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Financial Stability of Islamic Finance

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Abstract

The aim of this paper is to study the stability of the Islamic financial system. To do this, we are interested in the scoring method and the volatility of stock market indices.

The first empirical study includes all the components of the financial system, in particular, banks, insurance companies, leasing, factoring and investments companies.

The results of this study suggest that, Islamic finance saw a loss of 0.014% of its stability score, in 2007, against 0.43% and 1.675% for conventional finance, respectively in 2007 and 2008. In contrast, during the period of the Arab revolutions only Islamic finance depreciated.

In order to refine our research, we used the autoregressive conditional heteroscedasticit models to study the volatility of the DJ index and the DJIM index. The empirical results reveal that, the DJIM index is less volatile than the DJ index of emerging countries, Europe, Asia and the United States. However, the DJ Global Index is less volatile than the DJIM index, which seems paradoxical compared to previous results. From then on, we studied the volatility of the two indices before, during and after the crisis. The empirical results reveal that, the DJIM index is much more stable than the DJ index during the crisis (2007-2009). On the other hand, before and after the crisis (2002-2006 and 2010-2015), the DJ Global index is more stable but the difference is insignificant.

Keywords: Stability, Islamic finance, Conventional finance, DJ indices and DJIM indices

1. Introduction

The Islamic financial model is a participatory model based on microfinance. It is based on the real economy and characterized by its prudential system. Despite its small share in the global financial market, Islamic finance has been one of the most dynamic sectors in recent decades and has gained new momentum in the wake of the financial crisis (Mosab I. Tabash and Raj S. Dhankar, 2015). During the crisis period, financial instability has taken root in the conventional system while Islamic finance is showing some health.

Indeed, the literature does not lead to a consensus on the stability of Islamic finance and therefore the sense of this impact remains mixed. It is in this context that we need to shed new light, through an empirical study, by testing the financial stability of the two financial systems. In this regard, this paper comes to enrich the financial literature since it provides empirical evidence on the stability of Islamic finance via two methods namely the volatility of stock indexes and the scoring method.

Likewise, this paper focuses on a wide time interval (2002-2015) including the 2001 crisis, the 2007 crisis and the period of the Arab revolutions. In addition, this research paper is designed to contribute to an inconclusive debate on the importance of Islamic finance.

2. Literature Review

This section provides an analytical review of the works on the stability of the Islamic and conventional financial system. The results are mixed and these different findings bear witness to the complexity of this concept.

Trabelsi, L., and al. (2019) compared the performance of international Islamic, conventional and mixed (Islamo-conventional) portfolios. The methodology used in this paper is based on the Markov regime change model and the ratio difference test of Sharpe, Ledoit and Wolf (2008). The results show a difference in performance between conventional, Islamic and mixed portfolios, but it is not statistically significant. In the same spinning mill, Bahloul, S., and al. (2017) examined the comparative performance of the diversification of Islamic and conventional portfolios over the period 2002-2014. In this work, Bahloul, S., and al. (2017) have shown that Islamic market indices can provide good coverage, providing investors with additional investment alternatives. Over the same period, Abu-Alkheil, A., and al. (2017) have shown that conventional indices dominate during the pre-crisis and the crisis periods, which offers diversification opportunities to global investors who hold both types of indices in the same portfolio. Using the stochastic dominance test, based on the bootstrap of Linton, Maasoumi and Whang (2005), Abu-Alkheil, A., and al. (2017) showed that conventional indices dominate their Islamic counterparts during the pre-crisis and the crisis periods. In the post-crisis period, by cons, there is no indication of dominance of one over the other type of indices.

Miniaoui. H and al. (2015) examined the performance of Islamic and conventional indices of GCC countries and tested whether Islamic indices are less risky than conventional indices. The results of this investigation showed that the financial crisis has a negative impact on the average yields of the Bahraini index and has amplified the volatility of the indices of the United Arab Emirates, Kuwait and Bahrain. On the other hand, the crisis does not have a significant impact on the Islamic index and this throughout the study period 2006-2012. Given the political and geographical effects, Miniaoui, H., and al. (2015) demonstrated that the GCC country indexes admit increased volatility in 2006 following the loss of the Saudi stock market by 50% of its value. Thus, this loss is caused by bank panic of national and regional investors. In 2009, however, the United Arab Emirates, Kuwait and Bahrain indices reacted to the Dubai debt crisis, which created a high volatility in the indices of cooperation.

In summary, this research has shown that the DJIM index is less risky than the conventional DJ Global World index.

Like Grubel's (1968) research, Nekhili, R., and Muhammad, N. (2010) examined correlations between different markets in GCC countries. They used six market indexes from six GCC markets: UAE, Bahrain, Kuwait, Qatar, Saudi Arabia and Oman. The main conclusion of this review is that GCC markets are interdependent and do not provide any benefit to the international diversification of an investment portfolio. Despite the stock market interdependence and the homogeneity of GCC's markets, the results show high volatility differences between stock markets. These differences arise from the position taken by investors regarding the purchase or sale of shares. On the other hand, a strong persistence of volatility has been observed. This amounts to the fact that short selling is prohibited in these markets, hence the excessive sales of shares to liquidate the funds held.

Since Saudi Arabia and the UAE hold more than half of the market capitalization of the GCC market, 44% for Saudi Arabia and 21% for the UAE, they are likely to have the most impact in the GCC market. To confirm or reject this hypothesis, Nekhili, R., and Muhammad, N. (2010) studied the conditional volatility of the GCC country market indices. The daily closing prices for the period January 6, 2003 to January 1, 2009 were used. The use of the conditional VAR allowed to conclude a strong relationship between the volatility of the Saudi index and those of Kuwait, United Arab Emirates, Qatar, Oman and Bahrain. This finding can be explained by the uncertainty of the yields of Saudi firms. The empirical results of this work suggest that:

- In bearish periods, Saudi Arabia negatively affects the future volatility of the Abu Dhabi market.

- The Abu Dhabi market is influenced by past innovations in the Qatar market and the Omani index is negatively impacted by Bahraini and Qatari indexes.

- In bullish periods, the Saudi market positively affects all GCC markets with the exception of the Bahrain market.

In their paper titled "Political uncertainty and stock market volatility in the Middle East and North African (MENA) countries", Frankie Chau, Rataporn Deesomsak and Jun Wang (2014) investigated the impact of political uncertainty in the period of the Arab Spring on the volatility of the main stock markets in the MENA region. Because Islamic series contain some oil and gas industry indicators, Frankie Chau, Rataporn Deesomsak, Jun Wang (2014), hypothesize that the impact of the Arab Spring on Islamic clues is higher than conventional indexes. Then and using event analysis, Frankie Chau, Rataporn Deesomsak and Jun Wang (2014) found that stock prices react to political changes and collapse in troubled times. These results are comparable to those of Lobo (1999) who examined the American market during the 1998 election dilettante of the political scandal that took place. Similarly, Jackson (2008) and Chesneyet and al. (2011) have worked on terrorist attacks in many Western countries and confirm that the majority of these events have had a negative effect on the financial markets. This empirical validation was done using the GARCH method (because it allows to verify and control the conditional covariance of the returns of the stock market indices of the MENA countries) and the three international benchmarks namely, Arab index, Developed index and World index. Roughly, the results of this research work indicate that the Arab Spring conflicts and political uncertainty have increased the volatility of the MENA stock market indices (Bahrain, Kuwait, Oman, Egypt, Jordan and Lebanon) and especially those Islamic. This uncertainty was fueled by the lack of confidence of international investors in the region, resulting in a panic in the stock markets of the MENA countries.

Charles, A., Darné, O., and Pop, A. (2011) tried to verify whether Islamic indexes are more or less affected by unexpected changes in volatility regimes than conventional indexes. The results show that the Islamic and conventional indexes have been affected by the same degree of variance and admit the same trends (bearish or bullish). On the other hand, Islamic market indexes have higher average returns than conventional market indices, but they are also more volatile. According to Charles, A., Darné, O., and Pop, A. (2011), this volatility gap may be innate of the size factor. To answer this question, a study of the volatility of Canadian Islamic and conventional indexes took place. This empirical exercise resulted in the volatility of the Canadian Islamic Index being higher than that of the conventional index. To refine these results, Charles, A., Darné, O., and Pop, A. (2011) repeated Brown-Forsythe's tests to inspect the equality of variances across several size-defined subindices. The results of this test indicate that the size bias does not affect the equality of variances tests. However, the Shariaa-compliant large-cap portfolio is more volatile than large-cap companies included in conventional indexes. This amounts to saying that the Islamic index experienced abnormal volatility during the Asian crisis of 1997, the Russian crisis of 1998, the financial crisis of 2007 as well as the unexpected increase in interest rates, consumer price indices, commodity prices, unemployment rates and even terrorist attacks.

