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Re-examining Moroccan Stock Market Volatility Through the GARCH Lens

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Abstract : This paper models and estimates the volatility of daily stock returns at Casablanca Stock Exchange (MASI index), using a battery of symmetric and asymmetric GARCH models with alternative innovative distributions. We employ GARCH, GARCH-M, EGARCH, GJR-GARCH and APARCH using secondary data over the period September 2, 2019 through December 31, 2022. The findings show that the volatility shocks are highly persistent, with leverage effect confirming that negative news raise future risk more than positive news. APARCH (1,1) was also found to be more accurate in predicting stock returns based on information criterion and log likelihood. Furthermore, our findings show that the Moroccan Stock market exhibited near-normal return behavior before the onset of major shocks. However, the crisis and subsequent recovery periods were characterized by strong departures from normality, consistent with the presence of fat tails and volatility clustering that were captured by the APARCH model results.

Keywords : Volatility, GARCH Models, MASI, Covid 19

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1. INTRODUCTION

The stock market is a crucial mechanism for investors to trade a variety of financial assets and generate returns. Investors consider the market's movements when making investment decisions. For the financial sector and the economy as a whole, the stock market's ability to optimally allocate financial resources, increase the level of financial development, and facilitate economic growth depends on its behavior, which can be perceived through its efficiency and volatility [2].

According to Campbell et al. (1997) in "The Econometrics of Financial Markets" volatility is central to financial theory, representing unpredictability, uncertainty, and risk. The risk of volatility arises from shifts in market sentiment and risk aversion, which directly impact asset prices. High volatility suggests market dysfunction and mispricing, which can be particularly detrimental to risk-averse investors.

Conceptually, volatility serves as a statistical measure of return dispersion, often defined as standard deviation or variance. It gauges the level of uncertainty or risk tied to the magnitude of an asset's price changes. A market is considered "volatile" when it experiences large, sustained fluctuations in either direction. Historically, volatility has been the primary tool for evaluating security risk and is fundamental to portfolio management, risk management, and the pricing of derivatives. This has prompted financial professionals across all sectors to pay close attention to volatility to mitigate risk.

During the early 2020s, the world faced one of the greatest pandemics in modern history: Covid-19; originating from the outskirts of China in early January 2020, it has spread worldwide causing unprecedented repercussions on daily life and the economy and leading to uncontrollable deaths. Unexpectedly, the death toll has exceeded millions globally. Investors and markets have been faced with a high degree of uncertainty about the physical and financial impacts of the virus[9]. Indeed, this pandemic has made investors, policymakers, and the general public realize that natural disasters can inflict economic damage of a magnitude unknown until today [19].

How do stock markets react to a crisis or a sudden disruption? A substantial body of literature has documented the inefficient reactions of stock prices following the announcement of new information such as company earnings reports or the presence of abnormal returns [13]. Bora and Basistha (2020) have conducted an empirical study on the impact of Covid-19 on the volatility of stock prices in India using GJR-GARCH model. They found that the return on indices is lower during Covid 19 than the pre-Covid 19 period, and that the stock market in India has experienced volatility during this period.

The main objective of this paper is to model the volatility of daily returns on Morocco's Casablanca Stock Exchange (MASI index). The specific objectives are as follows:

- To identify the best-performing volatility model for daily MASI returns (full sample and by phase), using sGARCH, GARCH-M, EGARCH, GJR-GARCH, and APARCH with different distributions (Gaussian/ GED/ Student-t / skew-t).
- To estimate the impact of the Covid 19 pandemic on the Moroccan Stock market (using external regressors)

The remainder of this paper is structured as follows: the next section reviews established literature. Section 3 describes the dataset and presents summary statistics, while section 4 reports and discusses the empirical results.

2. LITERATURE REVIEW

To effectively analyze and forecast stock market volatility, it's crucial for practitioners and researchers to develop models capable of accurately capturing stylized facts while preserving desirable statistical properties. The literature offers a variety of models designed to meet these requirements, each with varying degrees of success in modeling specific aspects of volatility.

Among the most widely used parametric models are the ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) families, which become popular for their ability to model time-varying volatility. Table 1 showcases the 20 most cited articles from the WOS database, notably highlighting that the top positions correspond to works on volatility modeling. Notably, the most cited article on the list is "*Generalized Autoregressive Conditional Heteroskedasticity*" by Bollerslev (1986), with a total of 10,323 citations. This article introduced the fundamental GARCH model in volatility modeling. The second most cited article is by Nelson (1991), known for proposing the Exponential GARCH (EGARCH) model. Engle appears multiple times on the list (e.g., 2002, 1993), underscoring his major contributions to the field, particularly in the development of GARCH-related models and the exploration of news impact on volatility. Another influential author with several articles listed is Andersen (2003), who significantly contributed to volatility modeling and forecasting using realized volatility methods.

Table 1 : The 20 most cited articles on volatility between 1981 and 2024

R	TC	Titre	Auteur/s	J9	Année	C/y
1	10323	Generalized Autoregressive Conditional Heteroskedasticity	Bollerslev T	J Econom	1986	264,69
2	4706	Conditional Heteroskedasticity In Asset Returns - A New Approach	Nelson Db	Econometrica	1991	138,41
3	4216	On The Relation Between The Expected Value And The Volatility Of The Nominal Excess Return On Stocks	Glosten Lr	J Financ	1993	131,75
4	3921	Dynamic Conditional Correlation: A Simple Class Of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models	Engle R	J Bus Econ Stat	2002	170,48

