Modeling Volatility of Islamic Stock Indexes: Empirical Evidence and Comparative Analysis

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This paper aims to investigate the volatility behavior of Islamic stock indexes compared to their conventional counterparts. Four major Islamic stock indexes have been the subject of our paper namely the Standard and Poor's Shariah index (S&P Shariah), the Dow Jones Islamic Market (DJIM) index, the FTSE Islamic index, the MSCI Islamic World as well as their conventional counterparts, respectively, the S&P 500, the Dow Jones Industrial Average (DJIA), the FTSE All world, and the MSCI World Indexes. GARCH models (Generalized Autoregressive Conditional Heteroscedastic) are used to estimate the conditional variance, particularly the Exponential GARCH model due to its ability to capture the leverage effect and leptokurtosis as the main stylized facts usually observed in financial times series. GARCH models are used also with Gaussian and non-Gaussian distribution in order to take into account the thick tails of daily data distribution. The results reveal that Islamic stock indexes were significantly affected by the financial crisis but they were less volatile than their conventional counterparts. This finding confirms the relative resilience of Islamic indexes to the global financial crisis, which has affected the Islamic finance as soon as the crisis has affected the real sector of the economy.

JEL Classifications: C51, C52, G15.

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The financial crisis of 2007-2008 has shaken the fundamental principles of the current financial system. Several factors have been cited as the cause of the crisis. Ebrahim (2008) identified two main factors. First is the inadequacy of market discipline in the current financial system, which resulted from the low use of risk-sharing instruments. Indeed, an unbridled financial innovation has led to indiscriminate lending and excessive risk-taking (Aziz, 2010). Second is the staggering expansion of the size of derivatives, including credit default swaps (CDS) and the concept of "too big to fail," which tends to assure the big banks that the central bank would always come to their rescue to prevent them from going bankrupt in order to avoid systemic disturbances.

All these factors have contributed to the emergence of a financial environment characterized by unhealthy expansion in the volume of credit, excessive debt, and the unsustainable rise in asset prices. Thus, the onset of the crisis was unavoidable.

Consequently, the severity of crash and its repercussions on the global economy has led policy-makers to search for alternatives that could restore the dynamics in the global economy in recession since 2007. In the wake of the crisis, the global financial community has intensified efforts to reform the international financial architecture to ensure its stability and resilience in a more challenging environment. The challenge for the financial community was to not only undertake the necessary regulatory reform that will minimize potential risks, but to also build a new financial architecture that will promote greater efficiency in the financial intermediation process, including across borders (Aziz, 2010).

In fact, the system should provide financial services that add value to the real economy. The close link between finance and the real sector of the economy is one of the fundamental principles of Islamic finance. Islamic finance derives its key strength from its inherent underlying principles. Islamic financial transactions must be accompanied by an underlying productive economic activity that will generate legitimate income and wealth, thereby establishing a close link between the financial transactions and productive flows. This reduces the Islamic financial system from over exposure to risks associated with excessive leverage and imprudent risk taking.

Born in the 70s, Islamic finance has been developed in the oil-producing countries; today it is still highly concentrated in the Persian Gulf and South East Asia (Fadhlaoui, 2007). Thus, Islamic finance is becoming one of the fastest growing segments of the global financial industry. It is estimated that the size of the Islamic banking industry at the global level was close to \$820 billion at end of 2008. Several factors have contributed to the strong growth of Islamic finance, including: strong demand in many Islamic countries for *Shariah*-compliant products; growing demand from conventional investors and the capacity of the industry to develop a number of financial instruments that meet most of the needs of corporate and individual investors (Hasan & Dridi, 2010).

In addition to the activities in the banking sector, Islamic finance has extended their activities to the financial markets, namely funds management. The first Islamic index was launched on the market in 1998. This is the "Muslim social awareness index" SAMI. Since then, the main providers of conventional indices extended their range and propose a wide range of Shariah index to accompany the accelerated development of Islamic finance, especially the "Shariah Compliant" funds. Through this range of Shariah indexes, all geographic areas are covered as well as all sectors and all levels of capitalization.

Despite the increasing importance of Islamic finance over the past several years, empirical studies on Islamic finance are scarce. There are few empirical studies which estimated Islamic stock market volatility. In fact, the study of volatility is important to academics, policy makers, and financial market participants for several reasons. First, prediction of financial market volatility is important to economic agents because it represents a measure of risk exposure in their investments. Second, a volatile stock market is a serious concern for policy makers because instability of the stock market creates uncertainty and thus adversely affects growth prospects. Thus, studying Islamic stock market volatility is a promising area for investors wishing to invest according to the guiding principles of their faith. Furthermore, our paper aims to conduct a comparative analysis between Islamic and Conventional stock indexes in order to investigate the volatility in the last decade coinciding with the subprime crisis.

Our paper will be structured as follows: section 1 narrates the literature review, section 2 presents

the econometric framework, and section 3 the empirical finding before concluding.

LITERATURE REVIEW

Islamic finance provides the opportunity to invest in the stock market according to the principles of Shariah. In fact, the Islamic financial services industry has developed a stringent set of criteria for investment, specifically to facilitate investments in the various stock markets around the world. These criteria represent part of the screening process to identify companies with business activities that do not comply with a minimum Shariah compliant standard, thereby rendering their stocks ineligible for purchase by Shariah-based investors. The criteria include tests at the level of a company's primary business and at the level of its financial or capital structure. In the more recent decade, such Shariah "screens" have been adopted by the major international index providers to establish specialized Islamic market indexes (Aziz, 2010).

Since their launch in 1998, the Islamic indexes have been the subject of some academic researches. The first works focused on the feasibility of introduction of this new class of indexes, their mode of operation, and their ethical character. Then, other empirical studies have investigated their absolute and relative performance and tried to attribute the outperformance or underperformance to various explanatory factors. Thus, the majority of studies have focused on the performance of Islamic stock indexes compared to their conventional counterpart.

Ahmad and Ibrahim (2002) conducted a comparative study between Kuala Lumpur Shariah Index (KLSI) and Kuala Lumpur Composite Index (KLCI). They compared the risk and return performance of KLSI with KLCI during the period 1999 to 2002. The results revealed that KLSI underperforms during the overall period and decline period but it overperform in growing period. Moreover, they found that there is no significant difference in performance of both

indices during the given period.

Hakim and Rashidian (2002) analysed the risk and return of Dow Jones Islamic Stock Market Indexes (DJIM) from 1999 to 2002. They initially compared DJIM index with the Wilshire 5000 stock market index. They found that return and risk of the Islamic index are less than the Wilshire 5000. The study also examined the long run and short run relationship existing among the variables using unit root test, co-integration, and causality test. They found that Islamic index returns and Wilshire 5000 returns are not co-integrated.

