same formula (1). But the main change we introduced was to substitute the adjusted base cap ($BC \cdot K_t$) by the sum of the float capitalization of each one of the selected compliant companies on January 2, 2013 as a base cap for the Islamic indices. This gave us a total number of 493 observations until December 31, 2014 (date on which the companies were screened for Shariah compliance). Since the capping factors are all equal to 1[5], the formula (1) becomes:

$$
I_{j,t} = 1000 \frac{\sum_{i=1}^{n} fCap_{it}}{\sum_{i=1}^{n} fCap_{i,t_0}} \tag{2}
$$

Where

$$
\begin{array}{rcl}
I_{j,t} & : & \text{price of the index } j \text{ at time } t \text{ in basis points ;} \\
n & : & \text{number of selected Shariah compliant companies for construction of the Moroccan Islamic index ;} \\
fCap_{it} & : & \text{floating capitalization of company } i \text{ at time } t \text{ ;} \\
fCap_{i,t_0} & : & \text{floating capitalization of company } i \text{ on January 2, 2013.}
\end{array}
$$

To compare the long run volatility of the constructed Moroccan Islamic indexes with that of the MASI®float we next calculated daily log-returns for all indices for different reasons.

First, log-returns are scale-free summaries of indices' prices which allows comparison between the studied indexes. Also, log-returns are known to have attractive statistical properties (*e.g. persistence of variance, high excess kurtosis...*). More importantly, indexes' log-returns series are often stationary (integrated of order zero I_0), while indexes' prices are I_1 ($p_t \sim I_1$, so $r_t = \Delta log p_t \sim I_0$). Finally, I_0 series' autocorrelations rapidly decline as the lag increases, while for I_1 processes the estimated autocorrelation coefficients decay to zero very slowly.

When modeling for volatility, one should use specific models that handle all these properties of log-returns time series.

2.3 EGARCH(1,1) volatility model

Most of financial time series exhibit three main characteristics. First, periods of swings are followed by periods of relative calm which is known as volatility clustering or volatility pooling. Secondly, their distribution is leptokurtic meaning that it has fat tails. Third characteristic refers to leverage effect which means that changes in prices tend to be negatively correlated with changes in volatility.

The AutoRegressive Conditional Heteroskedastic (ARCH) model introduced in (Engle, 1982) and its generalization developed by Bollerslev (1986) are the bedrock models for dynamic volatility and takes into account these characteristics. These models have also the advantage to be practically easy to estimate in addition to allow diagnostic tests to be performed (Drakos et al., 2010). ARCH and GARCH model the variance of the error term from the mean equation on the previous squared error

[5]See http://www.casablanca-bourse.com/bourseweb/en/Weighting.aspx

terms. Lets consider the conditional mean equation written as a function of an exogenous variable and an error term:

$$Y_t = X_t'\theta + \epsilon_t \tag{3}$$

The conditional variance σ_t^2 is a function of ϵ_{t-i}^2 the lagged terms of the squared error terms from the mean equation, where q indicates the lag order of the squared error term in the variance equation. Then ARCH(q) model is expressed by:

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \cdots + \alpha_q\epsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 \tag{4}$$

α_0 and α_i are the coefficients.

But when an AutoRegressive Moving Average model (ARMA model) is assumed for the error variance, the model is a GARCH(p,q) given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2 \tag{5}$$

Where p is the order of the GARCH terms σ_{t-i}^2 and q is the order of the ARCH terms ϵ_{t-i}^2.

However, Baillie and Bollerslev (1989) posited that the GARCH models do not capture all the skewness and leptokurtosis (fat tails relative to the normal distribution) in the financial data. Also, Nelson (1994) found that the GARCH(p,q) model could not forecast when conditional densities are non-normal. Christie (1982) and Nelson (1991) pointed out the evidence of asymmetric responses of volatility and suggested the leverage effect[6].

In response to the weakness of GARCH model to handle this asymmetric feature, Nelson (1991) brought out the Exponential GARCH (EGARCH) model which is continuously demonstrated by economic literature to be superior comparing to the other asymmetric conditional variance models (*e.g. TGARCH*). Engle et al. (2001) discussed more stylized facts about volatility that should be handled by volatility models and studied the ability of GARCH-type models to capture these features. These stylized facts concern: (1) the pronounced persistence and mean reversion of volatility, (2) its asymmetry such that the sign of an innovation also affects volatility; and (3) the possibility of exogenous and pre-determined variables to influence volatility. An EGARCH(p, q) model is formally described by:

$$\log\sigma_t^2 = \omega + \sum_{k=1}^{q}\beta_k g(Z_{t-k}) + \sum_{k=1}^{p}\alpha_k\log\sigma_{t-k}^2 \tag{6}$$

Where $g(Z_t) = \theta Z_t + \lambda(|Z_t| - E(|Z_t|))$. σ_t^2 is the conditional variance. ω, β, α, θ, and λ are coefficients, and Z_t comes from an error distribution.

