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Modelling Stock Market Return Volatility: Evidence from Moroccan stock market

Modélisation de la volatilité des rendements des marchés boursiers : preuves du marché boursier marocain

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Abstract:

Generally speaking, the Moroccan all-share index (MASI), or the Moroccan stock market's daily returns, are being estimated and forecasted by the research and which is using General Autoregressive Conditional Heteroscedastic (GARCH) type models on a worldwide scale. The conditional variance was also evaluated using data from January 2007 to December 2021. Additionally, two of the most prevalent stock market characteristics namely the leverage effect, and volatility clustering, are both modeled by symmetric and asymmetric frameworks in this study.
In a similar vein, the research had been carried out for this paper demonstrates that the returns' variance was not steady. Nevertheless, it varied with time, which is a conditional heteroskedasticity operation. Additionally, the returns on the Moroccan stock market have also been computed using a variety of methods, including GARCH, GJR GARCH, EGARCH, and M- GARCH models. These strategies also display the leverage effect, volatility persistency, clustering effects, and last but not least, an asymmetric response to external shocks. Proving that, there is a risk premium for the MASI return series.

Keywords: ARCH effect, GARCH Models, leverage effect, volatility clustering, asymmetric GARCH models, symmetric GARCH models.
JEL Classification: G10, G14, C58
Paper type: Empirical Research

Résumé :

Le présent article se penche sur une étude de la variance des rendements du marché boursier marocain. Dans ce travail, The Moroccan All Share Index (MASI) et les rendements journaliers du marché boursier Marocain ont été estimé et prédits à travers les modèles de type General Autoregressive Conditional Heteroscedastic (GARCH). Nous avons également exploité les données de la période allant de janvier 2007 à Décembre 2021 pour évaluer la variance conditionnelle. Dans le même but, nous tenons à préciser que les deux caractéristiques les plus courantes du marché boursier, A savoir l'effet de levier et le regroupement de la volatilité sont représentés par des modèles symétriques et d'autres asymétriques.
La recherche menée dans cet article a démontré en conséquence que la variance des rendements du marché boursier n'est absolument pas constante. En effet, elle change avec le temps, ce qui implique une opération d'hétéroscédasticité conditionnelle. Nous tenons à préciser également qu'il a été essentiel d'employer des modèles diversifies tel que GARCH, GJR GARCH, EGARCH et M-GARCH afin de déterminer les facteurs sous -jacents contribuant à ces changements. Chose qui nous a fait remarquer l'existence de l'effet de levier, la persistance de la volatilité, les effets de regroupement et surtout une réponse asymétrique aux chocs extérieurs. La Preuve en est, dans une prime de risque pour la série MASI return.

Mots clés : effet ARCH, modèles GARCH, effet de levier, clustering de volatilité, modèles GARCH asymétriques, modèles GARCH symétriques.
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1. Introduction

Globally, when it comes to the stock market, one of the essential elements in conventional financial mechanics is volatility, which is expressed as a percentage change in stock returns. Since the volatility cannot be observed in practice but must be calculated from the stock's initial value, it can be thought of as a random variable that follows a dynamical system. The volatility figure's task also includes characterizing the historical volatility pattern to possibly use that knowledge to forecast volatility in the future. A crucial characteristic of these exchanges is the fact that it has been realized a daily or monthly profit on finance stock markets, which have fat tails (leptokurtosis), and are not normally generated as the models suggest, but leading to excess skewness Papa (2004). However, it is generally known that stock market volatility is persistent, asymmetrical, clustered, and long memory-sensitive.

Furthermore, the conditional mean of a random variable is described by the plurality of conventional time series econometric approaches. However, a lot of intriguing economic theories are built to operate with conditional variance underneath the assumption that volatility's variance is fixed (Merton, 1969; Black and Scholes, 1973). Furthermore, these hypotheses might be homoscedastic regression models that disregard volatility's characteristics. Engle (1982), for example, created the Autoregressive Conditional Heteroscedasticity (ARCH) model to adequately represent the characteristics of volatility in the settings. However, in contrast to conventional approaches with constant variances, this approach leverages lagged disturbances to account for the time-varying conditional variance of financial time series. The fact that so many dimensions were needed to fully depict the dynamics of conditional variance was another problem. To address these issues, Bollerslev (1986) have presented the common model (GARCH), which is an expanded version of the ARCH that permitted a more adaptable lag construction and may ultimately lead to fewer parameters within this model. Additionally, the ARCH and GARCH techniques can both detect Leptokurtosis and volatility clustering two often seen features. In fact, these models have the disadvantage of not considering the leverage effect because of their symmetry. Additionally, a number of asymmetry extensions to GARCH have now addressed the issue that a large negative shock in share prices will have a larger effect on the series' volatility than a similar-sized positive shock Tsay (2013). Additionally, instances that refer reference to asymmetric extensions include the Glosten-Jaganathan-Runkle (GJR) by Jaganathan et al. (1993). The Exponential GARCH model (EGARCH) by Nelson (1991), and the Symmetric GARCH in-Mean (GARCH-M) model created by Engle et al. As a consequence, by applying the MASI, these work approaches forecast stock price volatility using symmetry and asymmetry GARCH models. Furthermore, the main goal of this paper is to model stock returns volatility and asymmetric news effects in the global stock market using the MASI index. Given the preceding discussion and arguments, we set the following hypothesis.