Hussein and Omran (2005) compared the performance of ethical investment with their unscreened benchmarks. The study empirically tested whether returns of FTSE Global Islamic Index are significantly different from their index counterpart (FTSE All- World Index). The results showed that the 215 application of ethical screening do not have an adverse effect on the FTSE Global Islamic Index performance.

Hussein (2005) tested whether monthly returns of financial time stock Exchange (FTSE) Global Islamic index and Dow Jones Islamic Market Index are significantly different from their common index for the period January 1996 to December 2004. In short run period, Islamic indexes overperform statistically during whole period and second bull market period. In long run, Islamic indexes overperform during entire period and second bull market period. Finally, the study found that there is a similar performance between indexes.

Concerning studies about stock market volatility, Yusof and Majid (2007) attempted to explore the extent to which the conditional volatilities of both conventional and Islamic stock markets in Malaysia are related to the conditional volatility of monetary policy variables. Generalized Autoregressive Conditional Heteroskedasticity GARCH-M, GARCH models and Vector Autoregressive (VAR) analysis are used for the monthly data during the period starting from January 1992 to December 2000. The results showed that interest rate volatility affects the conventional stock market volatility but not the Islamic stock market volatility. This highlights the tenet of Islamic principles that the interest rate is not a significant variable in explaining stock market volatility. The results provided further support that stabilizing interest rate would have insignificant impact on the volatility of the Islamic stock markets.

Chiadmi and Ghaiti (2012) analyzed the volatility behavior of S&P Shariah index and its counterpart S&P 500 using GARCH models in the period from December 29, 2006 to March 09, 2011. The results revealed that volatility persistence of both stock indexes was very significant but S&P Shariah index was less volatile than the conventional index. This result is very important indicating that Islamic stock indexes are more resilient than conventional indexes especially on the crisis period. Nevertheless, the study presents some limitations, particularly it has been the object of studying a single Islamic stock index and has not taken into account some stylized facts of financial times series namely the leptokurticity and the leverage effect captured by the Exponential GARCH model. So, our paper aims to extend the previous study by investigating other Islamic stock indexes and using asymmetric GARCH models with normal and non-normal distribution of residuals.

ECONOMETRIC FRAMEWORK

Empirical studies have shown that linear models are usually unable to explain the relevant features of financial data. This disability can be explained by four major reasons. First, financial relationships may be nonlinear. Second, financial asset returns may have distributions that present fat tails and excess peakedness at the mean. Third, the volatility in financial markets tends to appear in clusters. Fourth, the volatility may rise more following a large price fall than following a price rise of the same magnitude.

Campbell, Lo, and MacKinlay (1997) defined a non-linear data generating process as one that

can be written as:

$$y_t = f(u_t, u_{t-1}, u_{t-2}, \dots)$$
(1)

where y_t is a non-linear process, f is a non-linear function and u_t is independent and identically distributed error term.

They also give a slightly more specific definition as:

$$y_t = g(u_{t-1}, u_{t-2}, \ldots) + u_t \sigma^2(u_{t-1}, u_{t-2}, \ldots)$$
(2)

where g is a function of past error terms only and σ^2 is a variance term.

Campbell et al. (1997) suggested a classification for process y_t . It may be linear if both $g(u_{t-1}, u_{t-2}, ...)$ and $\sigma^2(u_{t-1}, u_{t-2}, ...)$ are linear (e.g. ARMA models). If $g(u_{t-1}, u_{t-2}, ...)$ is not linear, the process is characterized as nonlinear in mean (e.g. GARCH models), whereas it is characterized as nonlinear in variance when $\sigma^2(u_{t-1}, u_{t-2}, ...)$ is nonlinear.

Consequently, non-linear and conditional heteroskedastic models are the basic econometric tools used to estimate asset returns volatility. In this section, we review succinctly the different ARCH models used in this paper.

ARCH AND GARCH MODELS

Traditional time series techniques such as ARMA models assume generally that the error term ε_t is white noise; that is, with a zero mean and a constant variance. However, high frequencies financial data are associated with heteroscedasticity, that is, the variance of error term change over time. In his analysis of UK inflation, Engle (1982) observed that forecast errors appeared into clusters, that is, large forecast errors tend to follow large forecast errors and small forecast errors to follow small forecast errors. He suggested the first form of heteroscedasticity in which the variance of the forecast error depends on the size of the previous disturbance.

Alternatively to usual time-series techniques, Engle (1982) suggested the autoregressive, conditionally heteroscedastic, or ARCH model. Engle's model and its derivatives are widely spread in modeling financial and economic time series. Coulson and Robins (1985) used ARCH model to study the volatility of inflation. Engle, Hendry, and Trumble (1985) used ARCH specification to model the term structure of interest rates. Engle, Lilien, and Robins (1987) proved the power of ARCH model in forecasting the volatility of stock market returns. Domowitz and Hakkio (1985) used also ARCH model for modeling the behavior of foreign exchange markets.

In ARCH model architecture, the conditional variance, denoted by σ_t^2 , depends on the information available at time t -1. It can be represented as a linear function of a constant (which is long term mean of the variance) and the square residual return, denoted by ε_t , observed at the preceding period t-1.

So, for mean equation of ARCH model, we have:

$$r_t = \mu + \varepsilon_t \tag{3}$$

where r_t is the asset return at time t, μ is average return, and the residual return is defined by:

$$\boldsymbol{\varepsilon}_t = \boldsymbol{\sigma}_t \boldsymbol{z}_t \tag{4}$$

where z_t is a white noise.

For Variance equation, we have this equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \dots \dots + \alpha_1 \varepsilon_{t-q}^2 \quad (5)$$

The conditional variance σ_t^2 should be strictly positive at any point of time. To ensure this, all coefficients would be required to be non-negative:

 $\alpha_i > 0 \forall i = 0, 1, 2, ..., q$, (Brooks, 2004). In practice, researchers usually encounter some difficulties. First, there is no clear approach that leads to determine the value of q. Second, the value of q might be very large. Third, the nonnegativity constraints might be violated.

To overcome some of these difficulties, Bollerslev (1986) had suggested generalizing the

ARCH modeling to the direction of the ARMA model. The model is known as the Generalized Auto-Regressive Conditional Heteroscedastic model (GARCH model). This model allows the conditional variance σ_t^2 to be dependent on its own lags. The specification of GARCH model is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \, \sigma_{t-j}^2 \quad (6)$$

Where p is the number of lagged σ_t^2 terms and q is the number of lagged ϵ_t^2 terms. All parameters $\omega, \alpha_i \forall i = 1, 2, ..., q$ and $\beta_i \forall j = 1, 2, ..., p$ should be positive to ensure the non-negativity of the conditional variance.

Although the standard GARCH model can capture several important phenomena in the financial time series, it is unable to capture other volatility properties such as leverage effect. For example, the model assumes that the effect of different shocks on volatility depend only on the size regardless of its sign. As shown in Equation (6), the model depends on summation of square of shocks. It is well known that volatility is higher after negative shocks than after positive shocks of the same magnitude (Nelson, 1991), in other terms, bad news increases volatility more than good news. This has led to the use of non-linear distribution to take into account that type of stylized fact. Such non-linear models are asymmetric GARCH models, for example, EGARCH model.