Beyond religious barriers, Islamic finance requires financial criteria for the valuation of investments. In order to ensure the compatibility of the selected securities, with their beliefs, investors in Islamic funds make use of a screening on the performance of the firms in question.

Hassan, A., Antoniou, A, and Paudyal, K. (2005) examined the impact of these restrictions on the performance of shariaa-compatible investments. They made a comparison between the performance characteristics of the Islamic index; index DJIM and Dow Jones-Americas index.

In addition, they used the multifactorial model that controls the size, the market to book ratio, the momentary effect and the temporal variation of betas. The results show that the expected returns of the Islamic portfolios are higher than the expected returns of the conventional portfolios. Empirically speaking, Hassan, A., Antoniou, A, and Paudyal, K. (2005) used the CAPM model to estimate an additional return earned by a fund. The results of this work suggest that the DJIM index outperforms the benchmark, and the alpha of the DJIM index is larger than that of the CRSP benchmark (0.8809, t = 2.80, 0.8053, t = 2.72). The DJ Americas index, on the other hand, admits the same trend as that of the CRSP benchmark. In other words, the assumption that a diversified portfolio is able to perform better than a screened portfolio is rejected.

In the same vein, Hussein, K. A. (2005) attempted to test whether investors who acquire Shariaa-compatible shares admit returns different from those who invest in conventional shares. To answer this question, Hussein, K. A. (2005) used monthly returns of four indices namely: DJ Global index, FTSE Global index, FTSE Global Islamic index and DJIM index. The results of the CAPM model suggest that the Islamic index has greater volatility compared to the DJ Global index. On the other hand, it admits a better performance over the entire bullish period, namely, December 1993 to December 2000 and from September 2002 to December 2004. On the other hand, in the bearish period the DJIM index underperforms the DJ Global index. The results of the FTSE indices tend to be similar. The application of ethical screens does not therefore have a negative impact on the performance of the DJIM index and FTSE Global Islamic index. Both Islamic indexes are riskier than the DJGI, FTSE All-World and the benchmark « Morgan Stanley World Index All International ».

On the other hand, Al-Zoubi, A. H., and Maghyereh, I. A. (2007) likened depositors in Islamic banks to investors, or shareholders, who earn dividends when the bank makes a profit or loses some of their savings if the bank announces a loss. As a result, the system of sharing losses and profits can reduce the expected bankruptcy costs. In addition, Al-Zoubi, A. H., and Maghyereh, I. A. (2007) bode that the shareholders of the Islamic firms admit returns lower than those of the shareholders of the non-Islamic firms because of the financial leverage. In this work, Al-Zoubi, A. H., and Maghyereh, I. A. (2007) compared the DJIM index and the DJIS index over the period January 1996 - May 2005 to study the impact of financial screening. The results suggest that the two Islamic indices have unique risk characteristics and the ex-ante screening adopted by the DJIS has no impact on the expected gains. As a result, the DJIM index and the DJIS index have the same performance and belong to the same risk class. Referring to the works of Zoubi and Maghyereh (2007), Sukmana, R., and Kholid, M. (2010) studied the resilience of Islamic and conventional stock indices in Indonesia. They examined the performance and risk of the Islamic Index Jakarta Islamic Index and its similar Jakarta Composite Index. Using daily data from January 2001 to December 2009 and ARCH and GARCH methods, Sukmana, R., and Kholid, M. (2010), tried to verify if the financial crisis affects the volatility of individual stocks. The first observation of this study is that the volatility of the two indices is affected by the financial crisis. As well, this work suggests that JAKISL is less risky and less volatile than JCI, especially during the crisis.

By adopting the same method, Hussein, A. K. (2004) examined the hypothesis that there is a difference between the return on an investment in the FTSE Global Islamic Index shares and an investment in the shares of the FTSE All-World Index. In addition, a comparison of gross and risk-adjusted returns associated with investments in FTSE Global Islamic Index stocks and the FTSE All-World Index was made. The results show that the Islamic index outperformed the conventional index by 0.019 over the bull market (January 1996-March 2000) and underperformed during the downtrend (April 2000-July 2003). In summary, Hussein A.K (2004) suggests that additional costs incurred in tracking Islamic funds have no impact on expected returns.

Indeed, the debate on the financial stability of the two financial systems is not yet closed and the results are still mixed. The majority of works on this subject deals with samples consisting mainly of banks or homogeneous stock market indices, such as the work of Nekhili, R., and Muhammad, N. (2010). Similarly, some studies have methodological shortcomings, such as the work of Hassan, A., Antoniou, A., and Paudyal, K., (2005) who compared the performance of the DJIM index and the Dow Jones-Americas index. By the way, Miniaoui, H., and al. (2015) did not study the correlation between the different markets of the GCC countries.

Thus, the literature does not lead to a consensus on the stability of Islamic finance and therefore the sense of this impact remains mixed. It is in this context that we need to shed new light, through an empirical study, by testing the financial stability of the two financial systems. In this regard, this paper comes to enrich the financial literature since it provides empirical evidence on the stability of Islamic finance via two methods namely the volatility of stock indexes and the scoring method.

Likewise, this paper focuses on a wide time interval (2002-2015) including the 2001 crisis, the 2007 crisis and the period of the Arab revolutions. In addition, this research paper is designed to contribute to an inconclusive debate on the importance of Islamic finance.

3. Methodology

In order to study the stability of both financial systems, Islamic and conventional, and to make a comparison between them, we will use two methods namely the z-score and the volatility of the stock indices. The Z-score function can be defined as follows:

$$L = \alpha + \beta_1 GIF + \beta_2 TIA + \beta_3 TP + \beta_4 CTI + \beta_5 GBF + \beta_6 ROE + \beta_7 IO + \beta_8 DIO$$
$$+ \beta_9 GA + \beta_{10} WF + \beta_{11} OFI + \beta_{12} DJI + \beta_{13} DJR + \varepsilon_{it}$$

Then, in order to derive the respective stability levels of the two types of finance, we will use the exponential transformation of the logit model. This probabilistic relation can be expressed as follows:

$$W = \frac{1}{1+Exp}\text{-L}$$

Table 1. Definitions of the Z-Score variables of the two financial systems

Variables	Definitions	Variables	Definitions
GIF	Gross insurance funds: Total funds of insurance companies	DIO	Domestic Insurance Obligation = total sum of domestic obligations
TIA	Total insurance asset: Sum of the assets of insurance companies.	GA	Global asset = Total sum of assets of institutions other than banks and insurance companies.
TP	Total premium: total insurance premiums	WF	Worldwide funds = Total sum of funds of institutions other than banks and insurance companies.
CTI	Cost to Income Bank ratio = Total cost / Net income	OFI	Other Financial Intermediaries
GBF	Global Banking Funds = total funds of banks	DJI	Dj index
ROE	Banking return on equity	DJR	World Index Total Return
IO	International Obligation = total sum of international obligations		

Although the term volatility refers to the notion of risk, it is going to be used in this work as a study of financial stability. So ideally, the least stable system is the most volatile. To do this, we will study the volatility of the Dow Jones Global Index and DJIM World Index indices and their subdivisions over the period 2002-2015. The dataset includes the daily closing prices of the conventional and Islamic stock indexes presented below.

- Dow Jones Global Index	- DJIM World Index
- DJ Asia Pacific Index	- DJIM Asia Pacific Index
- DJ Emerging Markets Index	- DJIM Emerging Markets Index
- DJ Europe Index	- DJIM Europe Index
- DJ U.S. Index	- DJIM U.S. Index

However, the Dow Jones Islamic Market Index was created in 1999 and is the second Islamic index, after Socially Aware Muslim Index created in 1998, made available to investors who want to invest in accordance with Shariaa. The DJIM index filters courses on two times. The first screening is done in accordance with shariaa by eliminating firms that invest in alcohol, weapons, pornography, tobacco and pork.

The second screening is done on the basis of the ratios and it admits three levels:

- Exclusion of companies whose total debt exceeds 33% of market capitalization or total assets.

- Exclusion of companies whose available cash exceeds 33% of their market capitalization or total assets.

- Exclusion of companies whose receivables exceed 45% of total assets.

The fundamental difference between an Islamic index and another conventional is that the former excludes some sectors deemed "unethical" and crowds out some companies that earn a significant income from the interest or exert excessive leverage (Frankie Chau, Rataporn Deesomsak & Jun Wang, 2014).

However, we will be interested in the conditional volatility expressed by the models of the ARCH class. These processes were initiated by Engle (1982) who proposed an ARCH (q) specification where the square of errors follows an autoregressive process of order q.

$$\varepsilon_t = \sigma_t * Z_t$$

Where Z_t represents the stochastic component which is a white noise and follows the reduced normal centered law and σt is the standard deviation such that:

$$\sigma^2_t = \alpha_0 + \alpha_1\, \varepsilon^2_{t-1} + \ldots\ldots + \alpha_q\, \varepsilon^2_{t-q}$$

$$= \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon^2_{t-i} = \alpha_0 + \alpha(L)\varepsilon_t^2$$

Knowing that α (L) is the delay polynomial, and α_0 and α_i are positive ∀ i.

