IRAFEM
International Review of Applied Finance, Economics and Management
International Review of Applied Finance, Economics, and Management IRAFEM VOL. 2 Issue 7 (2026)

Risk Dynamics in the Moroccan Equity Market: Conditional Volatility, Informational Efficiency and Value at Risk of the MASI Index (2020-2026)

Rabab Hamami[1], **Rachid Krami**[1]

[1] *Research Laboratory in Management Sciences of Organizations, National School of Business and Management (ENCG) of Kenitra, Ibn Tofail University, Kenitra, Morocco*

Abstract

The opening of Morocco's first financial futures market in April 2026 marks a new stage in the deepening of African capital markets, and it makes the measurement of market risk an immediate operational question for exchanges, clearing houses and investors. This article assesses the risk dynamics of the Casablanca Stock Exchange using 1,652 daily returns of the MASI index from January 2020 to August 2026, with the MASI 20 index of liquid stocks as a control series. The methodology combines distributional analysis, weak-form efficiency tests including heteroskedasticity-robust variance ratios, GARCH and GJR-GARCH models with an AR(1) mean equation and Student innovations, and the backtesting of value at risk. Returns display a kurtosis of 18.07, with extreme sessions seven times more frequent than under normality, and a significant leverage effect that a symmetric specification misses. Evidence against weak-form efficiency proves not robust: it survives neither the correction for heteroskedasticity nor the exclusion of the 2020 crisis, and both indices behave alike over their common period. Backtesting shows that Gaussian value at risk is rejected at both conventional levels, and that while historical and Student measures pass the Kupiec coverage test, none of the three passes the Christoffersen independence test. A conditional measure derived from the GJR-GARCH model corrects this shortcoming, passing every test at both the 95 and 99 percent levels in out-of-sample forecasting over 902 sessions. The initial margin adopted at launch covers the ordinary regime but fell short during five episodes of stress, which argues for margins driven by conditional volatility.

Keywords: African capital markets; Casablanca Stock Exchange; conditional volatility; market efficiency; value at risk; financial futures

1. Introduction

The deepening of African capital markets has proceeded unevenly. Exchanges have multiplied since the 1990s, but few have acquired the instruments that allow risk to be transferred rather than merely borne, and the absence of a derivatives segment has long confined African investors to directional exposure. Morocco crossed that threshold on April 6, 2026, with the first quotation of a futures contract on the MASI 20 index, making the Casablanca exchange one of the few African markets with an organized derivatives segment. Measuring market risk there ceased at that moment to be an academic exercise: pricing and margining such a contract requires precise knowledge of the volatility dynamics of its underlying and of the thickness of its distributional tails, and those quantities now govern the calibration of initial margins and the management of margin calls.

© 2026 The Authors. Published by IRAFEM. This is an open access article under the CC BY-NC-ND license

The observation period is unusually rich. It opens with the March 2020 crash, spans a full cycle of decline and recovery, peaks at 20,233.50 points on August 27, 2025, and closes on a 2026 marked by a pronounced return of volatility, allowing standard risk measures to be tested under varied conditions.

The article addresses three questions: ***what is the statistical structure of Moroccan market returns and does it depart from the assumptions underlying standard risk management models; does the market satisfy the weak-form efficiency hypothesis; and which method of computing value at risk withstands rigorous backtesting?***

The contribution is empirical and methodological. The article documents the risk properties of the Casablanca market over almost seven years of daily data and establishes two methodological results: the efficiency diagnosis depends on the treatment of heteroskedasticity and on the inclusion of crisis periods, and validating risk measures through the coverage test alone accepts models that the independence test rejects. It then proposes the measure correcting that shortcoming and validates it out of sample. The closest antecedent is Hamou et al. (2025), whose focus is the forecasting performance of classical volatility models on the MASI and MASI ESG indices. The present article differs in four respects: it brings in the MASI 20, the underlying of the new futures contract, as a control series; it validates the risk measures themselves, with coverage and independence tests in sample and out of sample, rather than volatility forecasts; it combines that validation with heteroskedasticity-robust efficiency tests; and it draws the implications for the initial margin of the futures contract.