EGARCH MODEL

The exponential GARCH model (EGARCH) has been introduced by Nelson (1991). Contrary to GARCH model, this model can deal with the leverage effect. The specification of EGARCH (p, q) is given as follows:

$$Ln(\sigma_t^2) = \omega + \sum_{j=1}^p \beta_j Ln(\sigma_{t-j}^2) + \sum_{i=1}^q \alpha_i \left[\left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{\pi}{2}} \right\} \right] + \sum_{i=1}^q \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \quad (7)$$

In the EGARCH model, the logarithm of the variance is modeled. Therefore, there is no need to impose the non-negativity constraints on the model parameters α , β , and γ . The parameters γ measure the asymmetry or the leverage effect. The EGARCH model allows the testing of the asymmetry. If $\gamma = 0$ then the model is symmetric and it can reduce to symmetric GARCH model. Notice that when ε_{t-i} is positive, the total effect of ε_{t-i} is $(\alpha_i + \gamma_i)|\varepsilon_{t-i}|$; whereas the total effect of ε_{t-i} is $(\alpha_i - \gamma_i)|\varepsilon_{t-i}|$ if ε_{t-i} is negative, (Kozhan, 2010). Therefore, the volatility generated by positive shocks should be less than that generated by negative shocks when $\gamma \prec 0$. In contrast, if $\gamma \succ 0$ then positive innovations are more destabilizing than negative innovations.

DENSITIES

The GARCH models are estimated using a maximum likelihood (ML) approach. The logic of ML is to interpret the density as a function of the parameters set, conditional on a set of sample outcomes. This function is called the likelihood function.

As already noted, financial time-series often exhibits non-normality patterns, that is, excess kurtosis and skewness. Bollerslev and Wooldridge (1992) proposed a Quasi Maximum Likelihood method (hereafter QML) that is robust to departure from normality. Indeed, they showed that under the normality assumption, the QML estimator is consistent if the conditional mean and the conditional variance are correctly specified. This estimator is, however, inefficient with the degree of inefficiency increasing with the degree of departure from normality (Engle & González-Rivera, 1991).

Since it may be expected that excess kurtosis and skewness displayed by the residuals of conditional heteroscedasticity models will be reduced when a more appropriate distribution is used, we consider three distributions in this study: the Normal, the Student's and the generalized error distribution.

Normal distribution. The normal distribution is by far the most widely used distribution when

estimating and forecasting GARCH models.

As written in Equation (3), we have: $r_t = \mu + \varepsilon_t$

Where r_t is the asset return at time t, μ is average return, and the residual return ε_t is defined by: $\varepsilon_t = \sigma_t z_t$ (Equation 4), where, z_t is a white noise.

The log-likelihood function of the standard normal distribution is given by:

$$L_T = -\frac{1}{2} \sum_{t=1}^{T} \left[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2 \right]$$
(8)

where σ_t^2 is the variance, and T is the sample size.

Student's distribution. Known as fat tail in financial time series, it may be more appropriate to use a distribution which has fatter tail than the normal distribution. Bollerslev (1986) suggested fitting GARCH model using student's distribution for the standardized error to better capture the observed fat tails in the return series.

For a Student-*t* distribution, the log-likelihood is

$$L_T = \sum_{t=1}^T \ln\left[\Gamma\left(\frac{\nu+1}{2}\right)\right] - \ln\left[\Gamma\left(\frac{\nu}{2}\right)\right] - 0.5 \ln \qquad (9)$$
$$[\pi(\nu-2)] - 0.5 \sum_{t=1}^T \left[\ln\sigma_t^2 + (1+\nu)\ln\left(1 + \frac{z_t^2}{\nu-2}\right)\right]$$

Where $\Gamma(.) = \int_0^\infty e^{-x} x^{\nu-1}$ is the gamma function; ν is the degrees of freedom and the parameter measuring the tail thickness $\Gamma(.) = \int_0^\infty e^{-x} x^{\nu-1}$.

When $\upsilon \to \infty$, we have the Normal distribution, so that the lower the υ the fatter the tails; z_t^2 is a white noise, σ_t^2 is the variance, and T is the number of observations.

Generalized error distribution. Finally, the log-likelihood function of the Generalized Error distribution is given by:

$$L_{GED} = \sum_{t=1}^{T} \left[\ln\left(\frac{v}{\lambda_v} - \mathbf{0}.5 \left| \frac{z_v}{\lambda_v} \right|^v \right) - (10) - (1 + v^{-1}) \ln(2) - \ln\Gamma\left(\frac{1}{v}\right) - \mathbf{0}.5 \ln\sigma_t^2 \right]$$

Where
$$\lambda_v = \sqrt{\frac{\Gamma\left(\frac{1}{v}2^{\frac{-2}{v}}\right)}{\Gamma\left(\frac{3}{v}\right)}}$$
 ,

υ is the degrees of freedom, 2 < υ ≤ ∞; Γ(.) = $\int_0^{∞} e^{-x} x^{υ-1}$ is the gamma function; $z_υ$ is a white noise and $σ_t^2$ is the variance.

To capture the non-normal density function, the generalized error distribution was used. It is a powerful alternative in cases where the assumption of conditional normality cannot be maintained. It can assume a Normal distribution, a leptokurtic distribution (fat tails) or even a platykurtic distribution (thin tails).

EMPIRICAL FINDING

Islamic Stock Indexes: Description and Screening Process

All Islamic indexes follow a common stock selection process which is called stock screening.

Due to the prohibition of some unlawful sectors, Shariah compliance criteria used by the providers of Islamic indices take the form of negative screens. While basic prohibitions and Shariah rules are strictly maintained in the screening process, indices may differ in some screening criteria. The benchmarks from which Islamic indices are selected are well-recognized conventional indices. In practice, Shariah scholars and regulators have developed qualitative and quantitative screens to filter out the stocks and to assess their compliance with Islamic principles. So to be included in the Islamic index, companies must have a lawful activity according to the Shariah guidelines and must respect some financial and extra-financial criteria. The independent Shariah boards carry out a two-step screening process regarding the scope of activities of firms and their financial ratios.

For example, The DJIM approach takes place on several levels. The first level examines the

debt ratios of the company. The ratio of debt / market capitalization was set by the Shariah Board of Dow Jones less than 33%. Then, a screening is established by minimizing the level of interest income unusable; Haram's share of income must be purified via a charitable donation. In terms of liquidity, many Muslim scholars consider it permissible for Islamic investors to buy shares of a company whose debts do not exceed 45% percent of total assets. The DJIM screening also requires that an Islamic investor may not purchase securities with a predetermined rate of return and a guaranteed capital, and he cannot buy the shares of companies whose main activity is illegal. In contrast, the Shariah Board index recommends the inclusion of companies with pro-environmental policies, or companies which provide humanitarian services.

