Volatility Modeling of Islamic Stock Indices Returns Using GARCH Models

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Summary: The purpose of this study is to find the GARCH specification and innovations distribution combination which best models the returns volatility of four major Islamic equity indices DJIM, S&P500 SH, FTSE SWORLD.IS and MSCI ISWD. The conditionally heteroscedastic autoregressive models considered are GARCH, EGARCH, AGARCH, NARCH, NGARCH, GJR GARCH, APARCH and NGARCH whereas the distributions considered are the normal, student, cauchy, laplace, logistics and EVD distributions. The study of the statistical properties of the different return series confirms that GARCH models are the most suitable for modeling purposes. The results of the estimations suggest that the combinations offering the best volatility modeling are: NGARCH-Laplace for the DJIM, APGARCH-Laplace for the S&P500 SH, GJR GARCH-Logistics for the SWORLD.IS and GJR GARCH-Student for the MSCI ISWD.

Keywords: Islamic Equity Indices, Volatility, GARCH, Stylized Facts.
Jel Classification Codes : C20, C58, G15.

I- Introduction :

Financial assets volatility modeling plays a very important role in the field of both conventional and Islamic financial markets. Volatility modeling and forecasting are nonetheless difficult because examination of the financial return series reveals a set of common and independently observed statistical properties and in different markets. These properties are known as stylized facts and have been described by many empirical studies. (Mandelbrot, 1963) and (Pagan, 1996) have pointed out that the empirical distributions of most daily stock price series tend to have fat tails. (Cont, 2001) has highlighted the phenomenon of leverage effect, which states that changes in the returns of an asset are negatively correlated with changes in its volatility. (Ding & Granger, 1996) and (McMillan & Ruiz, 2009) have shown that volatility is not constant over time but tends to appear in clusters. The GARCH model of (Bollerslev, 1986) allows to take into account many of these stylized facts and was used extensively in the literature to model all sort of financial series. But being symmetrical, the GARCH model cannot capture the leverage effect. In addition, this model is less efficient than the more sophisticated GARCH models which were developed later (Hansen & Lunde, 2005). These models include the AGARCH model (Engle, 1990) which takes into account the asymmetrical effects of positive and negative innovations, the EGARCH model (Nelson, 1991) which could take into account the sign of the innovation and its magnitude and requires no constraint of non-negativity of the conditional variance, the NARCH model (Higgins & Bera, 1992) which gives the dynamic of the conditional standard deviation raised to a power to be estimated, the NGARCH model (Kışınbay, 2010) which is a generalization of the NARCH model, the GJR GARCH (Glosten, Jagannathan, & Runkle, 1993) which allows for asymmetrical response of volatility to innovations in the market, the NAGARCH model (Engle & Ng, 1993) in which the impact of a negative return shock is greater than a positive return shock of equal absolute magnitude, the APARCH model (Ding, Granger, & Engle, 1993) which nests several GARCH specifications. Studies such as (Alberg, Shalit, & Yosef, 2008) have shown that asymmetric models perform best for modeling equity indices. But the literature on modeling the volatility of Islamic equity indices returns is not as abundant as it is for conventional indices. (Chiadmi, 2015) showed that Islamic stock market indices also exhibited these statistical properties and that long-memory GARCH models were more suitable for capturing the phenomenon of persistence of volatility.

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Nevertheless, the approach consisting in using distributions which fit the best the returns of Islamic stock market indices as a distribution of GARCH model innovations has not been explored. The purpose of this article is to find the best model-distribution combination for modeling the volatility of the four major global Islamic stock indices.

II– Methods and Materials:

The mean equation of the returns is assumed to follow an ARMA (1,1) process:

$$r_t = \varphi r_{t-1} + \theta \varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t = Z_t \sigma_t$$

The selected models for volatility modeling are GARCH, EGARCH, AGARCH, NARCH, NGARCH, GJR GARCH, NAGARCH and APARCH, all of order (1,1). Each model will be estimated using the distributions: normal, student, laplace, cauchy, logistics and EVD, for a total of 48 estimates for each series of return. First, Kolmogorov-Smironv test will be used to determine which distribution fits the best every return series and then based on AIC the best specification-distribution will be chosen for each series.

GARCH

(Bollerslev, 1986) generalized the ARCH model and created the GARCH model whose dynamics of conditional volatility is given by:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

This model makes the conditional variance dependent on its own lags in addition to lagged innovations.