5	2219	No Contagion, Only Interdependence: Measuring Stock Market Comovements	Forbes Kj	J Financ	2002	96,48
6	1855	Modeling And Forecasting Realized Volatility	Andersen Tg	Econometrica	2003	84,32
7	1704	Answering The Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts	Andersen Tg	Int Econ Rev	1998	63,11
8	1689	Measuring And Testing The Impact Of News On Volatility	Engle Rf	J Financ	1993	52,78
9	1123	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity	Baillie Rt	J Econom	1996	38,72
10	1056	Threshold Heteroskedastic Models	Zakoian Jm	J Econ Dyn Control	1994	34,06
11	977	Autoregressive Conditional Heteroskedasticity And Changes In Regime	Hamilton Jd	J Econom	1994	31,52
12	961	No News Is Good-News - An Asymmetric Model Of Changing Volatility In Stock Returns	Campbell Jy	J Financ Econ	1992	29,12
13	836	Quantiles Via Moments	Machado Jaf	J Econom	2019	139,33
14	812	Fitting Fully Observed Recursive Mixed-Process Models With Cmp	Roodman D	Stata J	2011	58,00
15	767	Tests Of Conditional Predictive Ability	Giacomini R	Econometrica	2006	40,37
16	743	Asymmetric Correlations Of Equity Portfolios	Ang A	J Financ Econ	2002	32,30
17	724	Modeling The Conditional Distribution Of Interest Rates As A Regime-Switching Process	Gray Sf	J Financ Econ	1996	24,97
18	710	Asymmetric Volatility And Risk In Equity Markets	Bekaert G	Rev Financ Stud	2000	28,40
19	683	Emerging Equity Market Volatility	Bekaert G	J Financ Econ	1997	24,39
20	674	Bayesian-Analysis Of Stochastic Volatility Models	Jacquier E	J Bus Econ Stat	1994	21,74

Source: R studio using Web of Science database

Although the most cited works are concentrated at the end of the 20th century, with foundational articles from the 1980s and 1990s, research is still ongoing, as evidenced by the presence of articles published as recently as 2019 (Machado JAF's article on "Quantiles via Moments"). This confirms that GARCH models are not just historically significant but are also fundamentally relevant for contemporary volatility research, including our analysis of the Moroccan stock market.

Previous research on African markets also highlights the importance of GARCH-type models for analyzing volatility. For instance, a study on the Dar es Salaam Stock Exchange (DSE) by Marobha and Pastory (2020), utilized GARCH (1,1), EGARCH (1,1), and PGARCH (1,1) models to forecast volatility. Their findings showed that while all three models were significant, the GARCH (1,1) and PGARCH (1,1) models indicated that positive shocks (good news) led to higher volatility than negative shocks. However, the EGARCH (1,1) model captured a more conventional leverage effect. Ultimately, the study found the PGARCH (1,1) model to be the most accurate for predicting stock returns, suggesting its potential superiority in capturing volatility dynamics within that market. Osagie et al. (2022) conducted a study on the effects of Covid 19 outbreak on the Nigerian Stock Exchange performance. The fundings from GARCH models revealed a high volatility in stocks returns and a loss in stock returns under the Covid 19 period. They also concluded that the Covid 19 has had a negative effect on the stock returns in the Nigeria Stock markets. An event study methodology was conducted by Harabida and Radi (2020) on the impact of the spread of the pandemic on the Moroccan financial market. The authors confirmed the negative influence of Covid 19 on Casablanca Stock Exchange. Rhatous et Daoui (2021) also conducted a study on the effect of Covid 19 outbreak on the Moroccan stock market from 01/01/2019 to 31/12/2020. The results from GARCH and EGARCH models revealed a negative effect on the stock returns. Aliyev et al. (2020) examined the volatility of the Nasdaq-100, using univariate symmetric GARCH and asymmetric EGARCH, GJR-GARCH models. The results revealed the persistence of the volatility and a strong leverage effect, where negative shocks cause much larger volatility increases than positive ones of the same magnitude.

3. DATA AND METHODOLOGY

3.1. Research design

This study primarily aims to assess the impact of the COVID-19 outbreak on the volatility of the Casablanca Stock Exchange (CSE) using a quantitative research design. Daily closing prices for the MASI index were collected from the CSE's official website (https://www.casablanca-bourse.com/) and other financial market websites such as Investing.com.

3.2. Study period

Our dataset spans from September 2, 2019, to December 31, 2022, covering the period Pre-Global, Pre-Domestic, Domestic Crisis and Recovery.

Table 2 : Event Windows

	Dates	Description
Pre-Global	2 Sep 2019 – 19 Jan 2020	Represents the period before widespread global awareness and concern about COVID-19
Pre-Domestic	20 Jan – 1 Mar 2020	Characterized by increasing international recognition of the virus and growing apprehension
Domestic Crisis	2 Mar 2020 – 30 Jun 2021	Encompasses the immediate shock of the pandemic's arrival in Morocco, including the first wave and subsequent waves of infection.
Recovery	1 Jul 2021 – 31 Dec 2022	Marks a period of increasing vaccination rates, the emergence of variants like Omicron, and a gradual return towards economic and social stabilization.

Source: Author's Computation

3.3. Analytical Framework and Model Selection

Data analysis was performed using Python and RStudio with respect to the specific objectives of the study.

3.3.1. Returns

In this paper, we focus on the closing price of MASI to examine the stock market volatility. By taking the natural logarithm of the price data, we aim to minimize the skewness observed in the distribution of stock prices.

Furthermore, we have calculated the return of MASI to examine stock price changes across these periods, using the formula indicated below:

$$R_t = \ln({}^{P_t}/_{P_{t-1}}) \qquad (1)$$

Where: R_t the return at time t, P_t the daily closing price at time t, and $P_{(t-1)}$ the previous day's closing price at time t-1.

3.3.2. Normality Test

Stylized facts about financial returns generally indicates a strong deviation from the normal distribution. Hence, checking for non-normality (especially leptokurtosis) is a crucial preliminary step, before selecting an appropriate GARCH specification. We carried out a basic descriptive statistic: mean, standard deviation, variance, skewness and kurtosis.

In addition to the above, a normality test, called the Kolmogorov-Smirnov test, is used to compare the cumulative distribution functions of the return variable with a normal distribution. Fundamentally, the Kolmogorov-Smirnov test is used to decide whether a sample comes from a population with a specific distribution. It generally compares the empirical distribution function with a normal cumulative distribution function and calculates the maximum distance between the two. An attractive advantage of this test is that it makes no assumptions about the distribution of the data.