The remainder of the article is organized as follows. Section 2 reviews the literature. Section 3 presents the institutional setting, the data and the methodology. Section 4 reports and discusses the results, and Section 5 concludes with the limitations of the study and directions for future research.

2. Literature review

2.1. Efficiency and predictability

The weak-form efficiency hypothesis, formalized by Fama (1970), holds that prices incorporate all information contained in their own history, so no strategy based on past returns alone can generate abnormal returns. Lo and MacKinlay (1988) showed that the usual autocorrelation test must be conducted with care: their variance ratio admits a homoskedastic and a heteroskedasticity-robust version, which may lead to opposite conclusions when volatility varies over time. Lo and MacKinlay (1990) also established that non-synchronous trading induces artificial positive autocorrelation in index returns, a central point in applied financial econometrics (Campbell et al., 1997).

The statistic has since been refined by Chow and Denning (1993) and by Wright (2000). Applied to emerging markets it delivers mixed verdicts: Smith and Ryoo (2003) reject the random walk in European emerging markets, while Magnusson and Wydick (2002), Appiah-Kusi and Menyah (2003) and Jefferis and Smith (2005) find African markets heterogeneous, efficiency improving with liquidity. Lo (2004) reframes efficiency as time-varying rather than binary, consistent with the period dependence documented below. Emerging markets generally show more autocorrelated returns, higher volatility and greater asymmetry than developed ones (Bekaert & Harvey, 1995, 1997, 2003; Harvey, 1995). On Morocco, Hamou et al. (2025) find that classical models capture volatility clustering but struggle with

exogenous shocks, while, to our knowledge, Moroccan scholarship remains sparse on the backtesting of market risk measures.

2.2. Conditional volatility and the leverage effect

That the variance of financial returns is not constant dates back to Mandelbrot (1963); Engle (1982) and Bollerslev (1986) provided the standard framework, synthesized by Engle (2001). The asymmetric extensions of Nelson (1991) and Glosten et al. (1993) capture the leverage effect, traced by Christie (1982) to rising financial leverage after a fall in equity value and formalized as a testing problem by Engle and Ng (1993). Bollerslev (1987) established Student innovations as the remedy for thick tails. Two cautions matter: near-unit persistence characterizes integrated specifications with undefined unconditional variance (Engle & Bollerslev, 1986) and often reflects unmodeled structural breaks (Lamoureux & Lastrapes, 1990), which Hamilton and Susmel (1994) address through regime switching. On emerging markets, Aggarwal et al. (1999) and Alagidede and Panagiotidis (2009) confirm volatility shifts and asymmetry across African markets.

2.3. Value at risk and its validation

Value at risk, popularized by Jorion (2007), is the maximum loss expected over a given horizon at a given confidence level. Its Gaussian version assumes normality, an assumption made problematic by the thickness of the tails. Comparative work favours conditional specifications with non-Gaussian innovations (Angelidis et al., 2004; Giot & Laurent, 2003; Kuester et al., 2006; McNeil & Frey, 2000), and a simple GARCH(1,1) proves hard to beat (Berkowitz & O'Brien, 2002; Hansen & Lunde, 2005). On validation, Kupiec (1995) proposed the coverage test and Christoffersen (1998) showed it insufficient, since a valid measure also requires temporally independent exceedances; Christoffersen and Pelletier (2004) propose a duration-based variant. Three extensions frame the limitations discussed in Section 5: quantile modeling (Engle & Manganelli, 2004), regime switching (Hamilton, 1989) and expected shortfall, coherent where value at risk is not (Artzner et al., 1999) and now governing prudential market risk capital (Basel Committee on Banking Supervision, 2019).

3. Methodology

3.1. Institutional setting: the Casablanca market and its reference index

The MASI is the broad index of the Casablanca Stock Exchange, covering all listed securities and serving as the reference for overall market performance and the natural support for an analysis of market risk.