EGARCH

The EGARCH model or Exponential GARCH was introduced by (Nelson, 1991), its conditional variance is given by:

$$\sigma_t^2 = exp(\omega + \gamma z_{t-1} + \alpha(|z_{t-1}| - E|z_{t-1}|) + \beta ln(\sigma_{t-1}^2))$$

Besides of taking into account the sign of the innovation and its magnitude, this model has the advantage to require no constraint to guarantee the non-negativity of the conditional variance and this by formalizing it in an exponential form.

AGARCH

The Asymmetric GARCH model introduced by (Engle, 1990), its conditional variance is specified as follows:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1} + \beta \sigma_{t-1}^2$$

This model takes into account the asymmetrical effects of positive and negative innovations. If the coefficient γ is positive, then a positive shock induces a lower increase in volatility than a negative shock of the same magnitude.

NARCH

(Higgins & Bera, 1992) proposed the Nonlinear ARCH in which the conditional variance is specified as follows:

$$\sigma_t^\delta = \alpha_0 \sigma^2 + \alpha(\varepsilon_{t-1}^2)^\delta$$

This model gives the dynamic of the conditional standard deviation raised to the power δ instead of using the conditional variance.

NGARCH

The original model of (Higgins & Bera, 1992) contained only ARCH lags but it can be generalized by including GARCH lags and hence becomes the following NGARCH model (Kışınbay, 2010):

$$\sigma_t^\delta = \omega + \alpha(\varepsilon_{t-1}^2)^\delta + \beta \sigma_{t-1}^\delta$$

The NGARCH model shares the same peculiarity as the NARCH model by modeling the conditional standard deviation raised to the power δ instead of the conditional variance but also includes its lagged values.

GJR GARCH

(Glosten, Jagannathan, & Runkle, 1993) introduced a volatility model, the GJR GARCH that allowed for asymmetric effects. The general model is written as follows:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

$$I_{t-i} = \begin{cases} 1 \ if \ \varepsilon_{t-i} < 0 \\ 0 \ if \ \varepsilon_{t-i} \geq 0 \end{cases}$$

This model allows for asymmetric effects to be taken into account. It assumes that the parameters of the squared residuals depend on the sign of the shock. The main difference from the standard model is an additional variable in the conditional variance equation which equals to the product of a dummy variable and the squared innovations.

NAGARCH

The Nonlinear Asymmetric GARCH model was introduced by (Engle & Ng, 1993), its conditional variance is specified as follows:

$$\sigma_t^2 = \omega + \alpha(\varepsilon_{t-1}\sigma_{t-1}^{-1} + \gamma)^2 + \beta \sigma_{t-1}^2$$

The parameter γ captures the leverage effect; if γ = 0, then the model is symmetric, if γ> 0, a negative shock will result in a higher volatility increase.

APARCH

(Ding, Granger, & Engle, 1993) introduced the Asymmetric Power ARCH model:

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^\delta + \beta \sigma_{t-1}^\delta$$

In this model, it is no longer assumed that the conditional variance is a linear function of squared errors. The parameter γ measures the leverage effect, the parameter δ plays the role of a Box-Cox transformation of the conditional standard deviation (Laurent, 2004). The APARCH model encompasses a variety of other models based on the values of its coefficients (Bollerslev, 2009).

Data

The database used for this empirical study was acquired from quotes.wsj.com, and consists of daily closing prices of the Shariah S&P500, Dow Jones Islamic Market, SWORLD.IS, and MSCI ISWD indices. For each index, the starting date is the oldest date of availability until 31/12/2017, these periods are summarized in table 1.

The log returns were then computed using the formula:

$$R_t = ln\left(\frac{S_t}{S_{t-1}}\right)$$

With: R_t: The return of the financial asset at time *t*, S_t: The price of the financial asset at time t, S_{t-1}: The price of the financial asset at time $t-1$, *ln*: Natural logarithm.

Returns are more frequently used instead of financial asset prices for modeling purposes, because financial returns can be assumed to be stationary over periods of time that are not too long (Posedel, 2005).