Hypothesis 1 (H1). which GARCH model is more effective for estimating and forecasting in this market.

Hypothesis 2 (H2). The volatility market of MASI has increased during the study period with the notable existence of the leverage effect in the case of GARCH modeling.

Therefore, to examine and evaluate the models' forecasting skills, i.e., which model effectively forecasts volatility, Theil's inequality coefficients, mean absolute error, and root mean squared errors are utilized. In the nutshell, this study's goal is to broaden and complement the existing research on the distinctive features of financial time series data at CSE (Casablanca stock exchange). Besides, agents, dealers, and specialists will be able to use it as a base to evaluate a fund's risk. It will be crucial to the judgment process for both individual and institutional investors so that they can trade their risks with a knowledgeable assessment.

2. Revue de littérature

In essence, we could claim that both the developed and developing countries, the financial markets have thoroughly examined the classic EMH, which followed the random walk assumption. The economic markets chaos test and non-linearity in returns patterns also ruthlessly refutes the EMH, which leads to opening the door to the possibility of property price forecasting. The sequential conditional variance of asset values could be utilized to describe the financial time series data using the martingale process.

In addition, the actual results of the financial market also point out to stylized interpretations of the pattern in the time series financial records. For the financial markets in Turkey, Egypt, Morocco, and Jordan, Assaf (2006) presents impartial evidence for the long-memory tendency in market returns; nevertheless, the recall for the profits is in two nations, namely Egypt and Morocco. In accordance with this, Alagidede (2011) analyzes the African dataset from 1995 to 2006 mainly relying on the FIGARCH model. Throughout this study, the stock markets of Egypt, Kenya, Morocco, Nigeria, Tunisia, and South Africa, have been shown evidence of prolonged recollection according to the author. Comparable to this, both the scholars Anoruo and Gil-alana (2011) use long-range dependence methodologies to investigate whether restoration occurred in the stock market values in eleven African nations. In each instance, the findings did not support the claim that any of the stock market price series had experienced mean reversion. However, Morocco, Egypt, Tunisia, and Nigeria's long memory in the return and volatility showed that these nations had a significant relevance. Therefore, throughout the course of this research, famous scholars like Boubaker et al. (2012) have examined a heavy tails and double-long memory in Tunisia, Morocco, and last but not least Egypt. Additionally, this research shows that the combined ARIMA- FIGARCH model accurately reflects long-memory patterns in market returns and volatility. Furthermore, several scholars have used the ARCH family of models to analysis and forecasting stock market volatility. For instance, Brooks (2007) calculated the volatility in diverse Middle Eastern and African equity markets, as well as the Moroccan Stock Index market, for the interval of 10 years (from 1995 to 2005). As a whole, the findings of this study demonstrate that most markets exhibit a standard leverage effect. Parallel to this, Alagidede et al. (2009) studied the level of volatility in the major African share prices, including Morocco, Nigeria, South Africa, Tunisia, Kenya, Egypt, and Zimbabwe, using asymmetric GARCH techniques. Their findings significantly and noticeably advanced the subject. Additionally, it has been observed that these markets are very volatile, even though traders often benefit from a higher risk-reward ratio. Strangely, markets with lower degrees of investor access and market liberalization tend to experience higher volatility. In 2015, Al-Hajieh has investigated the asymmetry of stock market volatility for 17 Islamic libraries using TGARCH and EGARCH models. He demonstrates that conditional variance exhibits prolonged endurance of volatility for all nations. Thus, the outcomes of EGACH and TGARCH likewise corroborate asymmetric function of the past residuals that characterizes the conditional variance. However, statistically speaking, this is not significantly for some countries such as: Tunisia, Morocco, Lebanon, Bahrain, and Oman. In the same vein, Coffie (2017) did, however, show signs of reversed volatility asymmetry in both the Moroccan and BVRM stock markets. Consequently, the GJR framework estimates and predict that the positive shocks will have a greater impact on future volatility than adverse threats. Md. Tuhin and Nurun Naher (2021) examine the performance of volatility modelling using different models and their forecasting accuracy for the returns of Dhaka Stock Exchange (DSE) under different error distribution assumptions. The study finds that ARMA (1,1)- TGARCH (1,1) is the most appropriate model for in-sample estimation accuracy under student's t error distribution. The asymmetric effect captured by the parameter of ARMA (1,1) with TGARCH (1,1), APARCH (1,1) and EGARCH (1,1) models shows that negative shocks or bad news create more volatility than positive shocks or good news. The study also provides evidence that student's t distribution