Let $r_{j,t}$ represent the compounded return of index j at time t, where subscript $j \in \{$*MASI Index, Dow Jones Moroccan Islamic Index, S&P Moroccan Islamic Index, MSCI Moroccan Islamic Index, FTSE Moroccan Islamic Index*$\}$ whose mean equation is given by:

$$r_{j,t} = E(r_{j,t}|\mathcal{G}_{j,t-1}) + \epsilon_{j,t} \tag{7}$$

Here ($r_{j,t} = \ln(I_{j,t}) - \ln(I_{j,t-1})$) and $\mathcal{G}_{t-1}$ is the information available at time $t-1$. $\epsilon_{j,t}$ are the random

[6]The leverage effect invokes the tendency of asset returns to be negatively correlated to their changes of volatility.

innovations (surprises) with $E(\epsilon_{j,t}) = 0$ and they are split into a stochastic component $Z_{j,t}$ and a time-dependent standard deviation $\sigma_{j,t}$ characterizing the typical size of the terms so that:

$$\epsilon_{j,t} = \sigma_{j,t} Z_{j,t} \tag{8}$$

$$Z_{j,t}|\Omega_{t-1} \sim \psi(0, 1, v) \tag{9}$$

$\psi(.)$ marks a conditional density function and v denotes a vector of parameters needed to specify the probability distribution of $Z_{j,t}$[7].

For our study, we based on the EGARCH(1,1) model to estimate the long run volatility of the constructed Islamic indices in addition to that of the MASI Index. For this case the EGARCH(1,1) model is explicitly described by:

$$\log \sigma^2_{j,t} = \omega_j + \beta_j \log(\sigma^2_{j,t-1}) + \gamma_j \frac{\epsilon_{j,t-1}}{\sqrt{\sigma^2_{j,t-1}}} + \alpha_j \left[\frac{|\epsilon_{j,t-1}|}{\sqrt{\sigma^2_{j,t-1}}} - E[|Z_{j,t-1}|] \right] \tag{11}$$

Since equation (11) defines the conditional variance, ω_j, β_j, γ_j and α_j are parameters to estimate. Note that the constraint of positiveness of these parameters is no longer persistent because $\log \sigma^2_{j,t}$ will be always positive.

β_j measures the persistence in conditional volatility disregarding anything happening in the market. The larger is β_j the longest is time that volatility takes to die. γ_j measures the asymmetric effect or the leverage effect aforementioned. When $\gamma_j = 0$ the model is symmetric, when $\gamma_j > 0$ then positive shocks (good news) generate more volatility than negative shocks (bad news) and vice-versa. The parameter α_j represents the magnitude effect or the symmetric effect of the model.

To estimate the long run volatility of indices through the EGARCH(1,1) model, two different forms of the conditional density $\psi(.)$ were tested. The Gaussian distribution and the standardized Student t-distribution. We selected the best fitting model based on the information criteria AIC and SIC.

Long term volatility is synonym to the unconditional variance of the EGARCH(1,1) model which is the variance of unconditional returns distribution. This variance is supposed to be constant over the entire period of data. Given the fact that for EGARCH model $E(\epsilon^2_{j,t-1}) = \sigma^2_{j,t-1}$ and by replacing $\sigma^2_{j,t} = \sigma^2_{j,t-1} = \overline{\sigma^2_j}$ in (11) we obtain:

$$\overline{\sigma^2_j} = \exp\left(\frac{\omega_j}{1 - \beta_j}\right) \tag{12}$$

3 Results and discussion

3.1 Shariah compliant companies

Based on the ICB and the GICS industry classifiers we collected for each company listed on Casablanca Stock Exchange (CSE), the first automated quantitative screening process resulted on

[7] Assuming that $Z_{j,t}$ is t-distributed with v degrees of freedom we have:

$$E[|Z_{j,t}|] = \frac{2\sqrt{v-2}\,\Gamma((v+1)/2)}{(v-1)\Gamma(v/2)\sqrt{\pi}} \tag{10}$$

Notice that $E[|Z_{j,t}|] = \sqrt{\frac{2}{\pi}}$ under normality.

the following Shariah compliant companies[8]. The following table 4 resumes these companies by sector of business activity.