The sample covers the period before and after the financial crisis. We will study four major Islamic stock indexes with their conventional counterparts. The stock indexes are:

The DJIM index: Launched in February 1999, the Dow Jones Islamic Market Index (Dow Jones 2010) reflects the evolution of societies from 66 countries around the world that meet the criteria of Islamic finance. The DJIMI family includes more than 90 indicators divided into different geographical areas, sectors, and company size.

The FTSE All Shariah: The FTSE Shariah All-World Index is the result of a joint initiative between FTSE and Yasaar to create a Shariah compliant index family. Yasaar is responsible for reviewing the Shariah compliance of existing and prospective constituents of the FTSE Shariah All-World Index, which is made up of the large and mid-capitalization stocks from the FTSE Shariah Global Equity Index Series. The FTSE Shariah Index covers all regions across both developed and emerging markets, to create a comprehensive Shariah indexing solution.

The S&P Shariah index: The Standard & Poor's was launched in 2006, the Islamic version of its benchmark S&P 500.

The MSCI Islamic: Launched in March 2007,

the family of Islamic indices Morgan Stanley Capital International provides a wide geographical coverage.

Empirical Results

The data consist of 1,053 daily observations of S&P Shariah index and its conventional counterpart from the period December 29, 2006 to March 09, 2011, 3,083 daily observations of the DJIM index and its conventional counterpart from the period December 31, 1998 to March 09, 2011, 877 daily observations of the FTSE All Shariah and its conventional counterparts from



Figure 1. Daily closing prices of S&P Shariah index



Figure 3. Daily closing prices of S&P 500 index

October 26, 2007 to March 09, 2011, and 831 daily observations of the MSCI Islamic World and its conventional counterparts from October 26, 2007 to March 09, 2011.

The analysis of the figures below shows that the Islamic stock index moves in the same direction as its conventional counterpart (Figures 1 and 3). In terms of evolution, we can identify three main phases. The first phase is characterized by a lull, it is spread over the first year, and we see a stagnation of both indexes. From December 2007, both indexes have entered a phase of decline that lasted until the first quarter of 2009, during which time both Islamic and conventional indices



Figure 2. Daily returns of S&P Shariah index



Figure 4. Daily returns of S&P 500 index

declined respectively by -30.82% and -39.06%. March 2009 marks the beginning of the third phase of regaining their pre-crisis level by March 2011.

Regarding the DJIM index and its conventional counterpart DJIA, we notice that the closing prices of both indexes show an alternation in terms of trend like S&P Shariah and S&P 500 indexes, with a sharp decline for both indexes in 2000 coinciding with the Internet bubble that has impacted the field of new information technologies. Both indexes are also affected in 2007-2008 period coinciding with the subprime crisis (Figures 5 and 7).



Figure 5. Daily closing prices of DJIM index



Figure 7. Daily closing prices of DJIA index

Furthermore, over the entire period, daily data show that both indexes move in the same direction whether it is rising or falling.

MSCI Islamic stock index was launched in full subprime financial crisis, which explains the decrease in the first year of existence. The graphs above show that both indices follow the same trend both the upside and downside of the market. March 2009 marked the end of the downward phase of the two indices and a gradual return on the rise, Islamic index permanently amplifies this trend. Indeed, the increase in both indices continued without reaching the level before the



Figure 6. Daily returns of DJIM index



Figure 8. Daily returns of DJIA index



Figure 9. Daily closing prices of MSCI Islamic index



Figure 11. Daily closing prices of MSCI Shariah index

crisis.

Finally, we compared the evolution of the FTSE Shariah Islamic with its benchmark FTSE All world index since its inception. In January 2007, the FTSE Shariah Index has replaced the former Islamic Stock Exchange index of Malaysia: Kuala Lumpur Shariah Index (KLSI).

When reading the chart above, on the evolution of FTSE Shriah and FTSE All World, we note that both indexes follow the same trend on the upside and downside. We can distinguish four main phases. The first phase is bullish; it starts from the start of the Islamic index FTSE Shariah which amplifies the trend of rising more than conventional FTSE All World index. This bull





Figure 12. Daily returns of MSCI Shariah index

episode lasted for 12 months, during which the two indices increased by 50% for FTSE Shariah and 34% for FTSE All World. The subprime crisis has affected the Malaysian stock market in January 2008 with a historically high level for both registered on January 11, 2008 indices. From that date, the two indices began a phase of decline that lasted until October 2008. During the downward period, both indices recorded a negative return of -42.04% for FTSE Shariah and -38.53% for the FTSE All World. Then, the two indices have entered a phase of stagnation until the first quarter of 2009, and then began to increase gradually from March 2009 to return to the levels before the crisis in early 2011.



Figure 13. Daily closing prices of FTSE Shariah



Figure 15. Daily closing prices of FTSE All World

We can also notice that the four series of Islamic closing prices are not stationary. We will proceed to the logarithmic differentiation of closing prices. Daily logarithmic returns seem to be stationary around a constant. We can note in Figures 2, 6, 10, and 14 that fluctuations take both positive and negative values around the mean. The returns evolution of four Islamic indexes show they are highly volatile. The same results are verified in the case of their conventional counterparts. Knowing that the distribution of



Figure 14. Daily returns of FTSE Shariah



Figure 16. Daily returns of FTSE All World

white noise mark an extreme regularity of the random Gaussian, we can observe clearly that the four logarithmic returns distribution of both Islamic and conventional indexes seem to be different from a white noise distribution's and cycles seem to occur due to the high variability of logarithmic returns.

Given the graphs showing the closing prices evolution and showing daily returns of Islamic indexes, it is clear that they have been significantly affected by the subprime crisis and therefore a significant volatility was recorded in this period, as well as their conventional counterparts.

We will decline the statistical properties of Islamic indexes and their conventional counterparts in Table 1 below.

First, the coefficient of kurtosis for the four Islamic indexes as well as their conventional counterparts is very high and greater than 3 (kurtosis value for a normal distribution). This excess kurtosis indicates a high probability of occurrence of extreme points for both conventional and Islamic indexes. Second, the coefficient of skewness of both Islamic and conventional indexes is different from 0 (the case of a normal distribution). This illustrates the presence of asymmetry, which can be an indicator of nonlinearity since the Gaussian linear models are necessarily symmetrical. The distributions of daily logarithmic returns of Islamic and conventional indexes do not follow a normal distribution as shown by the Jarque-Bera statistic whose probability is less than 0.05 for all indexes, which is a general feature of financial series.

We noticed in Figures 2, 6, 10, and 14 regarding daily returns of Islamic indexes, that strong variations are usually followed by strong variations and small variations are usually followed by small variations. This is the phenomenon of volatility clustering.