In fact, the ARCH model is an innovation of the Box-Jenkins ARMA model, which neglects the information contained in the residual factor of the series (constant variance) and which was initially schematized as follows:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-1} + \sum_{i=1}^{q} \Theta_i\, \varepsilon_{t-1}$$

Where φ_i and Θ_i are constant and ε_t is a process-independent error term.

Initiated by Tim Bollerslev (1986), the generalized form of the ARCH model represented the variance σ^2_t as the aggregation between the autoregressive term and the moving average of the residue squares. The GARCH model can be written as follows:

$$\varepsilon_t = \sigma_t * Z_t$$

With $\sigma^2_t = \omega + \alpha_1 \varepsilon^2_{t-1} + \ldots\ldots + \alpha_q \varepsilon^2_{t-q} + \beta_1 \sigma^2_{t-1} + \ldots.+ \beta_p \sigma^2_{t-p}$

$$= \omega + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-1} + \sum_{i=1}^{p} \beta_i \sigma^2_{t-1}$$

Where ω and $\alpha_t > 0$ and $\beta_j \geq 0$, $\forall$ i= 1…. p and j = 1 …. q

As for the model E-GARCH it is written in the following form:

$$\varepsilon_t = \sigma_t * Z_t$$

With $\text{Ln}(\sigma^2_t) = \omega + \sum_{k=1}^{q} \beta_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \text{Ln}(\sigma^2_{t-k})$

such as $g(Z_t) = \theta Z_t + \lambda (|Z_t| - E(|Z_t|))$

Where σ^2_t is the conditional variance.

This model was introduced by Nelson (1991), he suggests that the variance depends on the size and the sign of the delayed residuals. Although it does not impose any restrictions on the end of the parameter sign, this model is a limitation of the GARCH model. This is innate of the logarithmic form in which the conditional variance has been represented.

Like the GARCH and E-GARCH model, the GJR-GARCH model is meant to limit the persistence of volatility in time series. It therefore makes it possible to exponentially reduce the autocorrelation of errors. This model was advanced by Glosten, Jagannathan and Rukle (1993) and it is written as follows:

$$\sigma^2_t = K + \delta \sigma^2_{t-1} + \alpha \varepsilon^2_{t-1} + \Phi \varepsilon^2_{t-1} I_{t-1}$$

Where $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$ and $I_{t-1} = 1$ si $\varepsilon_{t-1} < 0$

4. Results and Interpretations

Table 2. Descriptive statistics of Islamic finance

Variable	Obs	Mean	Std. Dev.	Min	Max
r1	14	6.9005	5.300262	.829	17.114
r2	14	1.084071	.4368747	.451	1.741
r3	14	1.163071	.8257433	.115	2.54
r4	14	47.27143	5.40917	40.2	58
r5	14	.7812857	.615751	.067	1.819
r6	14	27.16571	6.382318	15.862	38.068
r7	14	.0152325	.0186524	.00113	.059565
r8	14	.0499177	.0439079	.000241	.117331

r9	14	.9699286	.7408345	.15	2.48
r10	14	50.24786	19.58571	16.42	81.7
r11	14	.0097725	.0088676	.0002056	.02559
r12	14	2065.726	492.4607	1195.49	2800.01
r13	14	2592.704	852.4866	1413.49	4051.23

Table 3. Descriptive statistics on conventional finance

Variable	Obs	Mean	Std. Dev.	Min	Max
r1	14	20.45727	5.445679	10.32215	27.40359
r2	14	59.58564	14.16993	37.923	81.249
r3	14	40.08273	7.160578	26.26898	48.42968
r4	14	60.39214	3.880075	54.31	66.88
r5	14	96.61992	37.35497	39.13813	148.5813
r6	14	23.50143	3.714478	17.95	28.72
r7	14	19.00136	5.385772	8.758	26.775
r8	14	49.66771	13.66571	28.328	70.682
r9	14	1338.745	4894.453	15.113	18344
r10	14	208.2017	73.8116	91.82195	305.3477
r11	14	50.03294	18.10082	22.42661	75.23461
r12	14	245.6221	55.6615	140.54	320.86
r13	14	3702.81	1181.3	1785.86	5646.15

Based on Tables 2 and 3 we note that the conventional insurance sector is significantly larger than the Islamic one. Conventional insurance has 34 times more premium than Islamic insurance. This seems totally logical because it admits a larger client and services portfolio than Islamic insurance. In addition, it admits 3 times more funds and 55 times more assets than takaful companies. In contrast, conventional banks are less profitable and less productive than Islamic banks.

Table 4. Stability of Islamic finance and conventional finance (per year)

Year	Islamic finance	Conventional Finance	
2002	97,5853%	88,3778%	
2003	97,4201%	88,1537%	
2004	97,3243%	88,7332%	
2005	97,3900%	89,2225%	
2006	97,4471%	89,6904%	
2007	97,4336%	89,3086%	
2008	97,4591%	87,8253%	
2009	97,4821%	89,5373%	
2010	97,5654%	89,9692%	
2011	97,4442%	90,3798%	
2012	97,3961%	90,4085%	
2013	97,4267%	90,4284%	
2014	97,4738%	90,5927%	
2015	97,5428%	91,0942%	
Average	**97,4565%**	**89,5515%**	
Wilcoxon test	**Ho:** score FI = score FC	**z** = 3.296	**Prob > |z| =** 0.0010
Student's test	**Ho:** mean(diff) = 0	**Ha:** mean(diff) < 0	Pr(T < t) = 1.0000
		Ha: mean(diff) != 0	Pr(|T| > |t|) = 0.0000
		Ha: mean(diff) > 0	Pr(T > t) = 0.0000

From Table 4, we note that Islamic finance is more stable than conventional finance. It admits an average stability score of 97.4565% against 89.5515% for conventional finance. In 2001, the economic world experienced a collapse caused by terrorist acts in the USA. Although these acts were attributed to a Muslim extremist community, conventional finance was more degrading than Islamic finance. In fact, investments in Sharia-compatible funds rose from $ 0.10142 trillion in 2000 to $ 0.16758 in 2004 [E&Y 2004-2014], and net profits rose from $ 0.1495 to $ 0.329 trillion. This stems from the fact that investors in Islamic funds are not ready to give up their profits which resulted in the increase of deposits from 0.1384 to 0.147 TD in 2004.

In 2007, Islamic finance saw a loss of 0.014% of its stability score against 0.43% and 1.675% for conventional finance, respectively in 2007 and 2008. By contrast, during the period of the Arab revolutions only Islamic finance depreciated. This depreciation resulted in a drop in the stability score of 0.17%. The latter, increased from 97.565% in 2011 to 97.396% in 2012. On the other hand, conventional finance has experienced a period of rivalry between 2010 and 2015, a period in which the global DJ index has risen from 253.9 to 307.9 dollars, that is to say 21.27% growth in 6 years only.

Thus and in accordance with Bourkhis and al. (2010) and Hasan and Dridi (2010), we can say that although Islamic finance is more sensitive to macro and micro changes, it presents a higher level of stability than conventional finance. However, in order to confirm these results, we used the study of time series. This method will allow us to study the dynamics of the volatility of Islamic and conventional stock market indices and to deduce which of the two indices is more stable.