Table 4: Compliant Companies on First Stage of Qualitative Screening

Sector	Dow Jones and FTSE		S&P and MSCI	
	Number of companies	%	Number of companies	%
Construction & Building Materials	8	15%	8	14.5%
Oil & Gas	3	5.66%	3	5.45%
Real Estate	4	7.54%	4	7.27%
Distributors	7	13.2%	7	12.7%
Food producers & Processors	6	11.3%	6	10.91%
Transport	2	3.77%	2	3.63%
Engineering & Equipment Industrial Goods	2	3.77%	2	3.63
Holding companies	-	-	2	3.63%
Materials, Software & Computer Services	7	13.20%	7	12.72%
Telecommunications	1	1.88%	1	1.81%
Utilities	1	1.88%	1	1.81%
Chemicals	2	3.77%	2	3.63%
Mining	4	7.54%	4	7.27%
Forestry & Paper	1	1.88%	1	1.81%
Electricity, Electrical & Electronic Equipment	2	3.77%	2	3.63%
Beverages	1	1.88%	1	1.81%
Pharmaceutical industry	2	3.77%	2	3.63%
Total of companies	53	100%	55	100%

Source: Elaborated by the authors based on the qualitative screening process results.

Only 53 from 74 listed companies were admitted Shariah compliant based on their ICB sector classifiers, while the GICS classification resulted on 55 compliant companies. This is because two companies of the sample had a Shariah non-compliant ICB classifier (*i.e. 8775 Specialty Finance*) while their GICS sector classifiers were admissible regarding Shariah law.

Table 4 outlines also the diversification of Shariah compliant sectors present in CSE naming 17 different sectors offered to investors to invest in. These are dominated by some of the high Value-Added industries, namely, Construction & Building Materials and Material, Software & Computer services which performed very well in 2014 (20.6%, 13.6% respectively)[9].

In the next quantitative screening, we calculated financial ratios provided by Dow Jones, FTSE, S&P and MSCI (presented in table 3 above). The calculation results revealed, ultimately, 13 Shariah compliant companies for the Dow Jones methodology, 13 for the FTSE, 19 for the S&P and 6 for the MSCI. Table 5 hereafter presents descriptive statistics of these financial ratios.

The different results of the second screening are mainly attributed to: (1) the difference between denominators used by same ratios; (2) the rejection thresholds set by each methodology; and (3) the additional non-permissible income ratio (R_4) set by the FTSE and S&P.

In fact, the Dow Jones and S&P use average market capitalization as denominator for the debt ratio (R_1) while FTSE and MSCI use total of assets of company. Asset-based screening used by these latter is a more conservative approach to measure debt level since assets are less volatile than average market capitalization. It ensures that companies do not pass the screening process given stock prices

[8]Note that for some sector screens such as (3577 Food Products, 5337 Food Retailers & Wholesalers) these were not eliminated since operators of these sectors are not involved in non-Halal food. Both for locally produced food or imported food, an import license is required from the ministry of commerce and ministry of agriculture to state for adherence of this food to Shariah law.

[9]See the annual report of Casablanca Stock Exchange for 2014, Accessed December 10, 2015 at www.casablanca-bourse.com.

Table 5: Descriptive Statistics of the Financial Ratios (R_1, R_2, R_3 and R_4)

	N	Max	Min	Mean	Median	SD	Kurtosis	Skewness
R_1: Debt Ratio								
Dow Jones	13	19.67%	0.00%	3.64%	0.01%	6.49%	2.50	1.86
FTSE	13	32,17%	0.00%	11.87%	10.16%	11.94%	-1.30	0.43
S&P	19	19.57%	0.00%	3.17%	0.00%	5.83%	3.73	2.10
MSCI	6	29.30%	0.00%	6.58%	0.01%	11.85%	3.48	1.92
R_2: Interest Ratio								
Dow Jones	13	22.89%	0.13%	5.22%	1.73%	7.27%	2.03	1.73
FTSE	13	7.34%	0.27%	2.87%	2.39%	2.28%	0.51	1.10
S&P	19	21.27%	0.14%	4.19%	2.46%	5.68%	4.27	2.16
MSCI	6	3.78%	0.27%	1.68%	1.45%	1.27%	0.37	0.86
R_3: Cash Ratio								
Dow Jones	13	30.08%	4.45%	16.05%	13.01%	9.13%	-1.17	0.44
FTSE	13	48.13%	14.91%	32.98%	38.72%	11.61%	-1.60	-0.26
S&P	19	45.89%	4.08%	23.07%	19.25%	13.44%	-1.43	0.10
MSCI	6	28.90%	14.91%	21.76%	20.44%	5.15%	-0.86	0.27
R_4: Non-Permissible Incomes Ratio								
FTSE	13	2.76%	0.00%	0.47%	0.23%	0.73%	9.25	2.89
S&P	19	0.00%	0.00%	0.00%	0.00%	0.00%	0.00	0.00

Source: Elaborated by the authors.

fluctuating upward. It has also the advantage to be applicable even for private equity while the market cap based screening concerns only listed companies. Furthermore, the average market capitalization denominator used by the Dow Jones methodology concerns only the last 24 months period while for the S&P, it covers a longer period of 36 months which contributes to distinguish the results.