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for errors improves forecasting accuracy. With such an error distribution assumption, ARMA (1,1)-IGARCH (1,1) is considered the best for out-of-sample volatility forecasting. Multiple studies predicted the global stock markets performances during the pandemic period. Topcu and Gulal (2020) investigated the pandemic impact on emerging stock markets of Asia is higher than that of the European markets. Libo Xu (2021) studied Canadian and US stock markets to explore the unexpected changes and uncertainty of markets. Liu et al. (2021) investigated the impact of the pandemic on the Chinese stock market crash risk by using the approach of GARCH processes. Szczygielski et al. (2021) examined the effect of COVID-19 uncertainty on Asia and found that it exceeds, Europe, Africa, Latin America, North America, and Arab markets indices returns. The literature on the volatility dynamics of PSX-100 is, however, limited. Recently, Ali et al. (2020) studied the relationship of PSX-100 volatility, exchange rate, and gold prices for two divided periods of 2001–2008 and 2008–2018.

3. Méthodologie de recherche

In empirical finance research, the models of the autoregressive conditional heteroscedastic and its extensions are mostly used to analyze and forecast the stock market volatility. As a result, various univariate GARCH variables have been used in this paper, including GARCH (1,1) and GARCH in-Mean (1,1) as symmetric models. The EGARCH (1,1) and TGARCH (1,1) samples are also used to mimic the stock return volatility on the Moroccan stock market as asymmetrical models. In each of these latest systems, there are also two main separate analyses, one for the conditional variance and the other for the conditional mean, which are illustrated below.

3.1. Data

In this study, the data were mainly gathered from the Bank AL Maghreb website, and it consists of daily price series of the market index MASI (Moroccan All Share Index). Further, the overall data span the months between January 2007 to December 2021. The primary data is transformed using a natural logarithmic formula. Additionally, to give a data set of continuously compounded returns, the daily returns are computed as seen below:

$$r_t = \ln(p_t) - \ln(p_{t-1}) = ln\left(\frac{p_t}{p_{t-1}}\right)$$

3.2.Symmetric GARCH Models

The conditional variance in an asymmetric GARCH templet is only impacted by the magnitude of the financial instrument as opposed to the sign of the underlying value. The potential impacts of an asset's positive or negative value on conditional volatility are not taken into account. Additionally, this approach often used symmetric GARCH models. Thus, below is a detailed discussion about them.

3.2.1. GARCH Models

Bollerslev (1986) was the first and most fundamental scholar who created the generalized autoregressive conditional heteroscedasticity (GARCH). It is in this model where he did describe it as the linear equation of the lagged conditional variances and the past squared residuals, as seen below.

$$\sigma_t^2 = \alpha_0 + \sum_{i-1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i-1}^{p} \beta_i \sigma_{t-i}^2 \qquad (1)$$

Where α_0 refers constant term, through α_1 , α_2 …, α_q are the ARCH specifications' variables, and by β_1 , β_2 , ..., β_q which are in turn the GARCH specifications coefficients or parameters. The ARCH and GARCH processes' corresponding orders are q and p, respectively. As a result, the simplest description is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (2)$$

3.2.2. GARCH-in-Mean (GARCH-M) Models

This framework, which is created by Engle et al, is another well prominent symmetric model. Since the risk is typically rewarded by a greater yield in the capital, the return of an asset may be influenced by its volatility, and this model is one option. The conditional mean of the return's series can also be dependent on its conditional variance when using this GARCH model variation. Additionally, the GARCH-M formula has been used to define the earlier and later calculations. For the conditional mean we have:

$$r_t = \mu_t + \varepsilon_t \quad (3)$$

Where:

$$\mu_t = \mu + \lambda \sigma_t^2$$

Because of this, the expression for conditional variance is similar to that provided by the GARCH (p, q) pattern in the Formulation 1 and its particular instance of the GARCH (1, 1) by Algebraic (2).

3.3.Asymmetric GARCH Models

The need to discriminate between positive and negative news and how it affects market volatility is what drives the asymmetrical methods. Regardless of whether the unanticipated is favorable or unfavorable, according to Engle et al, the news influence is the result of a shock on the time-varying conditional variance. Moreover, future volatility and current return have a negative link with each other. The leverage effect is the propensity for volatility to increase as return decreases while decreasing when return increases. Because conditional variance cannot respond asymmetrically, the symmetric models are unable to describe the leverage effect. As a result, numerous asymmetric GARCH model versions have been developed to address this issue. And, the list below discusses a few of them.