Table 5. Descriptive statistics of conventional indices

	DJ Asia Pacific Index		DJ Emerging Markets		DJ Europe Index		DJ U.S. Index		Dow Jones Global Index	
	PT	RI	PT	RI	PT	RI	PT	RI	PT	RI
Mean	121.9357	0.000155	229.1359	0.000260	264.1967	8.76E-05	333.9668	0.000185	240.1665	0.000147
Median	128.4000	0.000541	253.8300	0.000790	262.1600	0.000327	314.2800	0.000645	242.0000	0.000499
Maximum	172.4900	0.090085	355.8100	0.117624	407.8800	0.105123	537.3200	0.109116	341.6200	0.086635
Minimum	61.16000	-0.097360	73.77000	-0.154588	128.2300	-0.101296	165.3600	-0.096336	124.9000	-0.071600
Std. Dev.	26.94386	0.011752	76.66658	0.012667	63.07511	0.014132	93.99105	0.012559	55.61500	0.010208
Skewness	-0.599972	-0.519097	-0.512963	-1.321523	-0.000622	-0.054180	0.690118	-0.269696	-0.091494	-0.368539
Kurtosis	2.318856	10.19578	1.909475	23.65112	2.272260	9.788609	2.515215	11.84242	2.052872	11.65681
Jarque-Bera	289.7773	8045.285	341.2156	65975.35	80.61055	7016.340	325.7365	11945.20	141.6353	11489.23
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	445431.1	0.565391	837033.6	0.947958	965110.5	0.320141	1219981.	0.675253	877328.0	0.538322
Sum Sq. Dev.	2651248.	0.504378	21465597	0.585992	14529371	0.729302	32262926	0.576061	11295741	0.380544
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Table 6. Descriptive statistics of Islamic indices

	DJIM Asia Pacific Index		DJIM Emerging Markets Index		DJIM Europe Index		DJIM U.S. Index		DJIM World Index	
	PT	RI	PT	RI	PT	RI	PT	RI	PT	RI
Mean	1245.660	0.000130	1765.306	0.000107	2509.854	0.000119	2321.445	0.000196	2032.144	0.000156
Median	1318.470	0.000643	1926.720	0.000594	2552.760	0.000425	2147.490	0.000566	2033.720	0.000408
Maximum	1695.880	0.096905	2678.870	0.107995	3539.030	0.114505	3858.020	0.117405	3035.320	0.097746
Minimum	663.8300	-0.098780	778.4200	-0.120430	1246.240	-0.099083	1205.730	-0.096970	1073.260	-0.081855
Std. Dev.	266.5084	0.011885	478.4758	0.012521	595.9664	0.013906	712.0248	0.012119	502.1899	0.010358
Skewness	-0.526387	-0.518894	-0.425074	-0.646949	-0.213858	0.026436	0.750324	-0.075938	0.150571	-0.257326
Kurtosis	2.056857	11.33468	1.906507	12.47234	1.958992	11.16612	2.462813	11.79248	2.124557	12.89590
Jarque-Bera	304.0897	10737.36	292.0084	13911.74	192.7931	10150.53	386.6874	11770.39	130.4558	14945.89
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	4550396.	0.476494	6448664.	0.390754	9168495.	0.435691	8480237.	0.714829	7423422.	0.568650
Sum Sq. Dev.	2.59E+08	0.515829	8.36E+08	0.572508	1.30E+09	0.706196	1.85E+09	0.536335	9.21E+08	0.391848
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

The results shown in Tables 5 and 6 that the DJIM index is better rated than the DJ index in Asia, Europe, US and emerging countries. Similarly, the DJIM index is more profitable than the DJ index in Europe and US. On the other hand, the DJ Asia index and the DJ emerging index outperform the DJIM Asia index and the DJIM emerging index.

In theory, skewness measures the asymmetry coefficient of a distribution around its mean while kurtosis measures the level of flattening of a distribution in relation to a normal distribution. The results of the Jarque-Bera test show that the indices do not follow the normal law, so we reject the null hypothesis of normality of the series because the skewness and the kurtosis are respectively different from 0 and 3. Indeed, the test of Jarque-Bera is given by the following relation:

$$\text{Jarque-Bera} = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

Where S reflects asymmetry and K reflects flattening.

In continuity with the Jarque-Bera model, we studied the normality of the processes by means of the symmetry and flattening hypotheses defined by Z_1 and Z_2 such that:

$Z_1 = \frac{|S|}{\sqrt{(6/T)}}$ such that H_0: Z_1 follows the reduced normal centered law (T observation number).

$Z_2 = \frac{|K-3|}{\sqrt{(24/T)}}$ such that Z_2 follows the reduced normal centered law with H_0: flattening close to normal (T observation number).

Based on Z_1 and Z_2 we can conclude that the series distribution is asymmetric and leptocurtic. However, since Z_1 and Z_2 are greater than the tabulated value 1.96, we can reject the hypothesis of the Gaussian distribution of the series.

In addition, the descriptive statistics tables tell us that the series of returns do not follow the normal distribution. All in all, the skuwness coefficients are not zero and the kurtosis are not equal to 3 and the series of the returns have asymmetries on the left since the skuness is negative (except for DJIM Europe Index as it shows a positive skuness). Under the assumption of normality of the distribution, we notice that the series of returns follow the chi-square law with two degrees of freedom (at the threshold of 5%).

The general finding of stock index studies is that the price series are non-stationary. Despite this usual conclusion, it seems necessary to validate this conquest. To do this, we used the ADF test in its 3 forms namely:

1. Model with constant and trend.

2. Model with constant and without trend.

3. Model without neither constant nor trend.

These models can be schematized as follows:

$$\Delta Y_t = \alpha + \beta_t + \varphi\, y_{t-1} + \sum_{t=1}^{P} \theta_i\, \Delta y_t - 1 + \varepsilon_t$$

$$\Delta Y_t = \alpha + \varphi\, y_{t-1} + \sum_{t=1}^{P} \theta_i\, \Delta y_t - 1 + \varepsilon_t$$

$$\Delta Y_t = \varphi\, y_{t-1} + \sum_{t=1}^{P} \theta_i\, \Delta y_t - 1 + \varepsilon_t$$

Applying the ADF test on stock index series, we concluded that all series have a level of calculated statistical t over the critical values at the 1% threshold, which means that the series are non-stationary at the level of 1 %.

In order to make these series stationary we proceed to the logarithmic difference which is none other than the process of yields. This relation can be written in the following form:

$$R_t = \mathrm{Ln}\,(P_t) - \mathrm{Ln}\,(P_{t-1})$$

Where P_t and P_{t-1} are respectively the prices at the date t and t-1.

In support of the ADF and H_0 test, which states that the series of returns are stationary, we concluded that the series of returns are stationary at the 1% level.

Unlike previous work, we did not use the float method to specify ARMA model parameters. Rather, we used the ARIMA Model Forecasting test on the yield series. The results of this test suggest that the time series are of the ARMA (p, q) type as presented in the following tables:

Table 27. Results of the ARMA model test of conventional indexes

	Number of estimated ARMA models	Number of non-converged estimations	Selected ARMA model	AIC value
DJ Asia Pacific Index	25	0	(4,4)(0,0)	-6.05405573303
DJ Emerging Markets Index	25	0	(3,3)(0,0)	-5.93387180374
DJ Europe Index	25	0	(1,3)(0,0)	-5.68647550662
DJ U.S. Index	25	0	(3,3)(0,0)	-5.9294916161
Dow Jones Global Index	25	0	(2,3)(0,0)	-6.35323268313

Table 28. Results of the ARMA model test of Islamic indexes

	Number of estimated ARMA models	Number of non-converged estimations	Selected ARMA model	AIC value
DJIM Asia Pacific Index	25	0	(4,4)(0,0)	-6.03164543984
DJIM Emerging Markets Index	25	0	(2,3)(0,0)	-5.95298580028
DJIM Europe Index	25	0	(1,3)(0,0)	-5.71978275148
DJIM U.S. Index	25	0	(3,4)(0,0)	-6.00063302103
DJIM World Index	25	0	(3,2)(0,0)	-6.31467119291

Based on the stock index graphs, we notice that both types of indices had a bullish period until 2007. This increasing pace was resumed in 2009 and amortized in 2011 during political uprisings in Arab countries. We also notice that they have the same tendencies in times of crisis and out of crisis thing that coincides with the results of Charles, A., Darné, O., Pop, A. (2011) which states that:

- The Islamic and conventional indices have been affected by the same degree of variance and admit the same trends (bearish or bullish).

- Islamic market indexes have higher average returns than conventional market indices, but they are also volatile.

Based on the graphs of the series of returns, presented in Figure 2, we can notice that they are not homoscedastic. They are characterized by periods of strong disturbance and others of tranquility. We also visualize the existence of several volatility packages. This calls into question the assumption of constancy of so-called "Homoscedasticity" volatility.

In the same context, the models ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized ARCH) are widely used in the literature. In practice, they have been used to model unequal variances, or heteroscedastic, in financial time series and then study the existence of ARCH effect.

To this end, we used the regression model "Y" defined as follows:

$$Y = Xa + \varepsilon \text{ such as: } \varepsilon_t = u_t * h_t \text{ and } u_t \sim> N(0, 1)$$

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}{}^2 = \alpha_0 + \alpha(B)\, \varepsilon_t^2$$

With $\alpha(B) = \alpha_1 B + \alpha_2 B^2 + \alpha_3 B^3 + \ldots + \alpha_p B^p$

We suppose that: H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_p = 0$

H_1: $\alpha_1 \neq 0 \; \forall_i$

For there to be an ARCH effect, it is necessary that the hypothesis of equality of the coefficients is rejected if not $\sigma_t^2 = \alpha_0$. Empirically speaking, we use the following regression:

$$\hat{e}_t^2 = \alpha_0 + \sum_{ii=1}^{Pp} \alpha_i \, \hat{e}^2_{t-i}$$

As $\hat{e}_t$ is the set of estimation residuals deduced from the ARMA model.