Notice that for methodologies using average market cap as denominator (DJ and S&P), the means of debt ratios (3.64% and 3.17% respectively) are inferior than those given by the FTSE and MSCI using total of assets (11.87% and 6.58% respectively). The same remark applies for cash ratio (R_3). These quantitative screening emerged some zero debt companies for all methodologies ($\min(R_1) = 0.00\%$) but also companies with maximum accepted debt ratio of 32.17%.

As for the interest ratio (R_2), the means are relatively moderate ranging from 1.86% to 5.22% reflecting low levels of cash and interest bearing securities for admissible companies. Most importantly, some of these companies display near-zero interest ratios (0.13%, 0.14% and 0.27%) that refer to a quasi-absence of liquid assets.

With respect to cash ratio (R_3), the highest value is of 32.98% related to the FTSE and it is very near to the respective threshold of 33%. This refers to a moderate level of accounts receivables and cash representing nearly the third of totals of assets of the 13 filtered companies. For the Dow Jones, S&P and MSCI these levels are much lower.

Statistically, the four respective skewness values are all near-zero and the kurtosis values (excess kurtosis on the table less 3) are near that of a normal distribution. This explains that compliant companies of all screening methodologies have a balanced structure of balance sheets assets since when cash are added to accounts receivables, the correspondent cash ratios (R_3) of MSCI and FTSE evolve (32.98% and 21.76% respectively).

In general, this case is highly desirable in Shariah compliance screening because cash ratio aims to filter out companies operating in the real economy and for which business activities are not mainly associated with placing cash in banks or financial instruments generating interests. Concretely, investing in companies with high level of cash ratio (R_3) is equivalent to purchasing cash directly which is not permissible. Additionally, lower values of this ratio mean also that levels of accounts receivables of compliant companies are reasonable implying lower exposure to default risk of third parties of these companies.

Standard & Poor's and FTSE include a fourth ratio for non-permissible incomes in their Shariah quantitative screening. The results on table 4 are approximately identical (0.00% and 0.47% respectively). This supposes that 13 to 19 companies of the sample have a very negligible part of incomes from Shariah non-compliant activities and interest compared to their revenues (much less than the authorized threshold of 5%). Furthermore, some companies have zero percent of non permissible incomes represented by $\min(R_4) = 0.00\%$.

3.2 Construction of Moroccan float-weighted Islamic Indices

The final results of Shariah screening permitted to filter out 13 Shariah compliant companies using the Dow Jones methodology. These were considered for the construction of the index we called Dow Jones Moroccan Islamic Index (hereafter, DJMII for short) for which we modeled the volatility to compare to that of the MASI$^{\text{®float}}$. The construction of the index used equation (2) aforementioned.

In the same way we built the FTSE Moroccan Islamic Index (FTSEMII) containing 13 companies, the S&P Moroccan Islamic Index (SPMII) with 19 constituents, and the MSCI Moroccan Islamic Index (MSCIMII) regrouping 6 companies.

The considered period for data goes from January 2, 2013 to December 31, 2014 making about 493 daily observations. Figure 1 below resumes the evolution of the MASI$^{\text{®float}}$ and the four constructed Islamic indices (DJMII, FTSEMII, SPMII and MSCIMII) in basis points within this period.