III- Results and discussion:

Since 1963 and the work of Mandelbrot, many common statistical properties have been observed in many financial return series, regardless of their financial market. These properties are known as stylized facts. The figures 1,2,3 and 4 shows several stylized facts. Volatility is not constant over time and tends to appear in clusters; periods of high volatility tend to be followed by periods of high volatility and periods of low volatility tend to be followed by periods of low volatility. This is an indicator of the presence of memory in the process governing volatility. Moreover, the volatility resulting from a negative shock is greater than the volatility resulting from a positive shock of the same magnitude. This phenomenon is known as leverage effect. These findings support the choice using GARCH models to model volatility.

The distributions that best fit the returns of the different indices are all fat-tailed distributions, as shown in table 2. This clearly indicates that the normality assumption of returns must be rejected according to the Kolmogorov-Smirnov test for all series of returns with p-values < 0.05. This is also supported by the negative sign of the asymmetry coefficients which demonstrate that all empirical distributions are asymmetric with fatter left distribution tails, unlike a normal distribution which is symmetric. In addition, the kurtosis coefficients are far greater than 3, the kurtosis of a normal distribution, except for the case of the MSCI ISWD index which is lower (2.17). Table 3 shows which distribution is fitting the best the empirical distribution according to Kolmogorov-Smirnov test. It shows that the distributions offering the best fit are fat tailed distributions, namely the distribution of cauchy for the DJIM, laplace for the S&P500 SH and the SWORLD.IS and logistics for the MSCI ISWD which is consistent with the literature.

The results of the estimations of the different models associated to the different distributions of the study are summarized in tables 4,5,6 and 7. The GARCH specifications offering the best fit according to the Akaike information criterion are all asymmetrical. Namely NGARCH for the DJIM index with an AIC of -36836,94, APGARCH with an AIC of -11915,72, for the S&P500 SH index and GJR GARCH for the SWORLD.IS and MSCI ISWD indices with respectively an AIC of -17706,12 and-13596,96. The distributions offering the best adjustments are the laplace distribution for the DJIM and S&P500 SH index returns series, the logistics distribution for the SWORLD.IS and the student distribution for the MSCI ISWD index return series. These distributions don’t match our findings regarding the best fitting distributions summarized in table 2 suggesting that there is no need to find the distribution which fits the data the best before the estimating operation. But by doing so, even if the fitted distribution performs less than an estimated distribution, it will perform better than a normal distribution. Another finding of our study is we cannot model the volatility of all the Islamic indices returns using a unique model but in return we can limit the set of models for this purpose to asymmetric models only.

IV- Conclusion:

The statistical properties of a sample consisting of four major Islamic equity indices were highlighted, namely: non-normality of the empirical distribution of returns, heteroscedasticity, clustering of volatility, leverage effect and persistence of volatility. These observations indicate that modeling volatility using GARCH models is appropriate since they take into account more or less of these stylized facts depending on the chosen GARCH specification. The used models are: GARCH, EGARCH, AGARCH, NARCH, NGARCH, GJR GARCH, NAGARCH and APARCH, all of order (1,1). The property of non-normality of the returns and more specifically the fat tails of the empirical distributions led us to use in addition to the normal distribution, the distributions of student, laplace, cauchy, logistic and EVD. Specification-distribution combinations offering the best modeling of the volatility of Islamic equity index returns, according to the smallest AIC are: NGARCH-Laplace for the DJIM, APGARCH-Laplace for the S&P500 SH, GJR GARCH-Logistics for the SWORLD.IS and GJR GARCH-Student for the MSCI ISWD. These results suggest that asymmetric GARCH models outperform symmetric GARCH models and the laplace and logistics distributions outperform the normal distribution and may even outperform the student distribution which remains more used in the literature than the other distributions mentioned above. Hence, it would be interesting to use these distributions for modeling the volatility of financial asset returns. An extension of this work would be to check whether the superiority of these distributions remains effective in periods of low volatility where extreme returns tend to appear less frequently.