The Kolmogorov-Smirnov test is generally defined as follows:

$\boldsymbol{H_0}$: The data follows a normal distribution.

$\boldsymbol{H_1}$: The data does not follow a normal distribution.

Alternatively, the Shapiro-Wilk test can also be used with the same hypotheses as the Kolmogorov-Smirnov test. Published in 1965 by Samuel Shapiro and Martin Wilk, the Shapiro-Wilk test tests the null hypothesis that a sample $\boldsymbol{x_1, \ldots, x_n}$ comes from a normally distributed population. The Shapiro-Wilk statistic must be greater than zero and less than or equal to one, with small values of W leading to the rejection of the null hypothesis of normality.

3.3.3. Unit Root Test

When elaborating statistical inferences on a phenomenon from time series data, it is generally necessary for the sequence to first meet theoretical assumptions, of which the stationarity assumption is the most important, with a certain degree of rationality. The importance of stationarity is to ensure that statistical properties do not vary over time.

To test whether the series are stationary or non-stationary, the Dickey Fuller (DF), the Augmented Dickey Fuller (ADF) and the Phillips Perron (PP) unit root test are used. The following hypothesis are tested:

$\boldsymbol{H_0}$: Time series is non-stationary and follows a random walk

$\boldsymbol{H_1}$: Time series is stationary and does not follow a random walk

3.3.4. Heteroskedasticity Diagnosis

We examine the return series to confirm the presence of heteroskedasticity by performing an ARCH test on the residuals. The ARCH effect captures the serial correlation of heteroskedasticity. This phenomenon is evident when the variance/volatility of a particular variable exhibits clustering, a pattern influenced by a particular factor [**18**].

Given that stock return volatility is a common measure of risk, the ARCH effect can thus be interpreted as quantifying a financial asset's risk.

Engle's ARCH-LM on squared, demeaned returns:

$$H_0\text{: no ARCH up to lag q} \rightarrow \chi^2\ (q)$$

3.3.5. Symmetrical Volatility Models

In order to analyze the effect of Covid 19 on the stock market volatility, GARCH and GARCH-M models are used as a symmetrical forecasting models.

- **Generalized Auto Regressive Conditional Heteroskedastic (GARCH) Model**

An extension of the ARCH model, known as the Generalized ARCH or GARCH, was introduced by Bollerslev in 1986 to capture the volatility of financial asset returns. The GARCH (p, q) model is the most common type of GARCH model. It has two parameters: p and q. The p parameter determines the number of past squared errors that are included in the model, and the q parameter determines the number of past conditional variances that are included in the model.

The GARCH model has been shown to be effective in modelling the volatility of a wide range of financial asset returns. It is a widely used tool in financial forecasting and risk management. The simplest specification of this model is GARCH (1,1) described as follow:

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

Where ω is the constant term, α_1 is the parameter of ARCH specification, and β_1 is the parameter of GARCH specification.

- **GARCH Mean (GARCH-M) Model**

Another prominent class of symmetric models are the GARCH-M model, developed by Engle et al. (1987). These models are based on the hypothesis in financial markets that increased risk should correlate with higher expected returns. That is, a financial asset's return might be influenced by its volatility. The GARCH-M model was specifically formulated to capture this dynamic, allowing the conditional mean of a return series to be a function of its conditional variance. Mean equation:

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

For the conditional variance, it's the same as that of the GARCH(p,q) model.

3.3.6. Asymmetrical Volatility Models

Despite the success of ARCH and GARCH models, these models fail to capture certain important characteristics of financial and economic series [**15**]. The most interesting characteristic not accounted for is the leverage effect or asymmetric effect initially identified by Black (1976) and later corroborated by Nelson (1990) and others.

- **Exponential GARCH (EGARCH) Model**

Nelson (1991) introduced the Exponential GARCH (EGARCH) model. This model specifically addresses the asymmetry in the impact of positive and negative asset returns on volatility. The EGARCH specification is given by:

$$ln\,(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left[\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| - E(\varepsilon_{t-1})\right] + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \quad (4)$$

Where: γ is the asymmetric or leverage effect parameter.

- **Glosten, Jagannathan et Runkle GARCH (GJR-GARCH) Model**

The GJR-GARCH(p,q) model is another asymmetric GARCH model, introduced by Glosten, Jagannathan, and Runkle in 1993. This model is a simple extension of the standard GARCH that considers the asymmetric nature of investors' reactions to stock or index returns. The GJR-GARCH specification is given by:

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

$$I_{t-i} = \begin{cases} 1 \; si \; \varepsilon_{t-i} < 0 \; Positif \; Chock \\ 0 \; si \; \varepsilon_{t-i} \geq 0 \; Negatif \; Chock \end{cases}$$

- **Asymmetric Power ARCH (APARCH) Model**

The Asymmetric Power ARCH (APARCH) model, introduced by Ding, Granger, and Engle in 1993, is a highly flexible and widely used extension within the GARCH family of models for analyzing financial time series volatility. It is particularly valued because it can capture several important "stylized facts" often observed in financial returns.

For an (univariate) return series $r_t = \mu_t + \varepsilon_t$ with $\varepsilon_t = \sigma_t \mathcal{Z}_t$ and i.i.d. innovations $\mathcal{Z}_t$ (usually Gaussian or t-student), the APARCH (1,1) variance equation is :

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta, \quad \omega > 0,\ \alpha, \beta \geq 0, \delta > 0,\ |\gamma| < 1 \quad (6)$$

Where:

- δ power parameter. Lets the model describe variance ($\delta = 2$), standard deviation ($\delta = 1$) or any fractional power that best matches the empirical kurtosis.
- γ asymmetry (leverage) parameter. If $\gamma > 0$, negative shocks ($\varepsilon_{t-1} < 0$) raise future volatility more than positive shocks of the same magnitude.
- $\alpha, \beta,$ ARCH and GARCH persistence coefficients.