3.1.1. The financial futures market

The derivatives segment is the culmination of a decade-long process. Law No. 42-12 laid the legal foundation in May 2014 (Kingdom of Morocco, 2014), and the decree establishing the Futures Market Coordination Body, the joint supervisory organ of Bank Al-Maghrib and the regulator, followed in May 2019 (Futures Market Coordination Body, 2026). The process accelerated from November 2024, with the regulator's approval of the first contract in May 2025 and a full-scale test in September 2025. The first session was held on April 6, 2026.

According to the institutional communications of the exchange, the regulator and the market management company (Casablanca Stock Exchange, 2026; Moroccan Capital Market

Authority, 2026), the first listed instrument is a cash-settled firm futures contract on the MASI 20 index. Each contract represents 10 dirhams per index point, a notional near 13,000 dirhams, with an initial margin of 1,000 dirhams per contract, revisable by the clearing house according to volatility. The first session covered four quarterly maturities, for close to 17 million dirhams and 695 open contracts.

The MASI 20 index, created at 1,000 points on December 31, 2019 and substituted for the MADEX in January 2022, groups the twenty largest securities by free-float capitalization and liquidity. Being both the contract underlying and an index of liquid securities, it serves throughout as a control series: the analysis bears on the broad MASI, and each result is verified on the MASI 20.

3.1.2. Structure of the underlying market

The underlying market is concentrated, the five largest capitalizations accounting for around 45 percent of total capitalization at the end of 2025, and its liquidity is extremely dispersed, the most traded security recording 11.64 billion dirhams of turnover in 2025 against a few hundred thousand for the least active. That dispersion justifies comparing the two indices, since non-synchronous trading can induce artificial autocorrelation in a broad index (Lo & MacKinlay, 1990).

3.2. Data

The sample consists of daily closing prices of the MASI index from January 2, 2020 to August 31, 2026, that is, 1,653 observations and 1,652 returns, extracted from the Investing.com historical database (Investing.com, 2026). Annual coverage is complete for 2020 to 2025 and partial for 2026, with 158 sessions. A secondary sample, extracted from the same source, covers the MASI 20 index from December 9, 2020, the common period comprising 1,419 returns.

Two consistency checks were performed: the 247 sessions recorded for 2025 and the annual performance of 27.57 percent both match the figures published by the exchange (Casablanca Stock Exchange, 2026). The closing levels of August 31, 2026 (MASI 18,652.72 points; MASI 20 1,341.93 points) and the year-to-date performances (-1.03 and -9.67 percent) were checked against the daily market report of Bourse News (2026). Returns are computed as log differences in percentage points:

$$r_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where P_t denotes the closing level of the index at session t. The volume column being empty, no liquidity analysis is conducted.

3.3. Methods

The analysis proceeds in five stages.

- Risk-return profile: annual performances relative to the previous year's close, volatilities annualized by the square root of 252, and maximum drawdowns from a peak.
- Distributional analysis: third and fourth moments, the Jarque and Bera (1980) test, and empirical versus theoretical frequencies beyond two and three standard deviations.
- Weak-form efficiency: autocorrelations, the Ljung and Box (1978) test, the runs test, and the Lo and MacKinlay (1988) variance ratios in both versions, at horizons of two,

four, eight and sixteen sessions, conducted on the full sample, re-estimated excluding 2020, and replicated on the MASI 20 over the common period.

- Conditional volatility: the Lagrange multiplier test for ARCH effects, then comparative estimation of a symmetric GARCH(1,1) and an asymmetric GJR-GARCH(1,1), both with Student innovations and an AR(1) mean equation, retained because a constant mean leaves the standardized residuals autocorrelated, the asymmetry being assessed by a likelihood-ratio test.

The conditional variance of the asymmetric specification is written as:

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

where $\varepsilon_t = r_t - \mu - \varphi r_{t-1}$ is the return innovation and I_{t-1} equals 1 when $\varepsilon_{t-1} < 0$ and 0 otherwise. The symmetric GARCH(1,1) corresponds to $\gamma = 0$, and a positive γ measures the leverage effect. The mean equation is $r_t = \mu + \varphi r_{t-1} + \varepsilon_t$.