- Appendices:

Table (1): Study periods of each index

Indices	Initial date	Final date
DJIM	25/05/1999	31/12/2017
S&P 500 Sh	22/05/2011	31/12/2017
SWORLD.IS	29/10/2007	31/12/2017
MSCI ISWD	28/09/2009	31/12/2017

The source: Realized by ourselves

Table (2): Statistical properties and normality test

Index return	**Skewness**	**Kurosis**	**K-S D**	**P-value**
DJIM	-0,073	16,089	0,102	< 0,0001
S&P500 SH	-0,667	6,865	0,078	< 0,0001
SWORLD.IS	-0,411	9,839	0,105	< 0,0001
MSCI ISWD	-0,166	2,170	0,047	0,000

The source: Realized by ourselves using Xlstat

Table (3): Distribution fitting results

Indices returns	**Best fitted distribution**
DJIM	Cauchy
S&P500 SH	Laplace
SWORLD.IS	Laplace
MSCI ISWD	Logistics

The source: Realized by ourselves using Easyfit

Table (4): Estimations results DJIM

LLF	AIC	BIC	Model	Distribution
18425,47	**-36836,94**	**-36790,94**	NGARCH	Laplace
18397,80	-36781,59	-36735,59	GJR GARCH	Laplace
18365,75	-36719,51	-36680,08	APGARCH	Laplace
18366,40	-36718,80	-36672,80	AGARCH	Laplace
18368,22	-36720,44	-36667,87	GARCH	Laplace
18348,88	-36679,75	-36620,60	APGARCH	Student
18302,12	-36588,24	-36535,66	GJR GARCH	Student
18298,68	-36581,35	-36528,77	APGARCH	Logistics
18274,46	-36534,92	-36488,92	GJR GARCH	Logistics
18262,21	-36510,41	-36464,41	GARCH	Student
18247,29	-36478,57	-36426,00	AGARCH	Student
18243,11	-36470,23	-36417,65	NGARCH	Student
18229,77	-36447,54	-36408,11	GARCH	Logistics
18223,16	-36432,33	-36386,32	AGARCH	Logistics
18113,28	-36212,56	-36166,55	NGARCH	Logistics
18064,05	-36114,10	-36068,10	NAGARCH	Logistics
18037,23	-36060,45	-36014,45	NARCH	Normal
18032,81	-36051,62	-36005,62	GJR GARCH	Normal
18017,42	-36020,83	-35974,83	AGARCH	Normal
17977,41	-35942,83	-35903,40	NGARCH	Normal
17979,29	-35944,59	-35898,58	GARCH	Normal
17853,29	-35692,58	-35646,58	GJR GARCH	Cauchy
17829,05	-35646,11	-35606,67	GARCH	Cauchy
17791,89	-35569,79	-35523,78	NGARCH	Cauchy
17717,51	-35421,02	-35375,02	NARCH	Laplace
17685,22	-35354,44	-35301,86	APGARCH	Cauchy
17674,73	-35333,46	-35280,89	NARCH	Student
17464,43	-34914,86	-34868,85	NARCH	Cauchy
17460,83	-34907,67	-34861,66	AGARCH	Cauchy
17399,60	-34785,19	-34739,19	NARCH	Logistics
17076,80	-34139,60	-34093,60	NARCH	EVD
17073,68	-34133,35	-34087,35	EGARCH	EVD
17015,87	-34019,73	-33980,30	AGARCH	EVD
17016,22	-34018,44	-33972,43	GARCH	EVD
16906,99	-33799,98	-33753,97	GJR GARCH	EVD
16829,96	-33643,92	-33591,35	APGARCH	EVD
16818,89	-33621,78	-33569,21	APGARCH	Normal
16775,38	-33536,76	-33490,76	NGARCH	EVD
16509,03	-33004,06	-32958,06	EGARCH	Logistics
16406,60	-32797,21	-32744,63	EGARCH	Student
16212,38	-32410,76	-32364,75	EGARCH	Normal
15789,28	-31564,56	-31518,55	EGARCH	Cauchy
15669,71	-31325,43	-31279,42	EGARCH	Laplace

15486,15	-30958,30	-30912,30	NAGARCH	EVD
11067,53	-22119,05	-22066,48	NAGARCH	Student
10588,63	-21163,25	-21117,25	NAGARCH	Laplace
9102,07	-18190,14	-18144,14	NAGARCH	Cauchy
6652,33	-13290,66	-13244,65	NAGARCH	Normal