3.3.7. Model Selection Criteria

To select the most appropriate model among the various GARCH, GARCH-M, EGARCH, GJR-GARCH and APARCH specifications, we rely on established information criteria**: the Akaike Information Criterion (AIC)** (Akaike, 1974), **the Hannan-Quinn Information Criterion**, and **the Schwarz Information Criterion** (SIC) (Schwarz, 1978).

The AIC and SIC are calculated using the following formulas (Ghani and Rahim, 2019):

$$AIC = -2\ln(L) + 2k$$

$$SIC = -2\ln(L) + \ln(N)k$$

Here, L represents the likelihood function's value at the estimated parameters, N denotes the number of observations, and k is the count of estimated parameters.

For optimal model fit when comparing alternatives, a lower value for these information criteria is preferred.

4. RESULTS AND DISCUSSION

To uncover potential patterns, we started with a graphical analysis of the MASI stock market index.

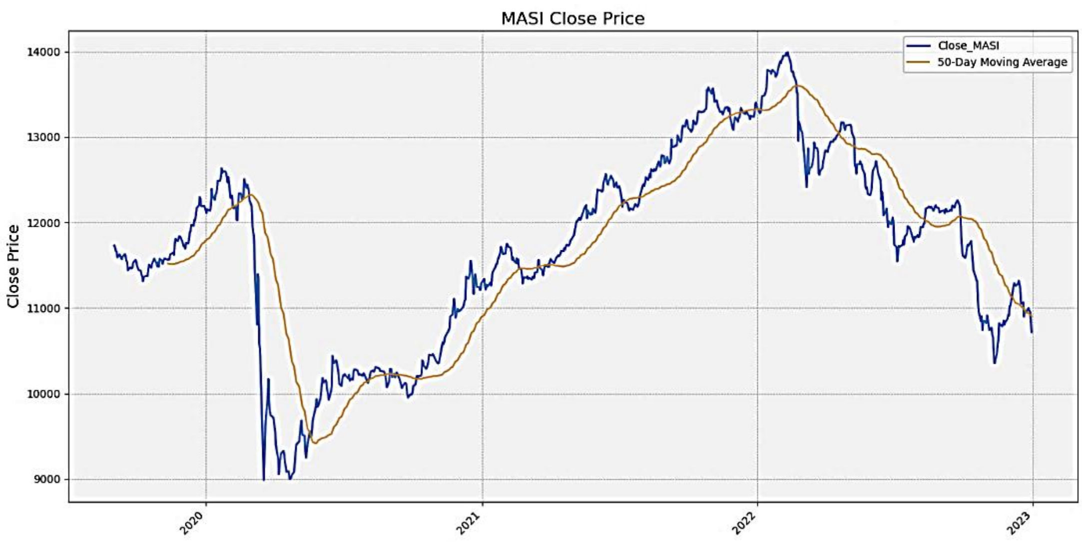

Figure 1 : Time plot of MASI stock price

The graph represents the closing price of the MASI over the examined period. During the pre-Covid period, the market was characterized by low fluctuations. On March 2, 2020, the first case of Covid 19 was confirmed in Morocco. The stock market reacted with one of its biggest drops, as shown in Figure 1. This was due to the anticipated negative impact of the pandemic on the national and international economy. According to Bank Al Maghrib (2020), on March 18, the cumulative decline reached 26.2%, while the market capitalization fell by 159.4 billion dirhams. However, signs of recovery appeared from May until the end of 2022.

Indeed, given the gradual resumption of economic activity, the improvement of the health situation, and the progressive relaxation of the containment measures, the Casablanca stock market started an upward trend with an increase of the MASI of 3.51%.

Figure 2 presents the log returns of MASI. Evidences of volatility are shown with the help of this diagram. The data shows a lot of short-term fluctuations (noise), which is common in daily stock market returns. Investors and traders operating on a daily basis can experience significant ups and downs, which is a testament to the inherent risk of daily trading. Indeed, Figure 2 shows that the series has experienced considerable ups and downs over the sample period. Furthermore, it can be seen that this volatility occurs in clusters. There seem to be phases where the market shows greater stability, with smaller movements in the daily returns of the MASI index. On the other hand, based on a visual inspection, the years 2019-2022, show signs of high volatility, with many large positive and negative returns over a short period.

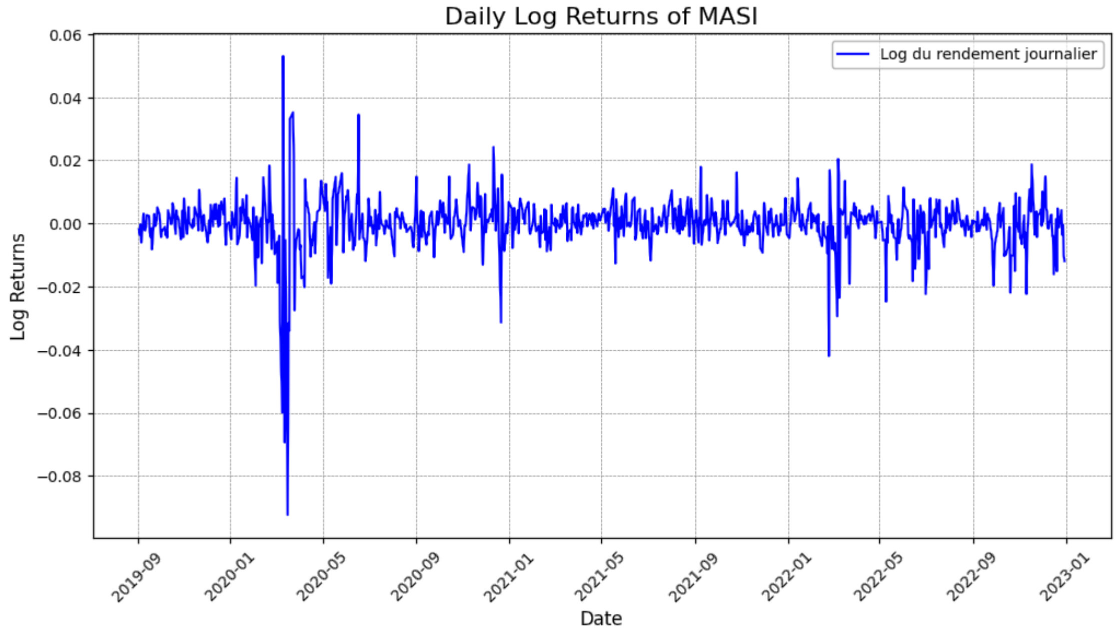

Figure 2 : Time plot of MASI log Returns (Rm)