This grouping volatilities packet is mainly due to correlations of financial series. Because of this correlation, a large movement corresponding to a high volatility is likely to be followed by a movement of the same magnitude. It is the same for small movements (Brooks, 2004). The volatility clustering is quantified by the autoregressive heteroscedastic volatility models. In fact, the ARMA models (autoregressive and moving average) time series suppose constant variance (homoscedasticity assumption). This model neglects potentially the information contained in the residual factor in the series. So, to address this problem, we model the volatility using a GARCH (1.1). Before modeling the volatility using GARCH models, we use ARCH Lagrange Multiplier test.

ARCH Lagrange Multiplier test. Since the ARCH model has the form of an autoregressive model, Engle (1982) proposed the Lagrange Multiplier (LM) test, in order to test for the existence of ARCH behavior based on the regression. The test statistic is given by NR^2 where R^2 is the sample multiple correlation coefficient computed from the regression of ε_t^2 on a constant $\varepsilon_{t-1}^2, \dots, \varepsilon_{t-p}^2$, and N is the sample size. Under the null hypothesis that there is no ARCH effect, the test statistic is asymptotically distributed as chi-square distribution with q

Table 1. Statistics Properties of Daily Returns of Islamic Stock Indexes and their Conventionalconterparts

	S\$P Shariah	S\$P 500	DJIM	DJIA	FTSE All Sahria	FTSE All World	MSCI Islamic	MSCI World
Obs	1053	1053	3083	3083	877	877	831	831
Mean	0.000263	0.000077	0.000154	0.000152	-0.00002	0.00002	-0.00005	0.0006
Median	0.001016	0.000898	0.000546	0.000402	0.000258	0.00009	0.000589	0.000930
Maximum	0.122799	0.115800	0.102682	0.110803	0.096252	0.098387	0.093807	0.147373
Minimum	-0.09085	-0.09035	-0.07859	-0.07873	-0.08439	-0.088483	-0.07553	-0.13370
St Deviation	0.015477	0.016985	0.011498	0.012774	0.014459	0.016745	0.013554	0.033167
Skewness	0.263343	0.021419	0.001989	0.179974	-0.141075	0.161587	-0.10866	0.138447
Kurtosis	12.64286	10.37128	10.39399	10.70916	10.26335	8.761433	10.68207	5.946362
JarqueBera	4091.876	2384.065	7022.952	7400.423	1930.708	1177.936	2045.001	292.6538
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

	S\$P Sharia	S\$P 500	DJIM	DJIA	FTSE All Sahria	FTSE All World	MSCI Islamic	MSCI World
F-Statistic	31.629	31.169	48.399	133.996	13.76436	29.10515	29.53814	72.50671
Probability	0.000	0.000	0.000	0.000	0.000220	0.000	0.000	0.000
NR^2	30.762	30.328	46.725	128.6318	13.58176	28.20263	28.58737	66.63403

 Table 2. Results of ARCH Lagrange Multiplier Test for Islamic and Conventional Indexes

Table 3. Coefficients of GARCH (1.1) Model for DJIA and DJIM Indexes

	DJIA			DJIM			
	Gaussian	Student's	GED	Gaussian	Student's	GED	
α_0	0.00000107 [0.0001]	0.00000107 [0.0021]	0.00000104 [0.0041]	0.000001 [0.0000]	0.0000009 [0.0013]	0.000001 [0.0007]	
α_1	0.086068 [0.0000]	0.084951 [0.0000]	0.085477 [0.0000]	0.080535 [0.0000]	0.077044 [0.0000]	0.078775 [0.0000]	
β_1	0,908927 [0.0000]	0.910415 [0.0000]	0.909932 [0.0000]	0.911689 [0.0000]	0.916768 [0.0000]	0.913873 [0.0000]	
υ		9.143704 [0.0000]	1.457629 [0.0000]		9.209713 [0.0000]	1.381061 [0.0000]	
σ^2	0.0002138	0.0002309	0.0002265	0.0001350	0.0001438	0.0001360	
LnL*	9391.781	9415.703	9425.129	3214.400	10025.01	10026.08	
AIC*	-6.297740	-6.313118	-6.319442	-6.095727	-6.501628	-6.502325	

degrees of freedom. The results of ARCH Lagrange Multiplier test are declined in Table 2.

The null hypothesis H_0 : there is homoscedasticity errors and no heteroscedasticity exists and the Alternative Hypothesis H_1 : there is no homoscedasticity error and there is heteroscedasticity exists.

We notice that the probability of $N R^2$ is less than 0.05 (P-value) for all stock indexes, so we reject the H_0 hypothesis for both Islamic and conventional indexes. Thus, ARCH effect exists. Now, we are going to estimate conditional volatility using GARCH (1.1) model with different densities.

Where $\sigma^2 = \alpha_0 / (1 - \alpha_1 - \beta_1)$ is the unconditional volatility and represents the volatility limit σ_t^2 when t tends to $+\infty$ for GARCH (1.1). LnL represents the log-likelihood of the parameters linked to the data and AIC is Akaike Information Criterion, which is a criterion used to select the best model.

Let us remember that the first term α_0 represents a minimum variance threshold below which the conditional variance does not go down. It is small and very close to 0 for Islamic indexes as well as their conventional counterparts (0.00000104 for DJIA and 0.000001 for DJIM, in the case of generalized error distribution).

The second term α_1 represents the sum of squared residuals, which reflects the impact of shocks on volatility. When a crash occurs at time t, the value of returns is very different from the average, and so the residue is very large. In view of Table 3, we can see that the subprime crash significantly impacted the volatility of the Islamic index (DJIM) as well as its conventional counterpart (DJIA). The magnitude of the impact of the shock is more important for the conventional index DJIA than the Islamic index DJIM regardless of the nature of the innovation distributions (0.085477 for DJIA and 0.078775 for DJIM, in the case of generalized error distribution).

The third term β_1 represents the sum of past variances modeling the persistence of volatility. This persistence seems to be significantly higher for both indexes DJIM and DJIA, whatever the distributional nature of innovation with a very small difference between both indexes (0.909932 for DJIA and 0.913873 for DJIM, in the case of generalized error distribution).

Test of equivalence of variances for DJIM and DJIA indexes. Regarding the unconditional volatility, it is clear from the table above, the DJIM is considerably less volatile than the DJIA. We used Fisher's test to confirm this finding. Let H_0 be the Hypothesis: the sample variances are homogenous and H_1 : the sample variances are not homogenous.

The statistic of Fisher's test consists in calculatingthis value: $F_{obs} = \sigma^2_{max}/\sigma^2_{min} =$ the biggest variance/the smallest variance

If $F_{obs} > F_{the}$, we reject the H_0 hypothesis, where $F_{the} = F_{n_1-1,n_2-2,0.95}$ is the value statistic displayed by Fisher table, $n_1 - 1$ and $n_2 - 1$ are degrees of freedom of both samples with 95% as a level of significance.