3.3.1. Exponential GARCH (EGARCH) Models

Throughout this approach, Nelson created the exponential GARCH paradigm (commonly abbreviated as EGARCH) to account for the asymmetrical impact of positive and undesirable asset returns. As a result, the EGARCH (p, q) standard is given below.

$$\log(\sigma_t^2) = \sigma_0 + \sum_{i-1}^{q} \alpha_i \left[\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right] + \sum_{i-1}^{p} \beta_i log(\sigma_{t-i}^2) + \sum_{i-1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \qquad (4)$$

Where the asymmetry impact value or leverage effect parameter is γ_i , so it displays the conditional variance's log. Additionally, the conditional variance will be favorable regardless of whether the parameters are negative. If there is a discrepancy between the current return and the anticipated volatility in the future, the consequence of leveraging is limited.

3.3.2. Threshold GARCH (TGARCH) Models

This method, which is widely employed to control the leverage effect, is unquestionably a key volatility paradigm. Additionally, it's also recognized as the GJR framework, which Glosten, Jagannathan and Runkle (1993) have produced for the first time in the history of volatility. The

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conditional variance TGARC-H (p, q) template is provided by the computation below for further illustrative example:

$$\sigma_t^2 = \alpha_0 + \sum_{i-1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i-1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i-1}^{q} \gamma_i \varepsilon_{t-i}^2 I_{t-i} \quad (5)$$

When $I_{t-i} = 1$, and if $\varepsilon_{t-i} < 0$, thus, $I_{t-i} = 0$, respectively. Also, γ_i which is mainly the leverage consequence factor. Also, this model will collapse onto the standard GARCH (p, q) operation If $\gamma_i = 0$. Moreover, if the shock is negative, its influence on volatility is$\alpha_i + \gamma_i$ (i.e.,$I_{t-i} = 1$), Moreover, if the shock is positive, the influence is α_i (i.e. $I_{t-i} = 0$). Thus, it can be concluded that for $\alpha_i > 0$, the influence of unfavorable reportage is higher than the effect of good news on conditional variance.

4. Résultats et discussion

4.1 . Normality Tests

To describe the informative properties of the MASI returns series during the course of the period studied, and numerous qualitative data are generated in this assessment and shown in Table 1 beneath.

Table 1. Summary statistics for the MASI stock index from January 2007 to December 2021.

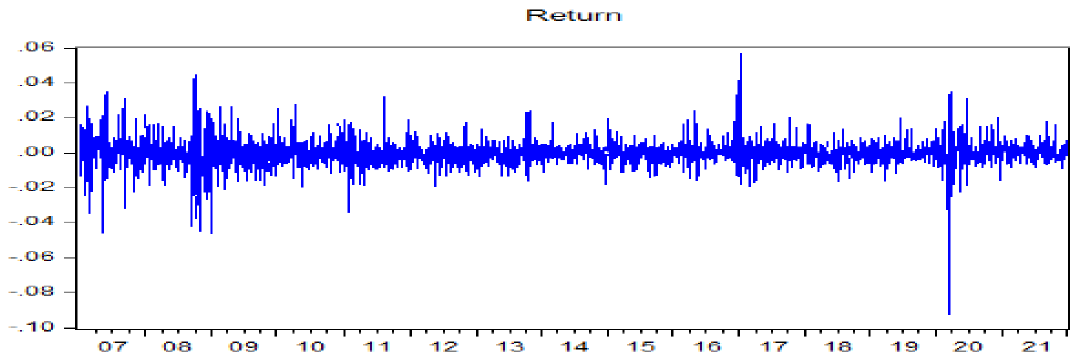
Mean	9.32E-05
Median	2.42E-05
Maximum	0.057316
Minimum	-0.091649
Std. Dev.	0.007043
Skewness	-0.826224
Kurtosis	20.13548
Jarque-Bera	46021.48
Probability	0.000000
Sum	0.347187
Sum Sq. Dev.	0.184820
Observations	3727

Note: The Jarque-Bera data point investigates the null hypothesis of a normal distribution and is distributed as $\chi 2$ with two phases of freedom.

Source : Authors' elaboration.

As shown from the above statistics, these descriptive analytics reveal that the market had a mean daily yield of 9.32×10^{-5} and that the Moroccan market had a standard deviation of 0.007043. In fact, negative skewness indicates an asymmetric pattern and a long-left tail in the stock price distribution, as well as more deviations towards lower values. On the other hand, the Kurtosis is also more than 3, which further suggests that the stock price distribution is leptokurtic and fails to follow a standard deviation, and thus the scientific process of normality is denied. Additionally, this was further supported by the tests of Jarque-Bera, which are significant at the 1% level.

Figure .1. The MASI daily returns series time graph.



Source: Authors' elaboration.