Thus, from these observations, it can be concluded that volatility is autocorrelated. This characteristic is called the presence of ARCH/GARCH effects [**18**].

4.1. Descriptive Statistics

In Table 3, we calculated the descriptive statistics of the price and log returns for the full sample. The statistical analysis of the MASI index shows that the average daily return is very small, with a standard deviation of 0.0086 indicating that the market is relatively stable, with few large price fluctuations. This could be due to several factors, including the size and liquidity of the market, as well as its level of development. A negatively skewed return suggests a greater likelihood of large losses in the stock market. A kurtosis value of 26,679 indicates a leptokurtic distribution, signifying a clear deviation from normality. This is further confirmed by the Jarque-Bera statistics, which strongly suggest that the null hypothesis of normality for the daily MASI returns ought to be dismissed at a 1% significance level.

Table 3 : Descriptive statistics for the entire sample

Variable	Close	log_returns
Count	836	836
Mean	11725,25281	-0,000107538
Std	1141,383821	0,00860947
Min	8987,89	-0,092316769
25%	10960,8375	-0,00285201
50%	11769,36	0,000107364
75%	12533,6125	0,003587425
Max	13991,47	0,053053615
Skewness	-0,292481359	-2,424845787
Kurtosis	-0,568090659	26,67875261
Jarque-Bera	23,16097518	25612,09132
Probability	9,3467E-06	0
Normality	Rejected	Rejected

Source: Author's Computation using Python

In table 4, it is observed that volatility nearly tripled during the Domestic crisis, standard deviation (std) jumps from 168,7 to 929,4 for Close prices, and remained 60% above the 2019 baseline even after June 2021 for log returns. These funding suggest a persistent volatility clustering, a key motivation for GARCH modelling.

A normal distribution is characterized by skewness and kurtosis values of 0 and 3, respectively. Table 4 reports the asymmetry and kurtosis statistics for our data. We find that the return series exhibits negative skewness, with a value of -2.501, and a kurtosis coefficient of 21.875. This significantly negative skewness indicates a greater propensity for negative returns (decreases) compared to positive returns (increases). Moreover, the kurtosis coefficient, which is considerably greater than 3, corroborates the presence of extreme values, as illustrated in Figure above (figure 2). Therefore, the empirical distribution of the return series is leptokurtic, signifying that it possesses fatter tails than a standard normal distribution.

Table 4 : Descriptive statistics for 4 phases (Pre-Global, Pre-Domestic, Domestic and Recovery Crisis)

Period	Pre-Global		Pre-Domestic		Domestic Crisis		Recovery	
Variable	Close	log_returns	Close	log_returns	Close	log_returns	Close	log_returns
Count	95	95	29	29	332	332	377	377
Mean	11747,613	0,001	12367,570	-0,001	10797,891	0,000	12481,786	0,000
Std	304,795	0,004	168,712	0,008	929,415	0,011	859,504	0,007
Min	11315,630	-0,008	12027,310	-0,020	8987,890	-0,092	10355,270	-0,042
25%	11524,055	-0,002	12263,190	-0,004	10149,323	-0,003	11985,350	-0,003
50% (Median)	11626,550	0,000	12340,240	0,000	10629,840	0,000	12617,070	0,000
75%	11967,840	0,004	12521,230	0,002	11541,345	0,004	13169,670	0,003
Max	12486,850	0,014	12633,570	0,018	12565,730	0,053	13991,470	0,020
Skewness	0,770	0,479	-0,206	0,157	0,015	-2,501	-0,474	-1,250
Kurtosis	-0,653	0,220	-0,807	0,753	-1,027	21,875	-0,535	6,019
Jarque-Bera	11,087	3,828	0,992	0,805	14,592	6965,643	18,584	667,323
p-value	0,004	0,148	0,609	0,669	0,001	0,000	0,000	0,000
Normality	Rejected	Accepted	Accepted	Accepted	Rejected	Rejected	Rejected	Rejected

Source: Author's Computation using Python

The results for Jarque-Bera normality test for log returns confirm our previous observation for crisis and recovery windows.

4.2. Normality Test Results

The rejection of normality in the daily MASI returns is not limited to the Jarque–Bera test. Additional normality diagnostics reinforce this finding (Table 5). In both cases, the p-values are far below the 1% significance threshold, leading to a unanimous rejection of the null hypothesis that the return distribution is Gaussian. These results confirm that MASI daily returns exhibit significant departures from normality, a feature consistent with the presence of skewness, leptokurtosis, and fat tails commonly observed in financial return series.

Table 5 : Normality test for full sample

	Test	Statistic	p-value	Result
0	Kolmogorov-Smirnov	0.484768	2.013605e-181	Probably not Gaussian
1	Shapiro-Wilk	0.769518	1.228199e-32	Probably not Gaussian

Source: Author's Computation using Python

For the sub-period analysis, the Kolmogorov–Smirnov and Shapiro–Wilk tests generally support the Jarque–Bera conclusions. During the Domestic Crisis and Recovery phases, the p-values from both tests are extremely small, leading to a clear rejection of normality. This pattern indicates that while the Moroccan stock market exhibited near-normal return behavior before the onset of major shocks, the crisis and subsequent recovery periods were characterized by strong departures from normality, consistent with the presence of fat tails and volatility clustering.