If $F_{obs} < F_{the}$, we accept the hypothesis.

Following the test result declined in Table 4, we conclude that DJIM index is less volatile than DJIA index. Thus, we can confirm the significant impact of the subprime crisis on the volatility of the Islamic index, but it is of lesser

scale than its conventional counterpart DJIA. This confirms the empirical results highlighting the relative resilience of Islamic assets to face the global financial crisis. About the most suitable model, we can retain the GARCH (1.1) with a Generalized error distribution for both indexes (DJIM and DJIA), as it minimizes the Akaike criterion and maximizes the log-likelihood.

Regarding S&P Shariah index and its conventional counterpart S&P 500 index in Table 5, it is clear that all coefficients of the GARCH (1.1) are very significant for both indexes, with little difference of α_1 coefficient measuring the impact of shocks on volatility (0.097740 for S&P 500, and 0.098654 for S&P Shariah, in the case of generalized error distribution), but the persistence of volatility is slightly more important for the conventional index (0.898077 for DJIA and 0.888939 for DJIM, in the case of generalized error distribution). It is due to the severe impact of the crisis. Finally, the unconditional volatility of S&P Shariah is also significantly lower than S&P 500. We confirm this finding by applying Fisher's test in Table 6. The difference is very significant, in fact, holding the GARCH (1.1) with a generalized error distribution minimizing the Akaike criterion and maximizing the likelihood, the unconditional volatility of the S&P 500 is two times higher than S&P Shariah. The same results are observed for FTSE Shariah and MSCI Islamic indexes (Tables 7, 8, 9, and 10) that confirm the persistence of the volatility for Islamic indexes but with a lesser magnitude than their conventional counterparts.

Table 4. Results of Fisher's Test for DJIM and DJIA Indexes

	Gaussian	Student's	GED
F _{obs}	1,58	1,60	1,66
F_{the}	1.01	1.01	1.01
The test result	$F_{obs} > F_{the},$ H_0 rejected	$F_{obs} > F_{the}$ H_0 rejected	$F_{obs} > F_{the}$ H_0 rejected

		S&P 500			S&P Shariah	
	Gaussian	Student's	GED	Gaussian	Student's	GED
$\alpha_{_0}$	0.00000294 [0.0000]	0.00000157 [0.0452]	0.000002 [0.0158]	0.0000032 [0.0000]	0.000002 [0.0141]	0.000003 [0.0079]
α_1	0.088232 [0.0000]	0.104018 [0.0000]	0.097740 [0.0000]	0.093636 [0.0000]	0.102103 [0.0000]	0.098654 [0.0000]
β_1	0.898366 [0.0000]	0.900956 [0.0000]	0.898077 [0.0000]	0.887777 [0.0000]	0.890314 [0.0000]	0.888939 [0.0000]
υ		4.901273 [0.0000]	1.171684 [0.0000]		7.250350 [0.0000]	1.318836 [0.0000]
σ^2	0.0002193	The condition $\alpha_1 + \beta_1 < 1$, is not verified	0.0004781	0.0001721	0.0002637	0.0002418
LnL	3094.021	3118.848	3128.547	3187.202	3202.858	3208.084
AIC	-5.867087	-5.912342	-5.930763	-6.045968	-6.073805	-6.083731

 Table 5. Coefficients of GARCH(1.1) model for S&P Shariah and S&P 500 Indexes

 Table 6. Results of Fisher Test About Equivalence of Variances for S&P 500 and S&P Sharia

	Gaussian	Student's	GED
F _{obs}	1.58	Condition $\alpha_1 + \beta_1 < 1$, is not verified	1.66
F_{the}	1.01	1.01	1.01
The test result	$F_{obs} > F_{the},$ H_0 rejected	We can't apply the Fisher's test	$F_{obs} > F_{the}$ H_0 rejected

Despite these conclusive results, GARCH model used to model the volatility presents some limitations; it does not take into account the phenomenon of asymmetric volatility. Nelson (1991) studied the asymmetric variance in variance with the EGARCH model. Nelson argued that there is an asymmetry between the effect of past positive and negative variations in the volatility. Asymmetries in the volatility dynamics are known by the term leverage effect since Black (1976) noted that the returns are negatively correlated with variations in volatility, in the sense that volatility tends to rise in response to bad news and fall in response to good news. We will model this asymmetry using EGARCH (1.1) with Gaussian, student's, and generalized error distribution.

Table 11 shows that the coefficients of EGARCH (1.1) model are all significant. The effect of negative asymmetry exists for both the Islamic index DJIM and his conventional counterpart DJIA. This means that for both indexes, negative past returns increased more volatility than past positive returns. For DJIM

]	FTSE All Sharia	h		FTSE	
	Gaussian	Student's	GED	Gaussian	Student's	GED
0	0.00000198	0.00000207	0.00000214	0.00000387	0.0000048	0.0000044
α_0	[0.00147]	[0.0265]	[0.0645]	[0.0038]	[0.0230]	[0.0310]
0	0.091447	0.081644	0.087059	0.094521	0.100576	0.097199
α_1	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0001]	[0.0002]
0	0.897317	0.902717	0.899737	0.891981	0.882061	0.885903
p_1	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
		12.12391	1.357393		6.707368	1.397421
υ		[0.0308]	[0.0000]		[0.0002]	[0.0000]
σ^2	0.000176	0.000132	0.000162	0.00028	0.00028	0.00026
LnL*	2680.478	2689.219	2695.553	2456.366	2468.994	2470.326
AIC*	-6.108397	-6.126070	-6.140532	-5.747634	-5.774898	-5.778022

Table 7. Coefficients of GARCH (1.1) Model for FTSE Islamic and FTSE Indexes

Table 8. Results of Fisher's Test for FTSE Sharia and FTSE Indexes

	Gaussian	Student's	GED
F _{obs}	1.59	2.12	1,60
F_{the}	1.01	1.01	1.01
The test result	$F_{obs} > F_{the},$ H_0 rejected	$F_{obs} > F_{the}$ H_0 rejected	$F_{obs} > F_{the}$ H_0 rejected

 Table 9. Coefficients of GARCH (1.1) Model for MSCI World Islamic and MSCI World

	MSCI Islamic World				MSCI World			
	Gaussian	Student's	GED	Gaussian	Student's	GED		
α_0	0.00000160 [0.0115]	0.00000169 [0.0500]	0.00000165 [0.0714]	0.000020 [0.0000]	0.000009 [0.0654]	0.000014 [0.0183]		
α_1	0.101301 [0.0000]	0.094866 [0.0000]	0.095191 [0.0000]	0.076943 [0.0000]	0.080186 [0.0001]	0.081275 [0.0004]		
β_1	0.888316 [0.0000]	0.895751 [0.0000]	0.893304 [0.0000]	0.906184 [0.0000]	0.916375 [0.0000]	0.908871 [0.0000]		
υ		5.890053 [0.0007]	1.292832 [0.0000]		6.259647 [0.0000]	1.333545 [0.0000]		
σ^2	0.000154	0.000180	0.000143	0.001185	0.002617	0.001420		
LnL*	2620.167	2632.176	2638.235	1700.628	1729.504	1723.522		
AIC*	-6.309210	-6.335768	-6.350386	-4.233777	-4.303380	-4.288444		