- Risk measurement and validation: one-day value at risk under three unconditional methods, historical, Gaussian and Student, then under a conditional approach based on the volatility predicted by the asymmetric model. Each measure is subjected to the Kupiec (1995) unconditional coverage test, the Christoffersen (1998) independence test and the joint conditional coverage test. The conditional measure is evaluated in sample and then in one-step-ahead out-of-sample forecasting, using an expanding window re-estimated every 25 sessions, with the first 750 observations serving as initialization. The unconditional measures are re-estimated on the same expanding window and at the same frequency, so that all measures rest on the same information set.

The conditional one-day value at risk at coverage level p is computed as:

$$\mathrm{VaR}_t(p) = \mu + \sigma_t\, t_\nu^{-1}(p)\sqrt{\frac{\nu-2}{\nu}} \tag{3}$$

where μ is the conditional mean, here the constant plus φ times the previous return, σ_t the predicted volatility and $t_\nu^{-1}(p)$ the p-quantile of the Student distribution with ν degrees of freedom, rescaled to unit variance. The Kupiec (1995) test compares the observed number of exceedances N over T sessions with the expected rate p through the likelihood ratio:

$$LR_{uc} = -2\ln[(1-p)^{T-N}p^N] + 2\ln\left[\left(1-\frac{N}{T}\right)^{T-N}\left(\frac{N}{T}\right)^N\right] \tag{4}$$

which follows a chi-squared distribution with one degree of freedom under the null hypothesis of correct coverage.

4. Results and discussion

4.1. Risk-return profile and regime heterogeneity

Over the whole period the index rises from 12,111.07 to 18,652.72 points, a cumulative return of 54.01 percent over 6.66 years and an annualized volatility of 14.41 percent. Annual profiles differ sharply (Table 1; Figure 1). 2021 pairs an 18.35 percent gain with the lowest volatility of the period, 6.83 percent, and 2024 gives 22.16 percent for 8.55 percent. 2025, strongest at 27.57 percent, carries 16.15 percent volatility and a 10.48 percent drawdown. 2026 sharpens the deterioration: 21.09 percent volatility, the highest of the period including the 2020 crash,

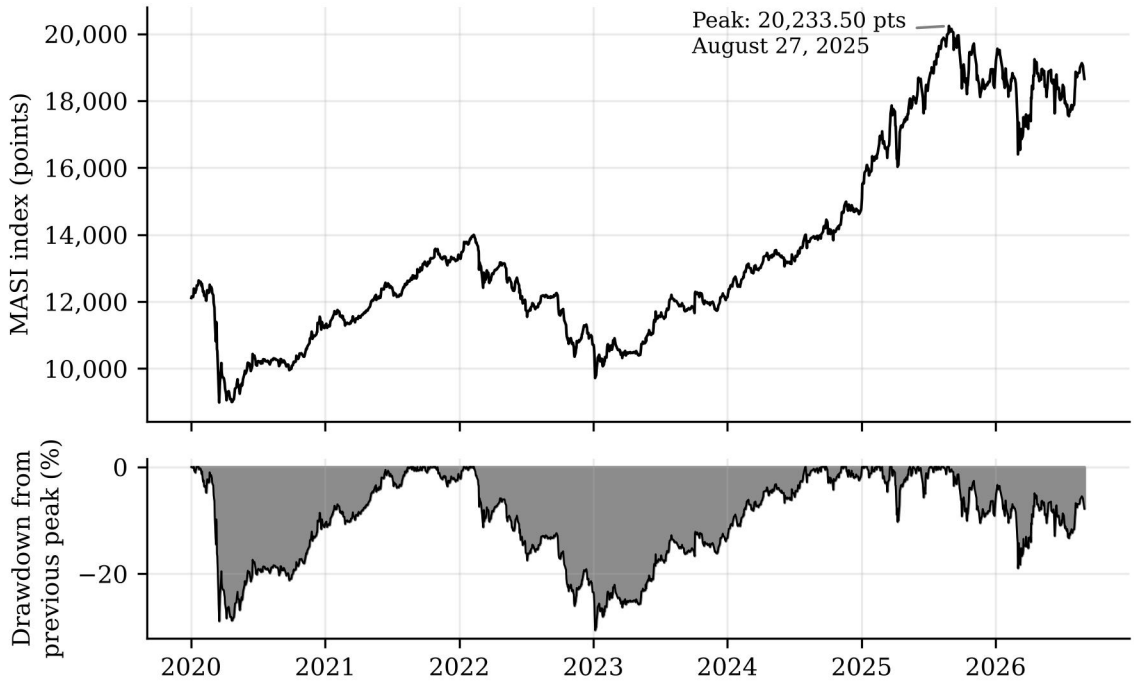
for -1.03 percent and a 16.14 percent drawdown, leaving the index 7.81 percent below its highest close of 20,233.50 points.