Table 6 : Normality test results for sub samples

Period	KS Stat	KS p-value	KS Normality	Shapiro Stat	Shapiro p-value	Shapiro Normality
Pre-Global	0,084344	0,489404	Accepted	0,979797	0,154522	Accepted
Pre-Domestic	0,156903	0,429189	Accepted	0,965734	0,450607	Accepted
Domestic Crisis	0,172401	4,25E-09	Rejected	0,721767	3,74E-23	Rejected
Recovery	0,106543	0,000351	Rejected	0,903245	9,09E-15	Rejected

Source: Author's Computation using Python

4.3. Unit Root Test results

To analyze the return series, we first check the stationarity scenario using Dickey Fuller (DF), Augmented DF (ADF), and Phillips-Perron (PP) statistics. The results are presented in Figure 3. The series Rm is stationary for full and sub samples; hence the null hypothesis of unit root is rejected. Therefore, the return series does not follow a random walk.

```
== Dickey-Fuller Test ==

Dickey-Fuller DF Test Statistic: -6.53993
Dickey-Fuller DF Test P-Value: 0.0
Reject Ho - Dickey-Fuller Test: Time Series Rm is Stationary

== Augmented Dickey-Fuller Test for Close ==

1. ADF :  -6.539929577185941
2. P-Value :  9.402214010692068e-09
3. Num Of Lags :  12
4. Num Of Observations Used For ADF Regression and Critical Values Calculation : 823
5. Critical Values :
         1% :  -3.438320611647225
         5% :  -2.8650582305072954
         10% :  -2.568643405981436
Reject Ho - Time Series is Stationary

== Phillips-Perron Test ==

Phillips-Perron PP Test Statistic:  -25.524092
Phillips-Perron PP Test P-Value:  0.0
Reject Ho - Time Series Rm is Stationary
```

Figure 3 : Result of unit root statistics

```
=== Pre-Global  (2019-09-02 → 2020-01-19) ===

-- Dickey-Fuller --
Statistic : -9.0180
P-value   :  5.879e-15
Result    : Reject H₀ → Stationary

-- Augmented Dickey-Fuller --
Statistic : -9.0180   (lags = 0)
P-value   :  5.879e-15
Result    : Reject H₀ → Stationary

-- Phillips-Perron --
Statistic : -10.0840   (lags = 12)
P-value   :  1.534e-15
Result    : Reject H₀ → Stationary
```

```
=== Domestic Crisis  (2020-03-02 → 2021-06-30) ===

-- Dickey-Fuller --
Statistic : -14.9357
P-value   :  1.345e-27
Result    : Reject H₀ → Stationary

-- Augmented Dickey-Fuller --
Statistic : -3.9022   (lags = 16)
P-value   :  0.002019
Result    : Reject H₀ → Stationary

-- Phillips-Perron --
Statistic : -15.1599   (lags = 17)
P-value   :  1.844e-22
Result    : Reject H₀ → Stationary
```

```
=== Pre-Domestic  (2020-01-20 → 2020-03-01) ===

-- Dickey-Fuller --
Statistic : -5.6199
P-value   :  1.152e-06
Result    : Reject H₀ → Stationary

-- Augmented Dickey-Fuller --
Statistic : -5.6199   (lags = 0)
P-value   :  1.152e-06
Result    : Reject H₀ → Stationary

-- Phillips-Perron --
Statistic : -5.5182   (lags = 9)
P-value   :  2.121e-05
Result    : Reject H₀ → Stationary
```

```
=== Recovery  (2021-07-01 → 2022-12-31) ===

-- Dickey-Fuller --
Statistic : -17.9186
P-value   :  2.912e-30
Result    : Reject H₀ → Stationary

-- Augmented Dickey-Fuller --
Statistic : -11.3421   (lags = 1)
P-value   :  1.048e-20
Result    : Reject H₀ → Stationary

-- Phillips-Perron --
Statistic : -18.5655   (lags = 17)
P-value   :  0
Result    : Reject H₀ → Stationary
```

Figure 4 : Result of unit root statistics for sub samples

4.4. Heteroskedasticity Test results

It is important to examine the residuals for any signs of potential heteroscedasticity. To test the existence of heteroscedasticity in the residuals of the MASI index return series, we utilize the Lagrange Multiplier (LM) test. This test is designed to examine the hypothesis that all α coefficients (from $\boldsymbol{\alpha_1}$ to $\boldsymbol{\alpha_q}$, where q represents the degree of ARCH effect) are equal.

Table 7 : LM Test

```
        ARCH LM-test; Null hypothesis: no ARCH effects

data:  Rm
Chi-squared = 327.34, df = 12, p-value < 2.2e-16
```

Source: Author's Computation

The ARCH LM-test output indicates a rejection of the null hypothesis, which posited the absence of ARCH effects in the series 'Rm'. The chi-squared value is 327.34 with 12 degrees of freedom, and the p-value is less than 2.2×10^{-16}, strongly suggesting the presence of ARCH effects in the volatility of the data series.

4.5. Empirical Analysis of the performance of GARCH-Type Models

Once the volatility is confirmed in the data, we'll move on to the next step of our analysis. This step involves comparing the performance of symmetric and asymmetric GARCH models including GARCH (1,1), GARCH-M(1,1) and EGARCH (1,1), GJR-GARCH (1,1), APARCH (1,1) with Normal distribution (norm), Student t distribution (std), Generalized Error distribution (GED), and Skewed Student t distribution (sstd) using Log Likelihood (LL), Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Shibata Information Criteria (SIC), and Hannan-Quinn Information Criteria (HQIC). The best model must have the lowest information criteria and the highest LL.