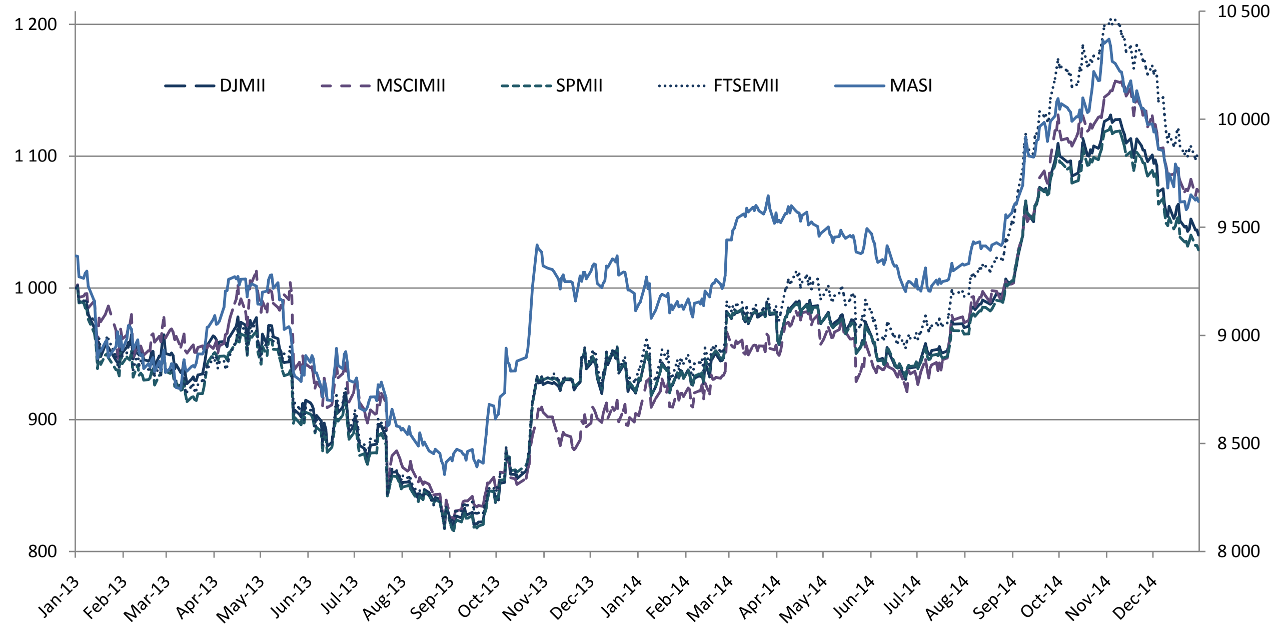

Figure 1: Evolution of Constructed Moroccan Islamic Indices and the MASI$^{\text{®float}}$

Figure 1 shows that all indices behaved relatively in the same way within the concerned period and followed the same trend upward and downward. However, it is worth noting that the five indices did not range within the same interval and the Islamic indices were more volatile compared to the MASI. Table 6 below supports this through descriptive statistics of the five indices.

Table 6: Descriptive Statistics of Studied Indexes

	MASI	DJMII	FTSEMII	SPMII	MSCIMII
Max	10370.92	1131.26	1203.68	1122.45	1157.12
Min	8356.4	817.50	817.98	815.76	819.53
Mean	9250.14	958.72	974.46	954.72	961.94
SD	442.57	71.21	91.25	70.05	77.72
C_v	4.78%	7.43%	9.37%	7.34%	8.08%

$C_v = SD/Mean.$

In terms of scale, the DJMII, FTSEMII, SPMII and MSCIMII varied around their respective means of (958.72, 974.46, 954.72 and 961.94 *basis points*) while the MASI fluctuated around its mean value of 10370.92 *bp.* This is mainly attributed to the difference between divisors of indices related to base market cap. The Islamic indices have a base market cap of the date January 2, 2013 while the MASI takes into consideration a base market cap of December 31, 1991.

As for volatility, coefficients of variation C_v on table 6 which measure the extent of standard deviation in relation to the mean show that Islamic indices are more volatile than the broad-based Moroccan All Shares Index (MASI).

3.3 Indices long run volatility estimation

In order to model the volatility through an EGARCH(1,1) model, we next calculated the log-returns of all indices. Figure 2 below plots their evolution through the considered period of study.