The application of Engle's ARCH test (1982) confirms the existence of an Arch effect. In addition, the graphs of the series of the yields show us that the series are highly volatile. We observe volatility groupings around 2001, 2007 and 2011 that coincide with either a crisis or popular uprisings. This amounts to saying that the series of yields react well to a negative shock than to a positive shock, which can be an indicator of non-collinearity.

After taking into account the existence of an ARCH effect, it is necessary to determine the optimum number of lag that each chronological series can contain. The appropriate methodology, in this case, is the estimation of vector autoregression. The results of this estimate are summarized in the following tables:

Table 33. Results of ARCH LAGS test of conventional indexes

		[1; 1]	[1; 2]	[1; 3]	[1; 4]	[1; 5]	[1; 6]	[1; 7]
DJ Asia Pacific Index	Akaike AIC	-6,0485	-6,0478	-6,0481	-6,0475	-6,0477	-6,0482	-6,0479
	Schwarz SC	-6,0451	-6,0427	-6,0413	-6,0390	-6,0375	-6,0362	-6,0343
DJ Emerging Markets Index	Akaike AIC	-5,9258	-5,9308	-5,9338	-5,9334	-5,9331	-5,9339	-5,9345
	Schwarz SC	-5,9224	-5,9257	-5,9270	-5,9249	-5,9229	-5,9220	-5,9209
DJ Europe Index	Akaike AIC	-5,6798	-5,6799	-5,6827	-5,6838	-5,6881	-5,6874	-5,6875

	Schwarz SC	-5,6764	-5,6748	-5,6759	-5,6753	-5,6779	-5,6755	-5,6739
DJ U,S Index	Akaike AIC	-5,9217	-5,9238	-5,9232	-5,9230	-5,9244	-5,9236	-5,9237
	Schwarz SC	-5,9183	-5,9187	-5,9164	-5,9145	-5,9142	-5,9117	-5,9101
Dow Jones Global Index	Akaike AIC	-6,3488	-6,3505	-6,3498	-6,3492	-6,3512	-6,3510	-6,3504
	Schwarz SC	-6,3454	-6,3454	-6,3430	-6,3407	-6,3410	-6,3391	-6,3368

Table 34. Results of ARCH LAGS test of Islamic indexes

		[1; 1]	[1; 2]	[1; 3]	[1; 4]	[1; 5]	[1; 6]	[1; 7]
DJIM Asia Pacific Index	Akaike AIC	-6,0265	-6,0258	-6,0275	-6,0274	-6,0279	-6,0287	-6,0291
	Schwarz SC	-6,0231	-6,0207	-6,0207	-6,0189	-6,0177	-6,0167	-6,0154
DJM Emerging Markets Index	Akaike AIC	-5,9487	-5,9480	-5,9479	-5,9490	-5,9496	-5,9515	-5,9518
	Schwarz SC	-5,9453	-5,9429	-5,9411	-5,9405	-5,9394	-5,9396	-5,9382
DJIM Europe Index	Akaike AIC	-5,7133	-5,7137	-5,7174	-5,7181	-5,7205	-5,7200	-5,7200
	Schwarz SC	-5,7099	-5,7086	-5,7106	-5,7096	-5,7103	-5,7081	-5,7064
DJIM U.S. Index	Akaike AIC	-5,9940	-5,9978	-5,9974	-5,9973	-5,9979	-5,9972	-5,9980
	Schwarz SC	-5,9906	-5,9927	-5,9906	-5,9888	-5,9877	-5,9853	-5,9844
DJIM World Index	Akaike AIC	-6,3095	-6,3112	-6,3109	-6,3104	-6,3126	-6,3123	-6,3115
	Schwarz SC	-6,3061	-6,3061	-6,3041	-6,3019	-6,3024	-6,3004	-6,2979

In order to select the number of lags optimums, we based ourselves on the criterion of AIC "Akaike Information Criterion" and that of SC "Schwarz". Based on these criteria, we noticed that the delays diverge for the DJ Emerging index, DJ index, US index and DJ Global index. In other words, the optimum lag to be retained according to the AIC criterion is not the same as that according to the criterion SC. Under the principle of parsimony that requires retaining the minimum minima, we chose the AIC criterion.

Then, we used the GARCH, E-GARCH and GJR-GARCH models to model the volatility of Islamic and conventional indices. To specify the most appropriate models for modeling the volatilities of both index types, we used the AIC and SC criteria and summarized the results in the following tables:

Table 35. Summary of ARCH, GARCH, EGARCH and GJR-GARCH tests of conventional indexes

		ARCH	GARCH	EGARCH	GJR-GARCH
DJ Asia Pacific Index	Akaike AIC	-6.119332	-6.343361	-6.360902	-6.362791
	Schwarz SC	-6.100635	-6.322965	-6.338806	-6.340695
DJ Emerging Markets Index	Akaike AIC	-6.335644	-6.340756	-6.385384	-6.369784
	Schwarz SC	-6.310154	-6.323763	-6.366692	-6.351092
DJ Europe Index	Akaike AIC	-6.029701	-6.089464	-6.118237	-6.117507
	Schwarz SC	-6.011017	-6.075876	-6.102950	-6.102220
DJ U.S. Index	Akaike AIC	-6.368088	-6.408568	-6.444034	-6.450561
	Schwarz SC	-6.345997	-6.391575	-6.425341	-6.431868
Dow Jones Global Index	Akaike AIC	-6.769984	-6.824893	-6.863133	-6.855073
	Schwarz SC	-6.749597	-6.809603	-6.846144	-6.838083

Table 36. Summary of ARCH, GARCH, EGARCH and GJR-GARCH tests of Islamic indexes

		ARCH	GARCH	EGARCH	GJR-GARCH
DJIM Asia Pacific Index	Akaike AIC	-6.328276	-6.349757	-6.374450	-6.371175
	Schwarz SC	-6.299381	-6.329360	-6.352354	-6.349079
DJIM Emerging	Akaike AIC	-6.283135	-6.308898	-6.333120	-6.330075

Markets Index	Schwarz SC	-6.259350	-6.293608	-6.316131	-6.313086
DJIM Europe Index	Akaike AIC	-5.824985	-6.116093	-6.144674	-6.140836
	Schwarz SC	-5.813095	-6.102504	-6.129387	-6.125549
DJIM U.S. Index	Akaike AIC	-6.405550	-6.420211	-6.464045	-6.462266
	Schwarz SC	-6.378361	-6.401519	-6.443653	-6.441874
DJIM World Index	Akaike AIC	-6.723283	-6.769815	-6.812484	-6.798280
	Schwarz SC	-6.702891	-6.754521	-6.795491	-6.781287

Based on the results presented in Tables 35 and 36 we retained the following models:

Table 37. Models selected for Islamic and conventional indexes

Index	Model	Index	Model
DJ Asia Pacific Index	GJR- GARCH	DJIM Asia Pacific Index	EGARCH
DJ Emerging Markets Index	EGARCH	DJIM Emerging Markets Index	EGARCH
DJ Europe Index	EGARCH	DJIM Europe Index	EGARCH
DJ U.S. Index	GJR-GARCH	DJIM U.S. Index	EGARCH

In view of the figure 3, showing the respective volatilities of stock market indexes, we note that the DJIM index is more stable than the DJ index. In other words, the DJIM index is less volatile than the DJ index of Europe, Asia, US and emerging countries. In order to improve our results, we used Fisher's Equality Variables test to compare the volatility averages of the different indexes.

Table 38. Fisher test of equality of variances

			Mean Abs.	Mean Abs.	Mean Tukey
		Std. Dev.	Mean Diff.	Median Diff.	Siegel Rank
Asia Pacific Index	DJ	0.000198	9.21E-05	7.77E-05	3720.997
	DJIM	0.000167	8.56E-05	7.53E-05	3578.003
Emerging Markets	DJ	0.000302	0.000111	9.22E-05	3670.418

Index	DJIM	0.000193	9.66E-05	8.48E-05	3631.587
Europe Index	DJ	0.000235	0.000133	0.000117	3608.574
	DJIM	0.000235	0.000127	0.000111	3696.426
U.S. Index	DJ	0.000277	0.000130	0.000105	3609.593
	DJIM	0.000178	9.72E-05	8.36E-05	3691.407
Global Index	DJ	0.000144	7.44E-05	6.37E-05	3576.418
	DJIM	0.000148	7.51E-05	6.45E-05	3725.603

Using the ANOVA method and the criteria of Bartlett, Levene and Brown-Forsythe, we concluded that regional Islamic indexes are more stable than conventional indices. Paradoxically, the DJIM index is more volatile than the DJ Global index between 2002 and 2015.