Figure 1 shows that extended durations of the low volatility are projected to precede the periods of low volatility, while long periods of high volatility are anticipated to following periods of high volatility. This suggests that volatility is clustering, particularly between 2008 and 2009, and that whilst the variance fluctuates through time, the return series move around a constant mean. The MASI index return may therefore be a stagnant sequence and may affect the ARCH.

4.2 . Stationarity Test

In this analysis, we used the well-known Phillips Perron assessment and Augmented Dickey-Fuller evaluation to examine the stationary scenario of the return Series. The outcomes of the stationary test are compiled in Table 2.

Table 2. Lists the outcomes of the MASI output sequence' unit root examination.

Dickey-Fuller Augmente Test	**t Statistique**	**1% level**	**5 % level**	**10% level**
Modèle [1]	-45.07250	-3.960503	-3.411012	-3.127320
Modèle [2]	-45.07795	-3.431919	-2.862119	-2.567121
Modèle [3]	-45.07862	-2.565583	-1.940909	-1.616642
Phillips-Perron Test				
Modèle [1]	-44.43971	-3.960503	-3.411012	-3.127320
Modèle [2]	-44.44687	-3.431919	-2.862119	-2.567121
Modèle [3]	-44.45467	-2.565583	-1.940909	-1.616642

Source : Authors' elaboration.

Corresponding, and based on the outcomes, the Phillips Perron and Augmented Dickey-Fuller t-tests have disproved the null hypothesis that the return has a unit root. The observed value of ADF and PP test values, as a result, are less than the critical values at the 1%, 5%, and 10% level of confidence. The results of both tests consequently demonstrate that the series is at a stationary.

4.3. Identification of the Model ARMA (p, q)

The mean equation must be made before the formula for the ARCH family model can be calculated. Additionally, the Box Jenkins method was used to create this mean formula for the ARCH family model, which is built on the Akaike information criteria, Schwartz information criterion, and Hannan-Quinn. The sustained AR and MA terms coefficients are also significant at the 5 percent level. As an outcome, table 3 beneath displays the outcomes of the mean equation scheme.

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Table .3. Estimation of ARMA (1.3) approach.

Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	7.91E-05	0.000140	0.565322	0.5719
AR (1)	0.634275	0.158631	3.998435	0.0001
MA (1)	-0.336582	0.158623	-2.121899	0.0339
MA (2)	-0.106170	0.048854	-2.173213	0.0298
MA (3)	-0.092289	0.018785	-4.912984	0.0000

Source : Authors' elaboration.

4.4. Test for Heteroscedasticity

This test is particularly designed for examining the residuals for signs of heteroscedasticity before using the ARCH technique is one of the most crucial steps. Hence, the Lagrange Multiplier (LM) test, which is a portmanteau test, is employed to determine whether heteroscedasticity exists in the return series' residual. Additionally, a statistically significant coefficient shows that the residuals from the MASI index mean equation contain evidence of the ARCH effect.

Table. 4. Results of ARCH-LM test

F-statistic	90.32770	**Prob. F (1,3723)**	0.0000
Obs*R-squared	88.23545	**Prob. Chi-Square (1)**	0.0000

Source : Authors' elaboration.

Since the predicted F-statistics is higher above than the critical threshold, the No-ARCH null hypothesis is ruled out according to the results of the ARCH-LM test in Table 4. Because the daily return on the MASI Index shows the ARCH, which is the facet of the path. We may also infer that the variance of the return on the MASI is non-constant for all the selected periods.

4.5. Serial correlation

The Ljung-Box Q-statistic is used in this test to assess the reliability of ARCH in the residuals. When there is no ARCH in the regression, the Q-statistics should also be unremarkable. Besides, both the autocorrelations and partial autocorrelations should all be Nil at all delays.
As seen in the table5, the return series display the ARCH effect as a result. In addition, notice the low p values demonstrates that the MASI squared residuals displayed an insignificant correlation among the error terms with all Q stats.
The ARCH-LM test and squared residuals of MASI outcomes provide proper resources for the generated ARCH family structures, allowing for their usage. The mean equation can be performed using the ARMA (1, 3) framework.

Table .5. Correlogram of residuals squared

Lag	AC	PAC	Q-Stat	Prob
1	0.005	0.005	0.1101	0.74
2	-0.002	-0.002	0.1258	0.939
3	-0.064	-0.064	15.333	0.002
4	-0.015	-0.015	16.215	0.003
5	-0.028	-0.028	19.04	0.002
6	0.000	-0.004	19.041	0.004
7	0.003	0.001	19.08	0.008
8	-0.011	-0.015	19.563	0.012
9	0.008	0.007	19.818	0.019
10	0.018	0.017	21.006	0.021
11	0.024	0.023	23.201	0.017
12	-0.009	-0.008	23.503	0.024

Source : Authors' elaboration.