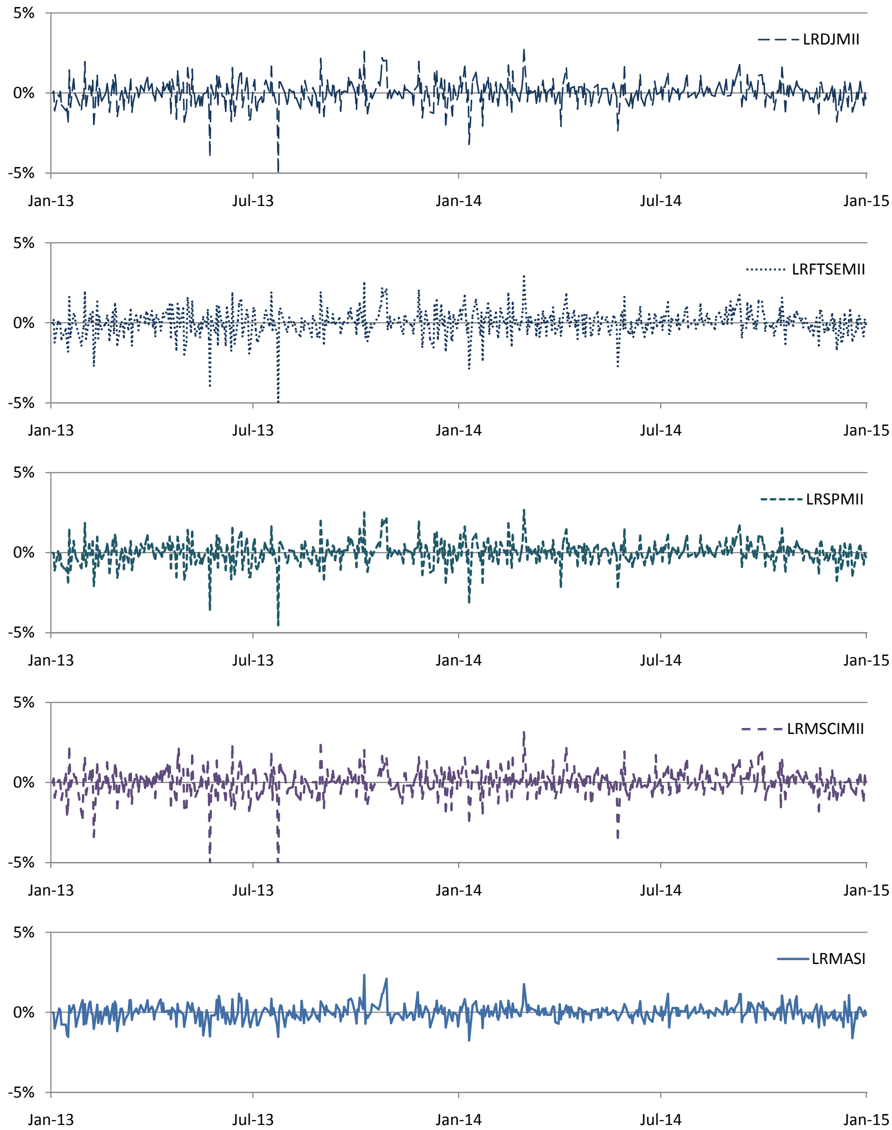

Figure 2: Log-returns of indices of comparison

It is clearly visible on figure 2 that log-returns of constructed Moroccan Islamic indices have a more volatile behavior compared to that of the MASI and this volatility tends to cluster. They varied within larger intervals reaching higher positive and lower negative values while the LRMASI fluctuated in a narrower interval. The behaviors of Islamic indices' returns are more turbulent than that of the MASI's returns and table 7 below confirms this through descriptive statistics.

Means and standard deviation calculated on table 7 show that higher average returns are connected with larger risk exposure; and the difference in returns between Islamic indices is mostly due to the screening criteria set by each methodology. Furthermore, Islamic indices are being highly exposed to risk compared to the MASI (high standard deviation values) which is mainly attributed to low diversification of the former.

In addition, distributions of Islamic indices' returns are left skewed (negative skewness) meaning that investing in Shariah compliant companies is associated with frequent small gains and few extreme losses. Conversely, log-returns' distribution of the MASI Index is right tailed (positive skewness) which refers to a more speculative behavior recording frequent small losses and few extreme gains.

Table 7: Descriptive Statistics of Indexes' Log-Returns

	LRMASI	LRDJMII	LRFTSEMII	LRSPMII	LRMSCIMII
Min	-1.76%	4.92%	-7.38%	-4.52%	-5.50%
Max	2.34%	2.72%	3.14%	2.66%	2.90%
Mean	0.005%	0.008%	0.014%	0.006%	0.019%
SD	0.50%	0.81%	0.91%	0.77%	0.84%
Skewness	0.10	-0.66	-1.55	-0.61	-0.80
Kurtosis	1.98	4.28	10.97	3.85	5.07
Jarque-Bera	78.90*	402.04*	566.16*	326.73*	2612.75*

* Significant at 1%.

Source: Summary of descriptive statistics calculated using Eviews9.

The kurtosis values of Islamic indices' returns assess that they are leptokurtic (higher than 3 of the normal distribution). As for returns of the MASI, these are platykurtic with a respective kurtosis of 1.98 less than 3. The non-normality of Islamic indices and MASI's returns is also supported by Jarque-Bera values (all significant at 1% meaning that we can easily reject the null-hypothesis of normality of returns distributions).

Table 8 shows the correlation coefficients between all indices returns. The correlation between Moroccan Islamic indices and the MASI is very high exceeding 0.74 (except for the MSCIMII 0.62). This is because all constructed Islamic indices regroup a part of companies listed on the MASI which is a broad-based index. The correlation coefficients inter-Islamic indices is the highest exceeding 0.83 which is due to cross-listed companies present in all indices.