	Gaussian	Student's	GED
F _{obs}	7.69	14.53	9.93
F _{the}	1.01	1.01	1.01
The test result	$F_{obs} > F_{the},$ H_0 rejected	$F_{obs} > F_{the}$ H_0 rejected	$F_{obs} > F_{the}$ $H_{_{0}}$ rejected

 Table 10. Results of Fisher's Test for MSCI ISLAMIC and MSCI Indexes

Table 11. Coefficients of EGARCH (1.1) for DJIM and DJIA Indexes

		DJIM			DJIA	
	Gaussian	Student's	GED	Gaussian	Student's	GED
Q	-0.229536	-0.204369	-0.21817	-0.225957	-0.198505	-0.204149
α_0	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
0	0.127555	0.111969	0.120749	0.100818	0.102202	0.100998
α_1	[0.0000]	[0.0000]	[0.0000]	[0.000]	[0.0000]	[0.0000]
07	-0.069400	-0.088791	-0.078355	-0.112760	-0.114772	-0.113355
γ_1	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ß	0.985935	0.987535	0.986736	0.983873	0.987200	0.986539
P_1				[0.0000]	[0.0000]	[0.0000]
		9.325166	1.499693		8.912048	1.448431
υ		[0.0000]	[0.0000]		[0.0000]	[0.0000]
LnL	10022.70	10063.75	10056.97	9801.403	9836.854	9839.709
AIC	-6.500133	-6.526122	-6.521718	-6.360651	-6.383022	-6.384876

and DJIA indexes, a slight difference is observed between the EGARCH coefficients.

Regarding S&P Shariah Index and its conventional counterpart S&P 500, all the coefficients of EGARCH model (1.1) are clearly significant (Table 12). We notice the existence of the negative asymmetry for both indexes. In view of the term measuring the impact of the shock on return, the magnitude of this impact is less for the Islamic index S&P Shariah compared to its conventional counterpart S&P 500 (0.096478 for S&P Shariah and 0.110174 for S&P 500, in the case of generalized error distribution). We also note that the autoregressive term quantifying the impact of previous volatility on current volatility, is also lower for S&P Shariah Index versus S&P 500 index (0.968178 for S&P Shariah and 0.982570 for S&P 500, in the case of generalized error distribution). The EGARCH (1.1) with a generalized error distribution is the best suitable for modeling the asymmetric volatility of both Islamic (S&P Shariah and DJIMA) and conventional indexes (S&P 500 and DJIA).

Regarding FTSE Shariah and MSCI Islamic indexes and their conventional counterparts, we can also notice that all the coefficients of EGARCH model (1.1) are clearly significant. We also note that the autoregressive term quantifying the impact of previous volatility on current volatility, is also lower for the two Islamic indexes (Tables 13 and 14).

		S&P Shariah			S&P 500	
	Gaussian	Student's	GED	Gaussian	Student's	GED
α_0	-0.36493 [0.0000]	-0.33120 [0.0000]	-0.3511 [0.0000]	-0.310214 [0.0000]	-0.216530 [0.0000]	-0.244580 [0.0000]
α_1	0.094479 [0.0003]	0.100026 [0.0013]	0.096478 [0.0047]	0.111267 [0.0000]	0.107999 [0.0003]	0.110174 [0.0015]
γ_1	-0.172442 [0.0000]	-0.180886 [0.0000]	-0.184521 [0.0000]	-0.145154 [0.0000]	-0.158202 [0.0000]	-0.152546 [0.0000]
β_1	0.966470 [0.0000]	0.970693 [0.0000]	0.968178 [0.0000]	0.974247 [0.0000]	0.985358 [0.0000]	0.982570 [0.0000]
υ		8.054136 [0.0000]	1.381061 [0.0000]		5.536603 [0.0000]	1.229837 [0.0000]
LnL	3214.400	3229.366	3231.887	3116.857	3139.136	3145.017
AIC	-6.095727	-6.122253	-6.127041	-5.908561	-5.948977	-5.960147

 Table 12. Coefficients of EGARCH (1.1) Model for S&P Shariah and S&P 500 Indexes

 Table 13. Coefficients of EGARCH (1.1) Model for FTSE ALL Shariah and FTSE Indexes

	F	TSE All Sharia	h	FTSE		
	Gaussian	Student's	GED	Gaussian	Student's	GED
α^{0}	-0.241375 [0.0000]	-0.235067 [0.0000]	-0.238067 [0.0000]	-0.095083 [0.0018]	-0.094768 [0.0260]	-0.097511 [0.0302]
$\alpha_{_1}$	0.121432 [0.0000]	0.116695 [0.0001]	0.117930 [0.0002]	0.103982 [0.0000]	0.102074 [0.0000]	0.105831 [0.0000]
γ_1	-0.111073 [0.0000]	-0.119002 [0.0000]	-0.117007 [0.0000]	0.121576 [0.0000]	0.136929 [0.0000]	0.125872 [0.0000]
β_1	0.983609 [0.0000]	0.983978 [0.0000]	0.983818 [0.0000]	0.997354 [0.0000]	0.997459 [0.0000]	0.997605 [0.0000]
υ		7.413288 [0.0000]	1.418603 [0.0000]		7.385978 [0.0001]	1.455543 [0.0000]
LnL	2697.415	2705.326	2709.024	2432.914	2446.004	2444.361
AIC	-6.144784	-6.160561	-6.169004	-5.723853	-5.752369	-5.748493

	MS	SCI Islamic Wo	rld	MSCI World		
	Gaussian	Student's	GED	Gaussian	Student's	GED
α_0	-0.270833 [0.0000]	-0.260295 [0.0000]	-0.260252 [0.0000]	-0.082426 [0.0003]	-0.025356 [0.0959]	-0.026276 [0.1107]
α_1	0.122873 [0.0000]	0.121528 [0.0005]	0.119578 [0.0014]	0.058160 [0.0002]	0.024950 [0.1124]	0.021918 [0.1628]
γ_1	-0.141072 [0.0000]	-0.147654 [0.0000]	-0.144570 [0.0000]	0.064368 [0.0000]	0.074214 [0.0000]	-0.067769 [0.0000]
β_1	0.981048 [0.0000]	0.982188 [0.0000]	0.982115 [0.0000]	0.994143 [0.0000]	0.998883 [0.0000]	0.998397 [0.0000]
υ		7.437413 [0.0067]	1.387711 [0.0000]		6.903031 [0.0000]	1.382900 [0.0000]
LnL	2643.172	2650.358	2655.188	1715.307	1742.739	1735.144
AIC	-6.362296	-6.377221	-6.388873	-4.267932	-4.333929	-4.314966

 Table 14. Coefficients of EGARCH (1.1) Model for MSCI Islamic World and MSCI World

It is evident from these conclusive results, that Islamic stock indexes were significantly affected by the global financial crisis. In fact, they recorded a very significant volatility due to the disruptions in the global financial system exposed to the disintegration because of the severity of the crisis and its negative impact on the entire economy. However, Islamic stock indexes have shown relative resilience compared to their conventional counterparts. This empirical result is already verified by a study by two researchers from the International Monetary Fund, Maher and Dridi (2010), who showed that during the crisis, Islamic banks have shown a greater resilience than their conventional counterparts.