Although this coincides with that of CHARLES, A., DARNÉ, O., POP, A. (2011), we assume that this superiority of volatility is insignificant because of its ephemeral effect. By dividing the study period into 3 sub-periods namely 2002-2006, 2007-2009 and 2010-2015, we noticed that Islamic finance is much more stable than conventional finance in times of crisis whereas in times of out of crisis the advantage of conventional finance is insignificant as presented in the following tables.

Table 39. Summary of ARCH, GARCH, EGARCH and GJR-GARCH tests

2002-2006		ARCH	GARCH	EGARCH	GJR-GARCH
DJ	Akaike AIC	-6.903029	-7.116306	-7.136308	-7.135486
	Schwarz SC	-6.871291	-7.080601	-7.096562	-7.095814
DJIM	Akaike AIC	-6.740697	-6.963495	-6.996193	-7.025648
	Schwarz SC	-6.704992	-6.923824	-6.952473	-6.982009

Table 40. Summary of ARCH, GARCH, EGARCH and GJR-GARCH tests

2007-2009		ARCH	GARCH	EGARCH	GJR-GARCH
DJ	Akaike AIC	-5.784540	-6.022531	-6.034317	-6.038330
	Schwarz SC	-5.730995	-5.968986	-5.974822	-5.978835
DJIM	Akaike AIC	-5.823576	-6.051457	-6.071355	-6.069773
	Schwarz SC	-5.764081	-5.991962	-6.005911	-6.004328

Table 41. Summary of ARCH, GARCH, EGARCH and GJR-GARCH tests

2010-2015		ARCH	GARCH	EGARCH	GJR-GARCH
DJ	Akaike AIC	-6.895800	-17.05293	-7.047877	-7.027269
	Schwarz SC	-6.865000	-17.02555	-7.017078	-6.996469
DJIM	Akaike AIC	-6.884273	-6.972861	-7.036456	-7.015804
	Schwarz SC	-6.853474	-6.945484	-7.005641	-6.985005

Table 42. Fisher test of equality of variances

	Variable	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
2002 - 2006	DJ	5.30E-05	3.70E-05	3.34E-05	1240.556
	DJIM	6.25E-05	4.17E-05	3.67E-05	1365.300
2007 - 2009	DJ	0.000331	0.000193	0.000154	780.1620
	DJIM	0.000296	0.000171	0.000139	788.8380
2010 - 2015	DJ	3.07E-09	1.94E-09	1.68E-09	1565.500
	DJIM	7.53E-05	4.76E-05	4.19E-05	1564.500

This finding suggests that Islamic indexes are less volatile in bearish trends and admit a similar behavior to conventional indices in bullish periods. This corroborates with the fact that Islamic finance admits an anticrisogenic protectionist aspect.

By and large, Islamic finance is more stable than conventional finance. This observation is consistent with that of z-score so the stability of Islamic finance is more than a fiction, it is a reality.

5. Conclusion

The purpose of this work is to study the stability of both financial systems, Islamic and conventional. It interested in the volatility of stock market indexes as well as the scoring method of Jakubík .P and Teplý .P (2007 and 2011).

The scoring method used in the first investigation focuses on macroeconomic data collected from Global Databank, IMF database, and the BIG FOUR annual reports. The empirical results of this method show that Islamic finance is more stable than conventional finance and that Islamic finance is more sensitive than conventional finance to macro and microeconomic changes.

In order to refine our research, we studied the volatility of the DJ Global index and the DJIM index. Overall, we used the EGARCH model for the regional indexes of the DJIM index (Asia Pacific Index, Emerging Markets Index, Europe Index and U.S Index), the DJ Emerging Index and DJ Europe Index. On the other hand, the GJR-GARCH is the most suitable model for the DJ Asia Pacific Index and the DJ U.S Index.

The results of this second empirical investigation reveal that the DJIM index is less volatile than the DJ index of emerging countries, Europe, Asia and the United States. In contrast, the DJ Global Index is less volatile than the DJIM index, which seems paradoxical compared to previous results. From then on, we studied the volatility of the two indices in the times of crisis and out of crisis. The results of these tests indicate that the DJIM index is much more stable than the DJ index in the times of crisis (2007-2009). On the other hand, before and after the crisis (2002-2006 and 2010-2015) the DJ Global index is more stable but the difference is insignificant. This confirms our research hypotheses and allows us to say that Islamic finance is much more stable than conventional finance. In other words, a diversified portfolio is not able to achieve better levels of performance and stability than a portfolio tracked.

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Appendix

Table 7. ADF test of the DJ Asia Pacific Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-2.054254	-2.007966	0.211750
Test critical values:	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 8. ADF test of the DJ Emerging Markets Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 3 (Automatic - based on SIC, maxlag=29)	Lag Length: 3 (Automatic - based on SIC, maxlag=29)	Lag Length: 3 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-1.778571	-1.693255	0.165973
Test critical values:	1% level	-3.431956	-3.960555	-2.565596
	5% level	-2.862135	-3.411037	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 9. ADF test of the DJ Europe Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-1.870314	-1.786589	-0.108453
Test critical values	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 10. ADF test of the DJ U.S Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-0.306389	-1.972896	1.078677
Test critical values:	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 11. ADF test of the Dow Jones Global Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-1.367108	-2.106555	0.486542
Test critical values	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 12. ADF test of the DJIM Asia Pacific Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-1.894178	-2.289213	0.208902
Test critical values	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 13. ADF test of the DJIM Emerging Markets Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-1.812145	-1.762428	-0.127494
Test critical values	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 14. ADF test of the DJIM Europe Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-1.856490	-2.310641	0.055890
Test critical values:	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 15. ADF test of the DJIM U.S. Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-0.169842	-2.498241	1.182187
Test critical values:	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 16. ADF test of the DJIM World Index

Null Hypothesis: PT has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-1.062873	-2.667920	0.647901
Test critical values:	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 17. ADF Test of the yields of the DJ Asia Pacific Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-60.08592	-60.09288	-60.08386
Test critical values	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 18. ADF Test of the yields of the DJ Emerging Markets Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 2 (Automatic - based on SIC, maxlag=29)	Lag Length: 2 (Automatic - based on SIC, maxlag=29)	Lag Length: 2 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-32.56718	-32.58618	-32.55081
Test critical values	1% level	-3.431955	-3.960554	-2.565596
	5% level	-2.862135	-3.411037	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 19. ADF Test of the yields of the DJ Europe Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 4 (Automatic – based on SIC, maxlag=29)	Lag Length: 4 (Automatic – based on SIC, maxlag=29)	Lag Length: 4 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-29.34149	-29.34662	-29.34166
Test critical values	1% level	-3.431956	-3.960555	-2.565596
	5% level	-2.862135	-3.411037	-1.940911
	10% level	-2.567130	-3.127336	-1.616641

Table 20. ADF Test of the yields of the DJ U.S. Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-46.73161	-46.73650	-46.72115
Test critical values:	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 21. ADF Test of the yields of the Dow Jones Global Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-52.71002	-52.70284	-52.70745
Test critical values:	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 22. ADF Test of the yields of the DJIM Asia Pacific Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-59.07566	-59.07275	-59.07676
Test critical values:	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 23. ADF Test of the yields of the DJIM Emerging Markets Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)	Lag Length: 0 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-51.24550	-51.24852	-51.24931
Test critical values:	1% level	-3.431954	-3.960553	-2.565595
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 24. ADF Test of the yields of the DJIM Europe Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 4 (Automatic - based on SIC, maxlag=29)	Lag Length: 4 (Automatic - based on SIC, maxlag=29)	Lag Length: 4 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-29.26205	-29.26215	-29.25789
Test critical values:	1% level	-3.431956	-3.960555	-2.565596
	5% level	-2.862135	-3.411037	-1.940911
	10% level	-2.567130	-3.127336	-1.616641

Table 25. ADF Test of the yields of the DJIM U.S. Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-47.44168	-47.44952	-47.42752
Test critical values:	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 26. ADF Test of the yields of the DJIM World Index

Null Hypothesis: RI has a unit root				
		Exogenous: Constant	Exogenous: Constant, Linear Trend	Exogenous: None
		Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)	Lag Length: 1 (Automatic - based on SIC, maxlag=29)
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-42.73927	-42.73434	-42.73203
Test critical values:	1% level	-3.431955	-3.960553	-2.565596
	5% level	-2.862134	-3.411036	-1.940911
	10% level	-2.567130	-3.127335	-1.616641

Table 29. Results of the White's test of conventional indices

	F-statistic	Prob. F(53,3599)	Obs*R-squared	Prob. Chi-Square(53)	Scaled explained SS	Prob. Chi-Square(53)
DJ Asia Pacific Index	8.993628	0.0000	427.2305	0.0000	1942.286	0.0000
DJ Emerging Markets Index	38.46104	0.0000	948.4936	0.0000	9700.704	0.0000
DJ Europe Index	46.39759	0.0000	682.6405	0.0000	2765.171	0.0000
DJ U.S. Index	51.79568	0.0000	1219.617	0.0000	6263.365	0.0000
Dow Jones Global Index	18.75683	0.0000	447.7876	0.0000	2408.595	0.0000