The source: Realized by ourselves using Matlab

Table (5): Estimations results S&P500 SH

LLF	AIC	BIC	Modèle	Distribution
5965,86	**-11915,72**	-11871,58	APGARCH	Laplace
5964,67	-11915,34	**-11876,72**	AGARCH	Laplace
5962,08	-11908,15	-11864,01	AGARCH	Student
5961,98	-11909,95	-11871,33	GJR GARCH	Laplace
5957,97	-11899,94	-11855,79	GJR GARCH	Student
5954,15	-11894,30	-11855,68	NARCH	Laplace
5952,74	-11893,47	-11860,36	GARCH	Laplace
5951,51	-11889,03	-11850,40	EGARCH	Laplace
5950,46	-11884,92	-11840,77	NARCH	Student
5948,96	-11881,91	-11837,77	EGARCH	Student
5948,82	-11883,63	-11845,01	GARCH	Student
5947,40	-11880,80	-11842,17	NGARCH	Laplace
5946,33	-11876,66	-11832,51	NAGARCH	Student
5941,79	-11869,57	-11830,95	AGARCH	Logistics
5938,19	-11862,38	-11823,76	GJR GARCH	Logistics
5925,39	-11836,78	-11798,15	EGARCH	Logistics
5924,31	-11836,63	-11803,52	GARCH	Logistics
5921,49	-11826,98	-11782,83	NGARCH	Student
5920,87	-11823,75	-11774,08	APGARCH	Student
5847,23	-11680,47	-11641,84	AGARCH	Normal
5845,70	-11677,40	-11638,77	GJR GARCH	Normal
5842,41	-11668,81	-11624,67	APGARCH	Normal
5839,82	-11665,63	-11627,01	NARCH	Logistics
5831,62	-11649,24	-11610,61	EGARCH	Normal
5830,84	-11647,69	-11609,06	NARCH	Normal
5827,54	-11643,09	-11609,98	GARCH	Normal
5795,39	-11576,79	-11538,16	NGARCH	Normal
5782,68	-11551,35	-11512,73	AGARCH	Cauchy
5782,02	-11548,03	-11503,89	APGARCH	Cauchy
5780,90	-11547,81	-11509,18	GJR GARCH	Cauchy
5778,58	-11543,15	-11504,52	NARCH	Cauchy
5777,56	-11543,12	-11510,02	GARCH	Cauchy
5774,03	-11534,05	-11495,42	NGARCH	Cauchy
5770,96	-11527,93	-11489,30	EGARCH	Cauchy
5747,03	-11480,07	-11441,44	AGARCH	EVD
5741,46	-11470,92	-11437,81	GARCH	EVD
5736,88	-11459,77	-11421,14	GJR GARCH	EVD
5735,61	-11457,21	-11418,59	NARCH	EVD
5696,93	-11379,86	-11341,24	EGARCH	EVD

5680,79	-11345,57	-11301,43	APGARCH	EVD
5536,88	-11059,75	-11021,12	NGARCH	EVD
4727,05	-9440,09	-9401,47	NGARCH	Logistics
3605,70	-7195,39	-7151,25	APGARCH	Logistics
3567,50	-7121,01	-7082,38	NAGARCH	Laplace
2991,58	-5969,16	-5930,53	NAGARCH	Logistics
2830,51	-5647,01	-5608,39	NAGARCH	Cauchy
2445,75	-4877,50	-4838,88	NAGARCH	Normal
2124,53	-4235,07	-4196,44	NAGARCH	EVD