Resilience is due to several factors. First, the adherence to Islamic principles has protected Islamic financial institutions against the damaging effects of the crisis. These principles include the requirement of ethical conduct in doing business; the risk-sharing principle; the availability of credit primarily for the purchase of real goods and services; restrictions on the sale of debt,

short sales, and excessive uncertainty; and the prohibition to sell assets not owned. Second, the inherent strengths of Islamic finance, including the close link between financial transactions and productive flows and the built-in dimensions of governance and risk management, had contributed to its viability and resilience (Aziz, 2009). These views were echoed by Governor Durmus YIImaz of the Central Bank of Turkey who noted that there was a lack of a consensus view on the role of Islamic finance on price and financial stability, but argued that during the recent crisis, Islamic financial institutions had demonstrated significant resilience. In particular, he noted that these institutions offer products that limit excessive leverage and disruptive financial innovation, thereby ensuring macroeconomic stability.

El-Said and Ziemba (2009) agreed that Islamic financial institutions have avoided the subprime exposure, but they are subject to the second round effect of the global crisis. They argued that because the global financial crisis originated from subprime mortgage portfolios that were spun off into securitized instruments subsequently offered as investments, Islamic financial institutions were not affected because Islamic finance is based on a close link between financial and productive flows.

Despite the resilience of Islamic finance to the crisis, it should be noted that some Islamic financial institutions have experienced deterioration in their financial situation with Dubai Islamic bank because its economy is based solely on non-productive sectors such as tourism and real estate (Masmoudi & Belabed, 2010).

Elsewhere, the unconditional volatility of conventional stock indexes was doubly higher (Tables 3, 5, 7, and 9). The persistence of volatility was also higher for conventional indexes. This is due to several factors. First, there is a place increasingly prominent attributed to the financial sector in modern economies making any crisis in this sector a source of instability in the economic system as a whole. Then, there's a growing integration of financial markets, driven by advances in the field of information technology and also the installation of complex financial instruments, so any shock in a financial center will probably spread to affect different investors in various financial markets. Finally, the crisis began in the United States of America, which is the greatest economy in the world and facing worrying macroeconomic imbalances marked by chronic federal budget deficit and growing public debt (Lim, 2008). This considerable fragility is also due to a lack of regulatory rigor that encouraged excessive risk-taking.

Kameel (2009) argued that the severity of financial crisis is due also to the imperfection of the monetary system where fiat money is mainly emitted in the form of debt generating compound interest. So the debt burden is growing exponentially which is imposed on productive real economy. Being unable to grow at the same rate as debt, the real economy finally succumbs and falls into a liquidity trap, where even low interest rates cannot encourage investment that is necessary to stimulate the economy.

CONCLUSION AND IMPLICATIONS

Islamic finance is a part of global finance; therefore, it has been affected by the crisis when it affected the real sector of the economy. Thus, at the beginning of this crisis which was essentially financial, Islamic financial institutions have been less affected for two main reasons: first, by applying the principle of prohibition of interest, Shariah councils forbade them to engage in speculative transactions with leverage effect (Hassoune, 2008) and secondly, because these institutions have not participated in the structuration of derivatives due to their speculative nature, which is prohibited by Shariah. Furthermore, risks of loss as the main principle of Islamic investment are shared between the surplus fund holder and the entrepreneur. There is no opportunity to expand credit and leverage beyond what can be supported by the real sector output (Krichene & Mirakhor, 2009).

Nevertheless, when the financial crisis has turned to an economic crisis and becoming after a systemic crisis affecting the real sector, Islamic finance was significantly affected. The subsequent tightening of liquidity and credit in the global financial markets did adversely impact all financial institutions in general, including Islamic financial institutions. As the financial crisis becomes prolonged, the global recession, the collapse in commodity and oil prices, and the sharp erosion of asset values that followed, affected the performance of the Islamic financial institutions. This has resulted in significant and persistent volatility of Islamic indexes as demonstrated in this paper. Islamic indexes had fallen together with the conventional stock indices but to a lesser extent. Indeed, we have demonstrated in our empirical study that unconditional volatility of conventional stock indexes was almost doubly higher than Islamic stock indexes. Despite the strong effect of financial crisis, Islamic finance has shown a relative resilience during the shock due to several factors.

In conclusion, the recent financial crisis has called into question the theoretical foundations

of the international financial system. Despite the severity of the crisis and its negative impact on the global economy, Islamic financial institutions showed a relative resistance which gave credibility to the Islamic finance and attracted more attention to its fundamental principles, namely the principle of sharing profits and losses. The technical flaws of traditional financial system added to the inherent shortcomings of the system with a lax regulatory environment which have created fertile ground for the emergence of the crisis. The adoption of the principles of Islamic finance may prevent the occurrence of these problems given the principle of sharing profits and losses. Especially, the experience of Islamic finance whose purpose is the approximation of the monetary and financial economics of the real economy deserves special attention when modern finance is beset by crises that could destabilize the global economic balance (securitization, excessive speculation ...) (Boudjellal, 2010).

However, Islamic finance as an emerging industry has again a number of challenges to overcome namely the harmonization of legal opinions due to the diversity of jurisprudence schools and the establishment of a suitable regulatory framework. The major challenge is the need for the design and development of a comprehensive and dynamic regulatory prudential supervisory framework that is uniquely and properly designed for an Islamic financial system. Such a framework will satisfy the requirements of any existing regulatory framework anywhere in the world, and go beyond them to ensure the stability of the system.

Furthermore, the current crisis will certainly challenge the classical models of finance. It has highlighted some limits of conventional models (Herlin, 2010). Despite the emergence of highly advanced models commonly used in finance like the GARCH models and their extensions, this model capture partially the stylized facts observed in financial markets, such as long memory and scale invariance. Previously criticized by Mandelbrot (1963), the classic model based on contestable assumptions seems to be inappropriate facing extreme risks which frequently affect the financial institutions.

The multi-fractal modeling (Herlin, 2010) opens new ways in mathematical modeling by proceeding to the application of fractals in finance. This track will allow Islamic finance to avoid the shortcomings of the classical modeling and the forecasting imperfections.

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