In line with numerous previous studies (for example, Gokcan (2000), Dana (2016), Epaphra (2017), Maqsood et al. (2017), Mahamat (2017), Sifouh and Bayoud (2021), and Adenomon et al. (2022)), we chose the lag for the GARCH models adopted in this study. The results in Table 8 reveal that the student t distribution delivers the highest Log Likelihood and the lowest information criteria (AIC, BIC, SIC, HQIC) compared to the gaussian and GED distribution. This funding is a strong indicator that the MASI return series exhibits leptokurtosis and fat tail which is not adequately captured by the normal distribution assumption. Based on the information criteria and LL, the APARCH (1,1) model is ranked first, consistently showing the lowest values across all four criteria, and the highest LL value (3125,50). However, the differences in information criteria values among the best-performing asymmetric models (GJR-GARCH and EGARCH) are relatively minor. The GJR-GARCH and APARCH models, particularly when using a student's t or Skewed Student's t distribution, consistently demonstrate a strong fit, suggesting the presence of an asymmetry or leverage effect in the data that these models are designed to capture.

The results from the Goodness of Fit Test strongly validate the use of fat tailed distribution (std, GED and sstd which are consistently high), indicating that these models effectively capture the conditional heteroskedasticity present in our data. In contrast, the p-values for all models using the Normal distribution are extremely low (e.g., 2.323e-08), leading to a strong rejection of the null hypothesis.

The combined evidence (Lowest IC, highest LL, acceptable Goodness of fit) revealed APARCH (1,1) with std distribution as the best model for subsequent analysis.

Table 8 : Results of GARCH Models for Full Sample

		Information criteria					Goodness-of-Fit Test	
Model	**Distribution**	Log Likelihood (LL)	Akaike	Bayes	Shibata	Hannan-Quinn	Statistic	p-value
GARCH	**norm**	3047,09	-7.2729	-7.2333	-7.2731	-7.2578	73.57	2.323e-08
	std	3123,13	-7.4525	-7.4072	-7.4526	-7.4351	15.72	0.6757
	GED	3110,52	-7.4223	-7.3771	-7.4225	-7.4050	28.02	0.08306
	sstd	3123,13	-7.4501	-7.3992	-7.4503	-7.4306	15.24	0.7070
GARCH-M	**norm**	3049,06	-7.2753	-7.2300	-7.2754	-7.2579	76.11	8.640e-09
	std	3124,05	-7.4523	-7.4014	-7.4525	-7.4328	25.10	0.1573
	GED	3111,66	-7.4226	-7.3717	-7.4229	-7.4031	42.71	0.001421
	sstd	3124,07	-7.4499	-7.3934	-7.4502	-7.4282	20.75	0.3510
EGARCH	**norm**	3055,85	-7.2915	-7.2463	-7.2917	-7.2742	54.91	2.400e-05
	std	3124,28	-7.4528	-7.4019	-7.4530	-7.4333	18.88	0.4645
	GED	3113,09	-7.4260	-7.3751	-7.4263	-7.4065	27.64	0.09068
	sstd	3124,30	-7.4505	-7.3939	-7.4508	-7.4288	18.93	0.4614
GJR-GARCH	**norm**	3054,57	-7.2884	-7.2432	-7.2886	-7.2711	53.23	4.314e-05
	std	3125,17	-7.4550	-7.4041	-7.4552	-7.4354	14.38	0.7609
	GED	3113,50	-7.4270	-7.3761	-7.4273	-7.4075	22.13	0.2776395
	sstd	3125,18	-7.4526	-7.3960	-7.4529	-7.4309	15.87	0.6662
APARCH	**norm**	3056,75	-7.2961	-7.2565	-7.2962	-7.2809	50.46	1.121e-04
	std	3125,30	-7.4577	-7.4124	-7.4578	-7.4403	14.81	0.7344
	GED	3114,05	-7.4307	-7.3855	-7.4309	-7.4134	25.39	0.14818
	sstd	3125,30	-7.4553	-7.4044	-7.4555	-7.4358	14.24	0.7696

Source: Author's Computation using R studio

In table 9, we present the result of the APARCH (1,1) model with std by incorporating our dummy variables. The parameter for the mean of the return series is found to be marginally significant ($\mu = 0{,}000392$), and therefore does not contribute to the model. However, the volatility dynamics (as captured by the GARCH & AR components) do contribute. The autoregressive coefficient of our ARIMA (1,0,0) model captures the covid era MASI dynamics well. Furthermore, we observe a significant constant (ω) but at a very low level of 3×10^{-5} , which implies that volatility has a tendency to revert to a low level over time.

Volatility is highly persistent with an ARCH effect $\alpha_1 = 17{,}3\%$ and a GARCH effect $\beta_1 = 79{,}1\%$, and this also satisfies the condition $\alpha_1 + \beta_1 = 96{,}4\% < 1$, suggesting that short-term and long-term factors substantially influence current volatility. The APARCH asymmetry parameter ($\gamma = 0{,}24$) confirming that negative shocks raise volatility more than positive ones, while the power parameter ($\delta \approx 1{,}58$) helps match the heavy-tailed distribution. Residual diagnostics are clean on the variance side (ε² Ljung–Box and ARCH-LM non-sig), so **APARCH (1,1)** is adequate. However, Covid and post-Covid variance dummies do not contribute significantly to the model, which is consistent with δ and γ already capturing the regime shift.