Table 8: Correlation Coefficients for the Returns of MASI, DJMII, FTSEMII, SPMII and MSCIMII

	LRMASI	LRDJMII	LRFTSEMII	LRSPMII	LRMSCIMII
LRMASI	1.0000				
LRDJMII	0.7687*	1.0000			
LRFTSEMII	0.7425	0.9635*	1.0000		
LRSPMII	0.7795	0.9914*	0.9607*	1.0000	
LRMSCIMII	0.6177*	0.8514*	0.8904*	0.8355*	1.0000

* Significant at 1% ($p < 0.001$).

Table 9 reports the results of Augmented Dickey Fuller (ADF) test. The purpose of this test is to find out whether these series are stationary by testing the null hypothesis of existence of a unit root. T-statistics shown on table 9 are all less than their respective critical values at 1% level of significance. Hence, it is to assume that all returns series are stationary in the mean but not in the variance.

Table 9: Augmented Dickey Fuller unit root test

	LRMASI	LRDJMII	LRFTSEMII	LRSPMII	LRMSCIMII
Trend & Intercept	-21.32*	-23.14*	-23.64*	-23.15*	-24.29*
Intercept	-21.30*	-23.09*	-23.56*	-23.09*	-24.22*
None	-21.32*	-23.11*	-23.57*	-23.12*	-24.24*

* Significant at level 1% ($p < 0.001$).

Table 10 reports the log-likelihood (LLH), Akaike Information Criterion (AIC) and Schwartz Information Criterion (SIC). Models based on the Student-t distribution generally produced the largest

LLH values and the lowest AIC and SIC values compared to models that assume the Gaussian distribution. Based on these criteria, we ranked the estimated models from the most descriptive to least as follow: Student-t EGARCH, Student-t GARCH, Normal EGARCH, Normal GARCH. Of the models evaluated, the EGARCH model with student-t distributions (*i.e., Student-t EGARCH*) is the most likely to be consistent with the data generating process for the five indexes returns.

Table 10: Log-likelihood, AIC and SIC for estimated models

	GARCH(1,1)						EGARCH(1,1)					
	Normal			*t-student*			*Normal*			*t-student*		
	LL	AIC	SIC	LL	AIC	SIC	LL	AIC	SIC	LL	AIC	SIC
LRMASI	1916.26	-7.76	-7.72	1928.50	-7.80	-7.761	1918.42	-7.762	-7.72	1928.50	-7.80	-7.75
LRDJMII	1679.84	-6.80	-6.76	1709.40	-6.91	-6.87	1681.60	-6.80	-6.76	1709.94	-6.91	-6.86
LRFTSEMII	1663.43	-6.73	-6.70	1695.23	-6.86	-6.81	1665.81	-6.74	-6.69	1696.01	-6.86	-6.80
LRSPMII	1701.51	-6.88	-6.85	1730.79	-7.00	-6.96	1702.14	-6.88	-6.84	1730.92	-7.00	-6.95
LRMSCIMII	1619.87	-6.55	-6.52	1668.53	-6.75	-6.71	1632.00	-6.60	-6.56	1668.53	-6.75	-6.71

Based on the selected t-EGARCH(1,1) model, we next estimated the parameters shown in Table 11 below. Note that for all indices' returns an ARCH test was initially performed to test for heteroskedasticity. The results of ARCH in lag 1 suggest that there is no problem of heteroskedasticity.

Table 11: Estimates of t-EGARCH(1,1) Model for Indices' Returns

	LRMASI	LRDJMII	LRFTSEMII	LRSPMII	LRMSCIMII
ω_j	-4.866^{***}	-4.519^{***}	-4.621^{***}	-5.307^{***}	-4.681^{***}
β_j	0.560^{**}	0.550^{**}	0.541^{**}	0.472	0.528^{***}
γ_j	0.093	0.059	0.078	0.068	0.096
α_j	0.240^{**}	0.291^{**}	0.322^{**}	0.284^{**}	0.309^{**}
Half-life[a]	3.11	4.00	4.70	2.79	3.90
Long-run volatility[b]	1.574E−5	4.352E−5	4.207E−5	4.314E−5	4.931E−5

[a] Half-life $= \ln(0.5)/\ln(\alpha_j + \beta_j)$

[b] Long-run volatility $= \overline{\sigma_j^2} = \exp\left(\frac{\omega_j}{1-\beta_j}\right)$

*,** and *** Significant at levels 1%, 5% and 10% respectively.