The source: Realized by ourselves using Matlab

Table (6): Estimations results SWORLD.IS

LLF	AIC	BIC	Model	Distribution
8860,45	-17704,89	-17658,03	GJR GARCH	Student
8860,06	**-17706,12**	**-17665,11**	GJR GARCH	Logistics
8858,90	-17703,79	-17662,79	AGARCH	Logistics
8857,90	-17699,79	-17652,93	AGARCH	Student
8855,16	-17694,31	-17647,46	EGARCH	Student
8847,12	-17680,24	-17639,23	EGARCH	Logistics
8832,15	-17648,29	-17601,43	APGARCH	Logistics
8830,00	-17644,01	-17597,15	NARCH	Student
8829,72	-17647,44	-17612,30	GARCH	Logistics
8828,94	-17643,87	-17602,87	GARCH	Student
8828,59	-17643,17	-17602,17	GJR GARCH	Laplace
8819,44	-17624,88	-17583,87	EGARCH	Laplace
8813,28	-17608,56	-17555,85	APGARCH	Student
8811,24	-17608,47	-17567,47	GJR GARCH	Normal
8811,08	-17606,17	-17559,31	APGARCH	Laplace
8807,53	-17601,06	-17560,06	EGARCH	Normal
8806,88	-17599,76	-17558,75	NARCH	Laplace
8805,94	-17599,88	-17564,74	GARCH	Laplace
8794,92	-17575,83	-17534,83	AGARCH	Normal
8792,15	-17570,30	-17529,30	AGARCH	Laplace
8789,29	-17562,59	-17515,73	APGARCH	Normal
8778,13	-17544,26	-17509,11	GARCH	Normal
8770,53	-17525,06	-17478,20	NGARCH	Student
8763,89	-17513,77	-17472,77	NGARCH	Logistics
8760,44	-17506,88	-17465,88	NGARCH	Laplace
8756,65	-17499,31	-17458,30	NARCH	Normal
8682,00	-17350,00	-17309,00	NAGARCH	Normal
8634,91	-17255,83	-17214,82	GJR GARCH	EVD
8627,40	-17240,80	-17199,80	NARCH	EVD
8626,89	-17239,79	-17198,79	AGARCH	EVD
8626,88	-17241,76	-17206,61	GARCH	EVD
8622,95	-17231,90	-17190,90	NARCH	Logistics
8606,11	-17198,23	-17157,22	EGARCH	EVD
8536,83	-17059,67	-17018,66	GJR GARCH	Cauchy
8533,81	-17053,61	-17012,61	AGARCH	Cauchy

8527,58	-17041,17	-17000,16	EGARCH	Cauchy
8520,05	-17028,09	-16992,95	GARCH	Cauchy
8499,65	-16985,29	-16944,29	NAGARCH	Cauchy
8427,41	-16838,81	-16791,95	APGARCH	Cauchy
8410,43	-16806,86	-16765,86	NGARCH	Normal
8407,98	-16801,96	-16760,96	NARCH	Cauchy
8401,83	-16789,65	-16748,65	NGARCH	Cauchy
8370,82	-16725,64	-16678,78	APGARCH	EVD
7295,22	-14576,44	-14535,44	NGARCH	EVD
4978,28	-9942,55	-9901,55	NAGARCH	EVD
4869,72	-9725,45	-9684,44	NAGARCH	Laplace
3597,78	-7179,55	-7132,69	NAGARCH	Student
2556,94	-5099,87	-5058,87	NAGARCH	Logistics

The source: Realized by ourselves using Matlab

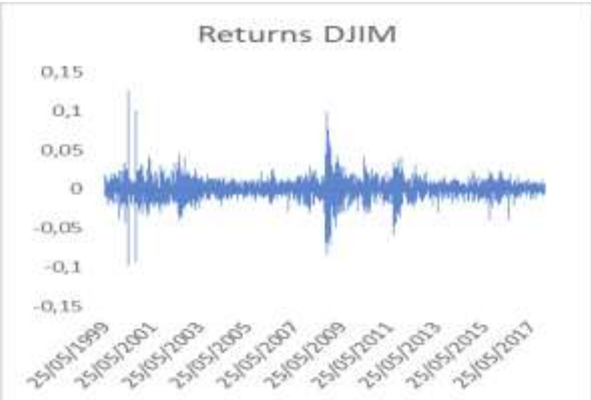
Table (7): Estimations results MSCI ISWD

LLF	AIC	BIC	Model	Distribution
6806,48	**-13596,96**	-13552,09	GJR GARCH	Student
6806,38	-13596,76	-13551,90	AGARCH	Student
6803,84	-13593,68	**-13554,42**	GJR GARCH	Logistics
6803,28	-13592,55	-13553,29	AGARCH	Logistics
6799,30	-13582,61	-13537,74	EGARCH	Student
6793,32	-13572,63	-13533,37	EGARCH	Logistics
6791,13	-13568,26	-13529,00	GJR GARCH	Normal
6791,02	-13566,03	-13521,16	NARCH	Student
6789,04	-13564,08	-13524,82	NARCH	Logistics
6789,02	-13564,04	-13524,78	GARCH	Student
6788,20	-13564,39	-13530,74	GARCH	Logistics
6787,30	-13560,60	-13521,34	AGARCH	Normal
6778,46	-13538,93	-13488,45	APGARCH	Student
6777,32	-13540,63	-13501,37	NGARCH	Logistics
6776,53	-13537,06	-13492,19	NGARCH	Student
6774,35	-13532,71	-13487,84	APGARCH	Normal
6773,72	-13533,44	-13494,19	EGARCH	Normal
6771,13	-13530,27	-13496,62	GARCH	Normal
6769,70	-13523,40	-13478,54	APGARCH	Logistics
6767,04	-13520,07	-13480,81	NARCH	Normal
6755,36	-13496,73	-13457,47	NGARCH	Normal
6749,76	-13485,52	-13446,26	AGARCH	Laplace
6748,86	-13483,72	-13444,46	GJR GARCH	Laplace
6742,59	-13469,18	-13424,31	APGARCH	Laplace
6741,28	-13468,55	-13429,29	NARCH	Laplace
6741,24	-13470,48	-13436,83	GARCH	Laplace
6740,24	-13466,47	-13427,22	NAGARCH	Laplace
6738,73	-13463,46	-13424,20	EGARCH	Laplace
6734,29	-13454,58	-13415,32	NGARCH	Laplace
6579,79	-13143,57	-13098,70	NAGARCH	Student
6558,49	-13102,97	-13063,71	GJR GARCH	EVD