Table 9 : APARCH Model with dummy variables

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model      : fGARCH(1,1)
fGARCH Sub-Model          : APARCH
Mean Model       : ARFIMA(1,0,0)
Distribution     : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000392    0.000184  2.12978 0.033190
ar1     0.107700    0.036161  2.97832 0.002898
omega   0.000027    0.000004  7.29877 0.000000
alpha1  0.173310    0.042144  4.11234 0.000039
beta1   0.791168    0.042054 18.81302 0.000000
eta11   0.238577    0.120092  1.98661 0.046965
lambda  1.582202    0.031184 50.73725 0.000000
vxreg1  0.000000    0.000004  0.00892 0.992883
vxreg2  0.000000    0.000002  0.00000 1.000000
shape   3.716776    0.489580  7.59177 0.000000
```

```
Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.2214 0.500 2.000  0.6380
ARCH Lag[5]    0.8180 1.440 1.667  0.7876
ARCH Lag[7]    2.9409 2.315 1.543  0.5248

LogLikelihood : 3125.185

Information Criteria
------------------------------------

Akaike       -7.4526
Bayes        -7.3960
Shibata      -7.4529
Hannan-Quinn -7.4309
```

Source: Author's Computation using R studio

To check whether our selected volatility model provides credible tail-risk estimates, we plot the daily returns of the MASI with the 1% conditional Value-at-Risk (VaR) limits from APARCH (1,1), std model (Figure 5). The blue line represents daily returns; the red/green lines represent the time-varying 1% VaR limits implied by our fitted APARCH-t model (1% lower and 99% upper conditional quantiles). The bands widen during turbulent periods and narrow during calm periods, which precisely corresponds to the volatility clustering our model is intended to capture. Most observations fall within the bands, with exceedances (blue crossing red/green) concentrated around shock dates. This pattern suggests that the model adapts to regime changes rather than completely ignoring them.

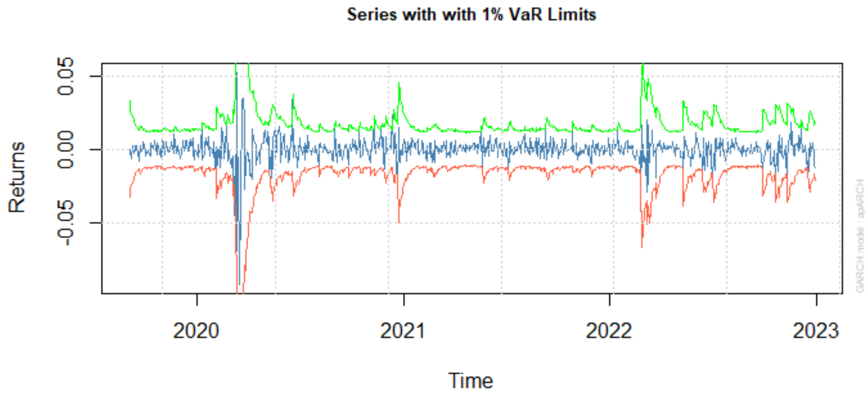

Figure 5 : Returns with Time-Varying 1% VaR limits from APARCH (1,1)

Finally, we tried to analyze the volatility of the MASI return series, under our four regimes. In the pre-Global period, volatility was extremely persistent 1,016 ($\alpha_1 + \beta_1$), indicating that past shocks have a long-lasting effect. However, the response to positive and negative return was mostly symmetric (the Sharpe parameter is extremely high, implying that a simple GARCH model would likely suffice). This funding can be explained by the relatively calm period, before Covid 19 emerged. In contrast, the pre-Domestic period, though short, shows a significant change in behavior, with persistence dropping to 0,842 and with high sensitivity to negative shocks and extreme movements ($\gamma = 0{,}97$). The Sharpe parameter also show a clear departure from a normal distribution (2,1), revealing a very fat-tailed distribution. This indicates that investors began to react to the early global pandemic signals and the uncertainty in financial markets. The Domestic crisis period marked a sustained regime of high persistence ($\alpha_1 + \beta_1 = 0{,}914$), and a strong leverage effect ($\delta \approx 2{,}48$), where negative news had a disproportionately impact on volatility, consistent with a period of severe uncertainty reflecting investors panic.

Finally, during the Recovery period, following the rollout of vaccines, the gradual reopening of economies, and a partial economic recovery, persistence remained high, while the asymmetric leverage effect largely disappeared, suggesting that confidence was gradually returning even though fat tails persisted reflecting occasional large movements.

Table 10 : APARCH estimates by period

Period	Alpha	Beta	Persistence	Lambda	Shape
Pre-Global	0,0498606	0,9658552	1,0157158	1,1062396	100
Pre-Domestic	0,0562579	0,7854174	0,8416753	1,3055948	2,1
Domestic Crisis	0,1850934	0,729359	0,9144524	2,4798809	4,2496966
Recovery	0,0502885	0,8990627	0,9493512	0,2240744	3,4925995

CONCLUSION

The results from the descriptive analysis showed a marked volatility spike during domestic crisis window, with a pronounced negative skew and a significant kurtosis, a pattern that persisted in the recovery period. We found that our return series exhibit a non-Gaussian behavior, and volatility clustering, motivating our use of fat-tailed likelihoods.

Our empirical analysis, which involved estimating a battery of symmetric and asymmetric GARCH models under alternative innovation distributions, determined that AR (1), APARCH (1,1) with std provides the best overall fit for our data. Estimates of the model ($\alpha_1 = 0{,}173$, $\beta_1 = 0{,}791, \alpha_1 + \beta_1 = 0{,}964$) show a long lived volatility, meaning that the variance has long memory and volatility are quite persistent, and the positive asymmetry coefficient indicates that bad news increases future risk more than good news, and returns exhibit heavy tails. Interestingly, after accounting for these dynamics, adding explicit COVID-19/post Covid period dummies did not improve the model, suggesting that the pandemic's main effect was to intensify these pre-existing behaviors rather than to fundamentally alter the market's structure.

These findings offer clear implications for various market participants. For market participants, the results underscore that market risk is both persistent and asymmetrically amplified by negative news. This suggests that risk measures and capital allocation strategies should be computed with fat-tailed models rather than simpler Gaussian assumptions. For policymakers, the slow decay of volatility following a shock highlights the need for a sustained, not just immediate, response. This includes maintaining liquidity provisions and vigilantly calibrating circuit breakers during periods of market stress, as risk does not dissipate quickly.

This study's limitations include its reliance on daily data and its focus on a single market. Future research could enhance these findings by incorporating high-frequency data to estimate realized volatility, exploring more complex models like regime-switching or long-memory GARCH variants, and including macroeconomic variables.

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