4.6.Volatility Analysis

Table 6 shows estimated coefficients with corresponding p-values for the analysis of the symmetries GARCH models and asymmetries GARCH prototypes. Additionally, these p-values relate to the question to test to what extent the coefficient estimates are equivalent to 0.

Table .6. the findings of the estimations for GARCH (1, 1), GARCH-M (1, 1), EGARCH (1, 1), as well as TGARCH (1, 1).

<u>GARCH (1.1)</u>

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$return_t = 6.75902372962 \times 10^{-5} + 0.251781813155 \ \times R_{t-1}$$

$$\sigma_t^2 = 1.91479341458 \times 10^{-6} + 0.138096937448 \varepsilon_{t-1}^2 + 0.816786454326\, \sigma_{t-1}^2$$

<u>GARCHM (1.1)</u>

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$return_t = -0.267138339697 \times GARCH + \ 7.49712285638 \times 10^{-5} + \ 0.251850312404 \ \times R_{t-1}$$

$$\sigma_t^2 = 1.90559668617 \times 10^{-6} + 0.137733828798\, \varepsilon_{t-1}^2 + 0.817368737258 \sigma_{t-1}^2$$

<u>EGARCH (1.1)</u>

$$\log(\sigma_t^2) = \sigma_0 + \sum_{i-1}^{q} \alpha_i \left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|\right] + \sum_{i-1}^{p} \beta_i log(\sigma_{t-i}^2) + \sum_{i-1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$$

$$return_t = -1.98246938179 \times 10^{-5} + 0.249083324952 \ \times R_{t-1}$$

$$\log(\sigma_t^2) = -0.631122013275 \ + 0.265359488816 \left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|\right] + 0.957463143909 log(\sigma_{t-i}^2) - 0.0136673074294 \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$$

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GJR GARCH (1.1)

$$\sigma_t^2 = \alpha_0 + \sum_{i-1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i-1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i-1}^{q} \gamma_i \varepsilon_{t-i}^2 I_{t-i}$$

$$return_t = 2.72092847744 \times 10^{-5} + 0.253248415071 \times R_{t-1}$$

$$\sigma_t^2 = 1.85286631113 \times 10^{-6} + 0.11826023676 \varepsilon_{t-i}^2 + 0.821076938582 \sigma_{t-i}^2 + 0.0352163086137\ \varepsilon_{t-i}^2 I_{t-i}$$

Source: Authors' elaboration.

Accordingly, the GARCH (1, 1) model's ARCH term α_1 and GARCH term β_1 are parameters that describe how volatility responds to incoming knowledge in the market and how much volatility remembers from the past, respectively. Both parameters are also significant and positive at the 1% scale. In other words, volatility news from prior periods can explain ongoing volatility. This shows that the lagged conditional variance and lagged squared disturbance affect conditional variance.

Further, the market has a memory that goes beyond only one quarter because the estimated β_1 coefficient (0.816786454326) is substantially higher than the actual α_1 coefficient (0.138096937448). Furthermore, recent surprises in the market's values have less of an impact on the volatility than do its lagged values. Further, a greater value of β_1 denotes a longer decay of time for the conditional variance shocks. Thus, volatility is persistent. However, huge market surprises only seem to cause relatively little volatility, according to the allow value error coefficient $\alpha 1$. The fact that the total of these coefficients ($\alpha 1$ andβ_1) is 0.954883, or almost one, suggests that the shock will last for a significant number of subsequent times. Later instances.

Additionally, the return series' mean equation is made to depend on a function of the conditional variance which simulating the GARCH-M (1, 1) paradigm. The variance term (GARCH) though it is not significant in the mean equation, is significantly more noteworthy when it is included in the variance equation. Although theoretically positive and insignificant, the coefficient of conditional variance in the mean equation value suggests that there is not a complete trade-off between risk and profits and that volatility has no appreciable impact on expected return.

In a manner similar to the TGARCH paradigms, the EGARCH approach integrates the leverage effects of shocks. According to the study's proposed model, the indicator γ_i is statistically significant and its low matching P-value confirms the rejection of the null hypothesis. This implies the existence of a leverage effect. The parameter is negative as well. This implies that positive market shocks (good news) have a smaller daily impact on stock market volatility than downside risks which means (bad news).

The latest model which is the TGARCH is employed to evaluate the asymmetric volatility in the MASI returns by examining γ_i the coefficient of the leverage effect. The fact that the coefficient of leverage effect or asymmetric term is positive (0.0352163086137) and statistically significant at the 1% scale further demonstrates that there are asymmetries in the headlines for these firms.

Subsequently, this shows that good or uplifting news affects volatility less than terrible or unfavorable news. The additional coefficient of the asymmetric component (0.0352163086137) establishes the difference between information that is good and data that is unfavorable for the MASI market.