6558,02	-13102,04	-13062,78	AGARCH	EVD
6557,58	-13103,16	-13069,51	GARCH	EVD
6539,38	-13064,77	-13025,51	EGARCH	EVD
6506,36	-12998,72	-12959,46	AGARCH	Cauchy
6502,70	-12991,40	-12952,15	GJR GARCH	Cauchy
6499,70	-12987,41	-12953,76	GARCH	Cauchy
6497,90	-12981,81	-12942,55	NAGARCH	Cauchy
6497,25	-12980,50	-12941,24	EGARCH	Cauchy
6497,08	-12978,17	-12933,30	APGARCH	Cauchy
6477,66	-12941,33	-12902,07	NARCH	EVD
6471,81	-12929,62	-12890,36	NGARCH	Cauchy
6471,19	-12928,38	-12889,12	NARCH	Cauchy
6428,18	-12840,36	-12795,49	APGARCH	EVD
6180,77	-12347,54	-12308,28	NGARCH	EVD
4028,24	-8042,49	-8003,23	NAGARCH	Normal
2571,04	-5128,08	-5088,83	NAGARCH	EVD
1912,20	-3810,40	-3771,14	NAGARCH	Logistics

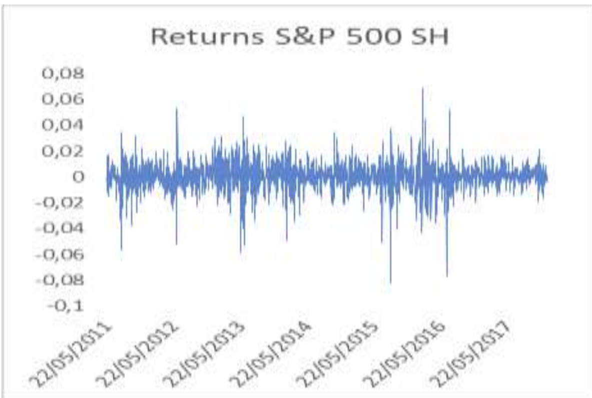
The source: Realized by ourselves using Matlab

Figure (1): DJIM returns



The source: Realized by ourselves based on quotes.wsj.com

Figure (2): S&P500 SH returns

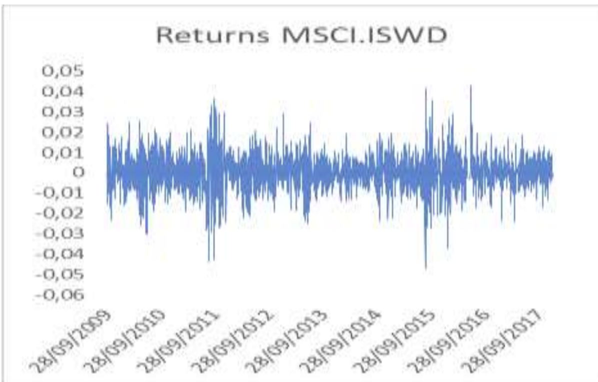


The source: Realized by ourselves based on quotes.wsj.com

Figure (3): SWORLD.IS returns

The source: Realized by ourselves based on quotes.wsj.com

Figure (4): MSCI.ISWD returns



The source: Realized by ourselves based on quotes.wsj.com

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