According to the estimation results we can find that the leverage effect γ_j are all positive meaning that good news generate more volatility than bad news. It is interesting to observe that leverage effects for the MASI and MSCI Moroccan Islamic Index are higher (0.093 and 0.096 respectively) compared to those of the Dow Jones, FTSE and S&P Moroccan Islamic Indexes. This implies that good news have more effect on volatility of the MASI and the MSCIMII. In general, this supposes that Moroccan stock market is more sensitive for good news, a result that is in contrast to other studies for developed countries.

Furthermore, since constructed Islamic indices include only companies with low dept to equity ratio (less than 33%) which have very low or no financial leverage, it was expected to find smaller leverage effects for these indices compared to that of the broad-based MASI index.

Moreover, the symmetric effects measured by α_j are all significant at 5% for all indices meaning that volatility is sensitive to market events during the concerned period. Also, significant and positive α_j and β_j indicate that past fluctuations have positive influence on future volatility.

In respect to persistence of volatility, estimated β_j are all significant at 5% level of significance and they are almost equal (except for the SPMII). The MASI has the highest β_j of 0.56 which means that volatility of the index is the most persistent and takes the longest time to die. The half-life ratios which measure the period it takes a shock to decay over time show that the volatility for the MASI takes about 3.11 days to disappear while volatility of DJMII, FTSEMII and MSCIMII takes longer time to die (4, 4.7 and 3.9 days respectively).

As for long run volatility, we can declare that screening the stock market under Shariah compliance resulted in more volatile indices. As shown in table 11, the MASI has lower long term volatility compared to that of the constructed Islamic indices for the examined period. But surely, investors in Shariah compliant stocks do not sacrifice financial performance because of their ethical investment.

4 Conclusion

This paper has considered the Shariah-compliance screening of the Moroccan stock market using four different methodologies of world leading equity index providers (*i.e., Dow Jones Islamic Market World Index; S&P Global BMI Shariah Index; MSCI ACWI Islamic; FTSE Shariah All-World Index*). The first step of qualitative screening resulted in 55 Shariah-compliant companies for indexes using ICB broad industry classifiers (namely, Dow Jones and FTSE), and 57 Shariah-compliant companies for S&P and MSCI using GICS sector classifiers.

The second quantitative screening process based on financial ratios resulted ultimately in 13 Shariah compliant companies for the Dow Jones, 13 for the FTSE, 19 for S&P and 6 for the MSCI. The main differences between the outputs of Shariah-compliance screening processes are attributed to: (1) the use of different broad industry classifiers, (2) the use of different denominators for financial ratios, (3) the use of a fourth financial ratio by some indexes which measures the part of non-permissible incomes in relation with revenue, and (4) the adopting of different thresholds for financial screens by equity index providers.

These compliant companies were next used to construct four Moroccan Islamic indexes by means of the same method of calculation of the broad-based Moroccan All Shares Index (MASI).

The results show that returns of constructed Moroccan Islamic indices were higher and more volatile compared to that of the MASI. This indicates that investors in Shariah-compliant stocks do not sacrifice financial performance for their risky investment. Additionally, returns of Moroccan Islamic indices are left skewed which means that investing in Shariah-compliant companies records small gains and few extreme losses while investing in the MASI is contrarily associated with a more speculative behavior recording small losses and few extreme gains.

The comparison of two volatility models, namely GARCH(1,1) and EGARCH(1,1), assuming both Gaussian and Student-t distributions concluded in selecting t-EGARCH(1,1) for volatility modeling based on likelihood, AIC and SIC values. Empirical evidences suggest that the EGARCH model provides a better description and more parsimonious representation of data; and EGARCH(1,1) is sufficiently flexible to accommodate characteristics of data than the traditional GARCH model.

The estimates of parameters indicate that there is a positive leverage effect for all indices meaning that volatility of returns is influenced more by good news than bad news. Furthermore, the leverage effect is positively higher for the MASI compared to Islamic indices which is due to its large capitalization in one hand, and low debt to equity ratios for companies included in the Moroccan Islamic indexes in another hand.

Persistence of volatility of returns is found to be significant and almost equal for all indices meaning that volatility takes time to die. Based on the half-life values, the index that reverts to mean faster is the FTSEMII followed by DJMII, MSCIMII, MASI and lastly SPMII. It means that FTSEMII takes the longest time to revert to its mean or for any shock in volatility to decay.

In conclusion, on the arrival of the new banking law that introduced Islamic finance for the first time in Morocco, we suppose that these results could be very helpful for the Moroccan financial authorities in consideration with the construction of Islamic equity indices for Muslim investors seeking to invest ethically in accordance to their religious convictions but also for index funds managers and other equity market players.

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