Positive shock: The following is the estimation of the time-varying volatility:

$$\sigma_t^2 = 1.85\ \times 10^{-6} + 0.118260\ \varepsilon_{t-i}^2 + 0.821077\ \ \sigma_{t-i}^2$$

Negative shock: The following is the estimation of the time-varying volatility:

$$\sigma_t^2 = 1.85 \times 10^{-6} + (0.118260 + 0.035216)\varepsilon_{t-i}^2 + 0.821077\sigma_{t-i}^2$$

Overall, the modeling of information, news, or events is a highly important factor in determining the volatility of an asset.

4.7. ARCH-LM test for heteroscedasticity

The ARCH-LM test is used to examine if there is an ARCH impact in residuals, and as the p-value is larger than 0.05. Hence, the findings demonstrate that there is evidence to support the null hypothesis that there is no arch impact. To put it another way, the statistical tests do not support the existence of any extra design impacts in the regression of the prototype, which demonstrates that the variance equation was appropriately adapted to the market.

Table .7. Results of ARCH-LM test

	F-statistic	Probability
GARCH (1, 1)	2.201555	0.138
GARCH-M (1, 1)	2.225733	0.1358
EGARCH (1, 1)	5.570533	0.0183
TGARCH (1, 1)	2.76885	0.0962

Source : Authors' elaboration.

4.8.Specifications of GARCH Models.

Various reliability indicators are employed in this research to assess the efficacy of these estimating techniques. The parameters of the Schwarz criterion (SC), Hannan-Quinn, Akaike information criterion (AIC), and log-likelihood were all evaluated. Additionally, the minimum of the AIC, Hannan-Quinn criteria, SC value, and highest log p likelihood value are taken into consideration when choosing the best-fitted models for both the symmetrical and asymmetrical effects.

Table .8. Measures for various GARCH approach reconfigurations.

	Log likelihood	AIC	SC	Hannan_Quinn
GARCH (1,1)	14006.86	-7.515761	-7.50741	-7.51279
GARCH = M (1,1)	14006.87	-7.515226	-7.505205	-7.511661
EGARCH (1,1)	14005.23	-7.514346	-7.504325	-7.510781
TGARCH (1,1)	14009.15	-7.516451	-7.50643	-7.512886

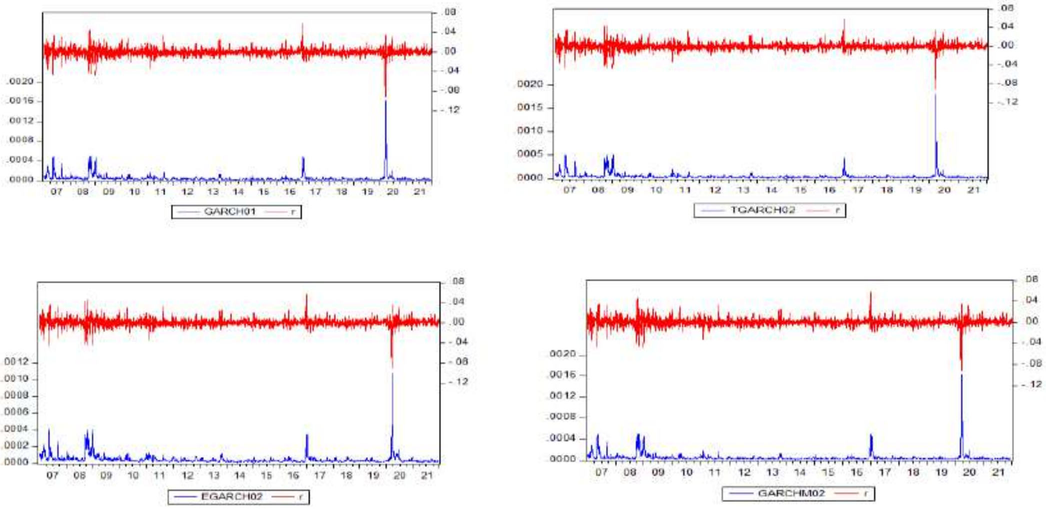
Source : Authors' elaboration.

As a result, with only a small deviation, the results of the precision measurement taken for each of the four anticipated categories are displayed in the table 8 above. Furthermore, depending on these metrics, we believe that the TGARCH (1, 1) paradigm is a more effective way to capture the key components of the MASI score, such as volatility and leverage effects.

4.9. Conditional Variance

Charts 2(A) through chart 2(D) are showing the observed and the estimated MASI for the entire time period from 2007 to 2021. These computed empirical models include a strong fit to the observed MASI time series, as shown by the Conditional variance from the years from the same era coexisting with those of the original plot of the series, such as instances of big fluctuations in returns. Because Figure 2(d) has a cleaner fitted trajectory, it is clear from a detailed examination of these plots that the TGARCH (1, 1) model fits the observed MASI index adequately.