Table 30. Results of the White's test of islamic indices

	F-statistic	Prob. F(53,3599)	Obs* R-squared	Prob. Chi-Square(53)	Scaled explained SS	Prob. Chi-Square(53)
DJIM Asia Pacific Index	8.476886	0.0000	405.4076	0.0000	2070.406	0.0000
DJIM Emerging Markets Index	42.69668	0.0000	856.2391	0.0000	4603.380	0.0000
DJIM Europe Index	56.68235	0.0000	835.2827	0.0000	3827.290	0.0000
DJIM U.S. Index	55.59355	0.0000	1475.965	0.0000	7081.359	0.0000
DJIM World Index	24.32768	0.0000	542.5816	0.0000	3280.079	0.0000

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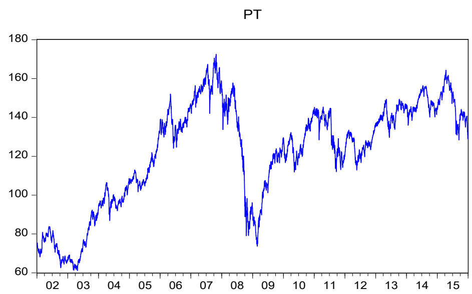
Table 31. Results of the ARCH effect test of conventional indices

	F-statistic	Prob. F(1,3650)	Obs* R-squared	Prob. Chi-Square(1)
DJ Asia Pacific Index	50.08470	0.0000	49.43383	0.0000
DJ Emerging Markets Index	61.72561	0.0000	60.73238	0.0000
DJ Europe Index	112.6179	0.0000	109.3070	0.0000
DJ U.S. Index	174.0723	0.0000	166.2395	0.0000
Dow Jones Global Index	158.6328	0.0000	152.1089	0.0000

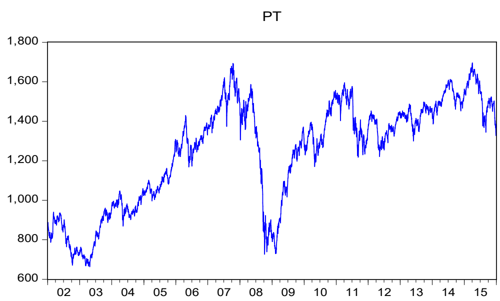
Table 32. Results of the ARCH effect test of Islamic indices

	F-statistic	Probability	Obs* R-squared	Probability
DJIM Asia Pacific Index	40.69586	0.000000	40.26871	0.000000
DJIM Emerging Markets Index	136.3052	0.000000	131.4677	0.000000
DJIM Europe Index	129.5236	0.000000	125.1523	0.000000
DJIM U.S. Index	158.1737	0.000000	151.6819	0.000000
DJIM World Index	169.5151	0.000000	162.0747	0.000000

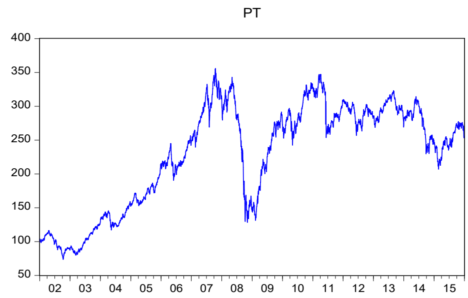
DJ Asia Pacific Index



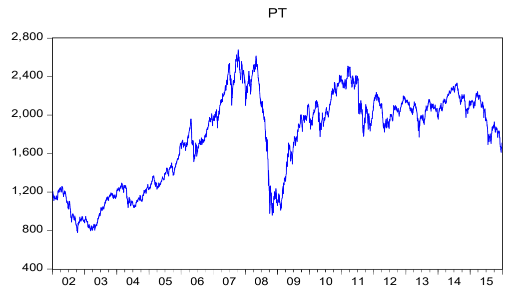
DJIM Asia Pacific Index



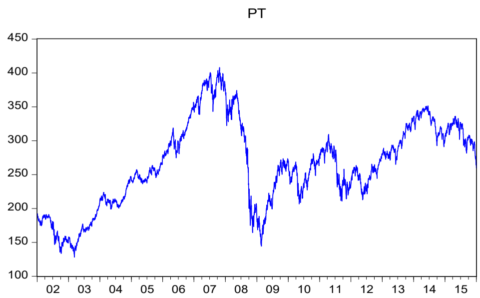
DJ Emerging Markets Index



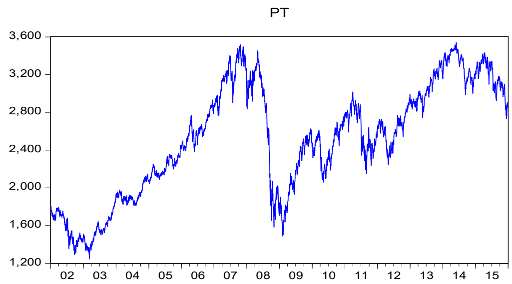
DJIM Emerging Markets Index



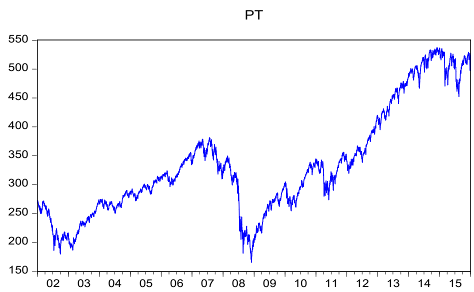
DJ Europe Index



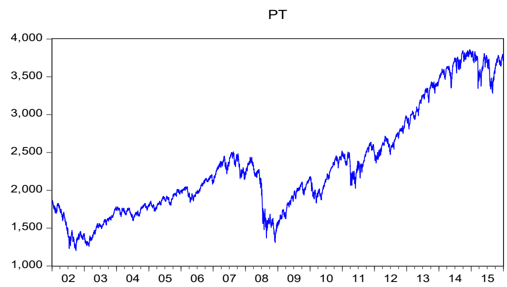
DJIM Europe Index



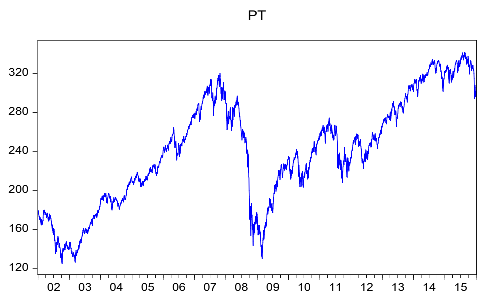
DJ U.S. Index



DJIM U.S. Index



Dow Jones Global Index



DJIM World Index

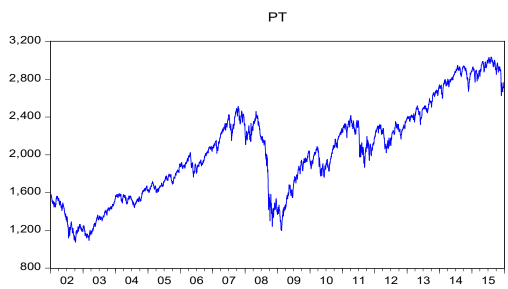
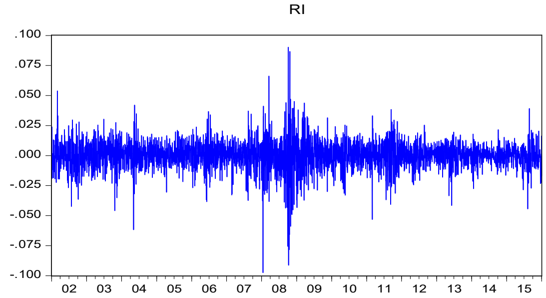
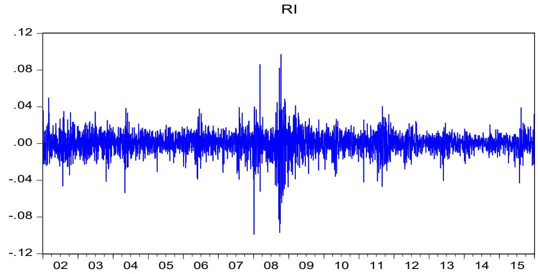


Figure 1. Stock indexes

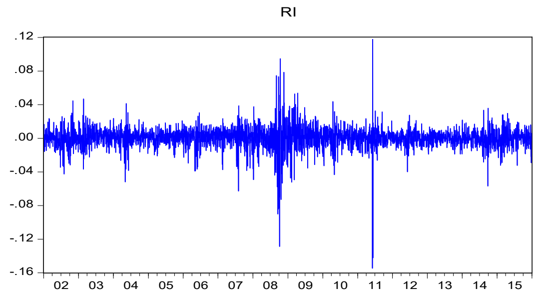
DJ Asia Pacific Index



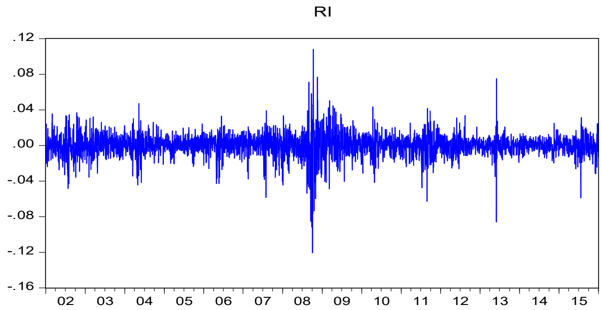
DJIM Asia Pacific Index



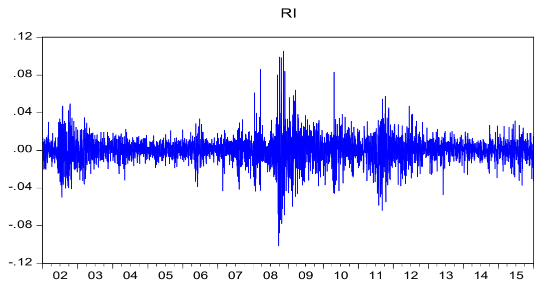
DJ Emerging Markets Index



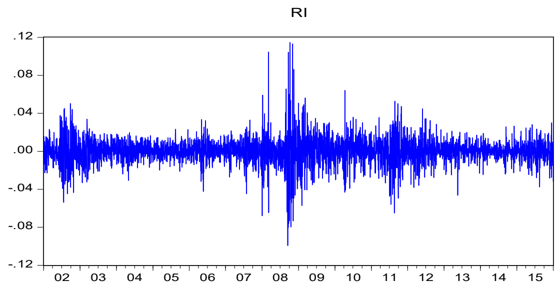
DJIM Emerging Markets Index



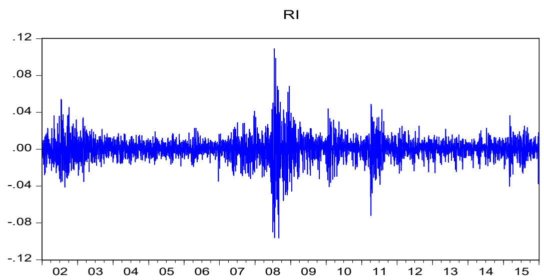
DJ Europe Index



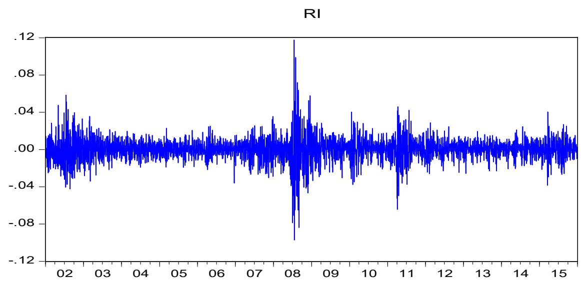
DJIM Europe Index



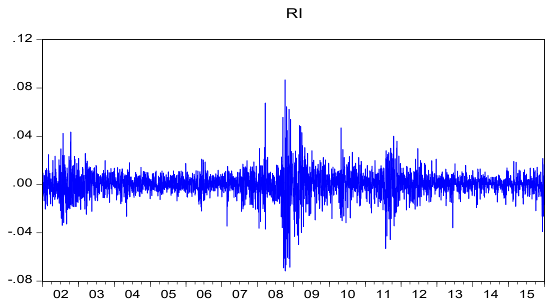
DJ U.S. Index



DJIM U.S. Index



Dow Jones Global Index



DJIM World Index

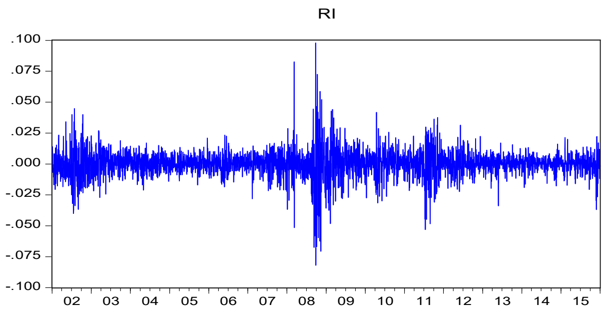
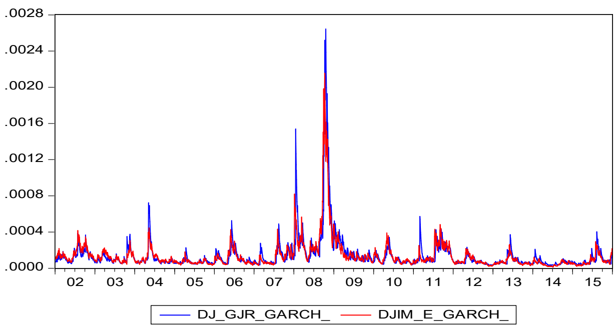
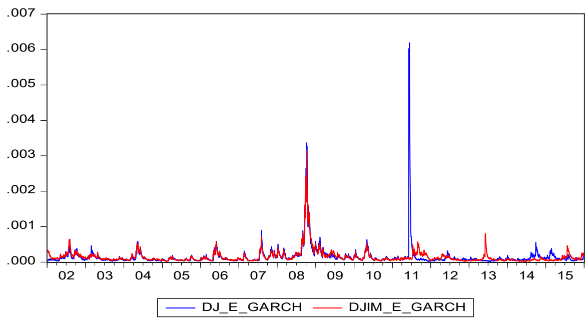


Figure 2. Yields on stock market indices

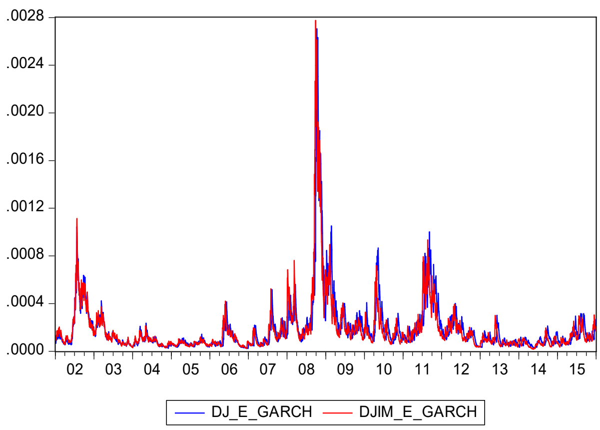
Asia Pacific Index



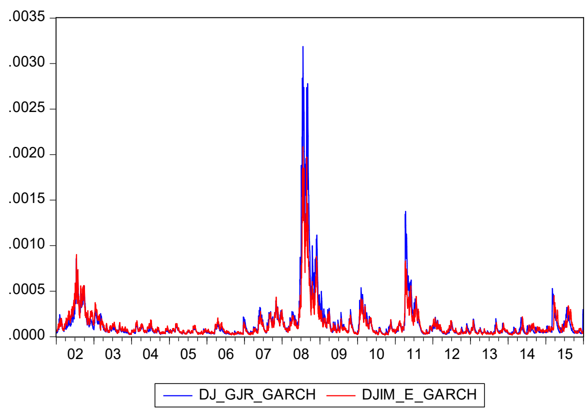
Emerging Markets Index



Europe Index



U.S. Index



Global Index

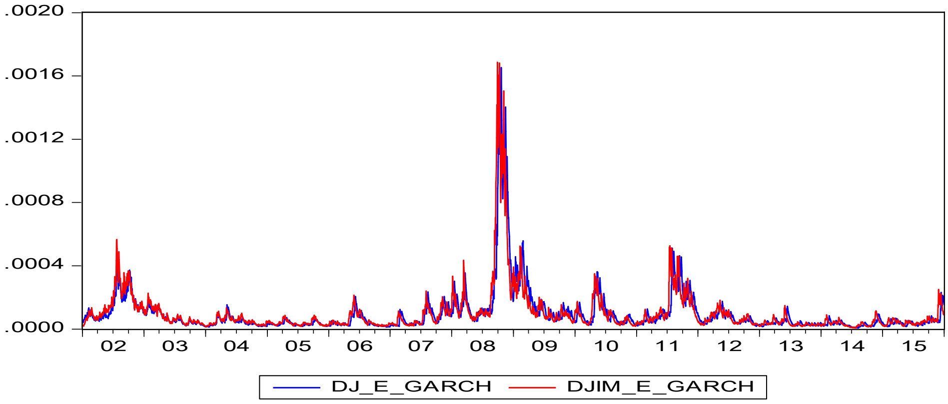


Figure 3. Volatility of stock indexes

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