Figure 2. (A) A graph of the observed and predicted MASI index using GARCH (1, 1) Model.
(B) A graph of the observed and predicted MASI index using GARCH-M (1, 1) Model.
(C) A graph of the observed and predicted MASI index using EGARCH (1, 1) Model.
(D) A graph of the observed and predicted MASI index using TGARCH (1, 1) Model.



Source : Authors' elaboration.

4.10. Forecast GARCH volatility

To assess the accuracy of the out-of-sample forecast, three measures have been found. The first one is the Root Mean Squared Error also known (RMSE), which was previously written by Bollerslev and colleagues in 1994 and Poon and Granger (2001). The second is the Mean Absolute Error, also (MAE), which was originally developed by Hansen and Lunde (2005), and the third, Theil's Inequality Coefficients. The design that has the closest predicted volatility consequently also has the lowest loss value and highest Theil's Inequality Coefficients. According to Andersen and Bollerslev, 1998, the secret to properly integrating multiple signals is choosing the best forecasting models.

Table .9. Evaluation of forecast MASI index

	RMSE	**MAE**	**TIC**
GARCH (1,1)	0,007066	0,004905	0,989851
GARCH M (1,1)	0,007067	0,004902	0,985453
EGARCH (1,1)	0,007067	0,004907	0,9817
TGARCH (1,1)	0,007067	0,004907	0,982005

Source : Authors' elaboration.

As it is customary, there are not many differences between the best and worst fitting models. For instance, the assessing measure MAE does not distinguish between the forecasting capacities of GARCH, EGARCH and GJR. This demonstrates that the inventions GARCH, EGARCH, and GJR to capture the asymmetry, or leverage effect, when forecasting the MASI index, generate superior predictions. The RMSE also favor the TGARCH model. In contrary, TIC favors the EGARCH model. When examining the outcomes of the MASI index, TGARCH comes out on top when it comes to RMSE and MAE measurements; GARCH and EGARCH are tied.

5. Conclusion

The study of volatility dynamics has become a topic of concern to researchers, academics, practitioners and regulators. In fact, volatility modelling is of paramount importance and its forecast is crucial in portfolio selection, value at risk, asset pricing, hedging strategies and option pricing. This paper has analyzed some important stylized facts in volatility returns of MASI. In fact, the main objective of this article is to characterize the behavior of volatility using both symmetric and asymmetric (GARCH) models, in order to design an adequate model for forecasting this latent variable in the Moroccan context. Throughout the study, which ran from January 2007 to December 2021.After the unit's root test, volatility clustering, and ARCH impact were confirmed, the corresponding models—GARCH (1, 1), GARCH-M (1,1), EGARCH (1,1), and TGARCH (1,1)—were utilized for this study. The outcomes further demonstrate that the leverage coefficient exhibits the anticipated signal in the TARCH (positive and significant) and EGARCH (negative and significant). On the other hand, visual inspection of return Figure confirming the existence of volatility clustering. As far as long memory is concerned, results show strong evidence of long memory in the volatility of the Moroccan stock market.

In a similar spirit, the AIC, SIC, Log-Likelihood, and Hannan-Quinn Criter were used to determine which of the many GARCH model parameters was most suitable. This demonstrates that both the GARCH (1, 1) and M-GARCH (1, 1) approach were found to be the finest prototype to represent the symmetric impact. Furthermore, it is found that the TGARCH (1, 1) framework is the most effective model for capturing the asymmetrical volatility based on the highest Log-Likelihood rates, where the minimum of the AIC and SC requirement and the Hannan-Quinn criterion.

Our analysis shows that the leverage impact and volatility clustering of the Moroccan financial markets are better captured by the TGARCH (1, 1) model. Another interesting result from earlier studies is that the optimal in sample fit framework does not always provide the most accurate out-of-sample prediction. According to earlier research, the minimum lag sequence is suitable for detecting changing volatility and producing precise answers (Gokcan, 2000; Javed and Mantalos, 2013). As a matter of fact, the GARCH models are frequently utilized for forecasting with the least lag sequence (Terasvirta, 2006). The TGARCH (1, 1) prediction models is the most suitable to use for anticipating an increase on the Moroccan benchmark based on the factors used in this study.

Finally, there are areas where further studies might be useful. For example, future research should focus on modelling and forecasting GARCH models with high frequency trading (i.e., intra-day) data. Further research may also consider exploring variety of models including other conditional variance models such as APARCH and long memory models such as FIEGARCH, FIAPARCH and CGARCH in order to allow a superior insight into the dynamics of this market. Lastly, similar study should be conducted in other African stock markets in order to provide a wider insight into how GARCH models are capable of modelling volatility in African stock markets.

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