Table 1. Annual performance and risk of the MASI index

Year	Sessions	Close	Performance	Annualized volatility	Return/risk ratio	Max drawdown
2020	250	11,287.38	−6.80%	20.54%	−0.33	−28.86%
2021	249	13,358.32	+18.35%	6.83%	+2.69	−3.96%
2022	254	10,720.25	−19.75%	11.91%	−1.66	−25.99%
2023	249	12,092.88	+12.80%	12.24%	+1.05	−9.35%
2024	246	14,773.19	+22.16%	8.55%	+2.59	−4.25%
2025	247	18,846.35	+27.57%	16.15%	+1.71	−10.48%
2026 (to Aug. 31)	158	18,652.72	−1.03%	21.09%	−0.05	−16.14%

Note. Source: authors' calculations. Performances computed relative to the previous year closing level, except for 2020, computed from the first available session. The ratio divides the performance by the annualized volatility; the 2026 performance is not annualized. Maximum drawdowns are measured within each calendar year, starting from the previous year's closing level, whereas Figure 1 measures the drawdown from the highest previous close over the whole sample. Session counts refer to daily closing prices (1,653 in total), not to returns (1,652), the first price of the sample having no previous close.

Figure 1. The MASI index and drawdown from peak, January 2020 - August 2026



Note. Source: authors' construction. The lower panel measures, at each session, the gap between the index level and its highest previous closing level.

4.2. Distribution of daily returns

Table 2 reports the distribution. The mean daily return is 0.0261 percent for a standard deviation of 0.9078 percent, with 52.97 percent of sessions positive. The distribution is left-

skewed at -1.236 and displays a kurtosis of 18.07, an excess of 15.07 over the Gaussian value; the Jarque-Bera statistic of 16,051.3 rejects normality. Sessions beyond three standard deviations account for 1.94 percent of the sample against 0.27 percent under normality, so extreme events are seven times more frequent than the Gaussian assumption predicts, while sessions beyond two standard deviations, at 5.15 against 4.55 percent, depart little from it.

Extreme movements cluster in time. The three largest declines, 9.23 percent on March 16, 2020, 6.93 percent on March 12 and 5.99 percent on March 9, all belong to the crash, as does the largest rise of 5.31 percent on March 10. The cumulative log return of 43.19 percent would fall to 3.69 percent without the ten best sessions.

Table 2. Distributional properties of daily MASI returns (N = 1,652)

Statistic	Value	Gaussian benchmark
Mean	0.0261%	–
Median	0.0399%	–
Standard deviation	0.9078%	–
Minimum	−9.23% (March 16, 2020)	–
Maximum	+5.31% (March 10, 2020)	–
Skewness	−1.236	0
Kurtosis	18.069	3
Jarque-Bera	16,051.3 ($p < 0.001$)	Normality rejected
Sessions beyond 2 standard deviations	5.15%	4.55%
Sessions beyond 3 standard deviations	1.94%	0.27%
Positive sessions	52.97%	–

Note. Source: authors' calculations.

4.3. Weak-form efficiency: a diagnosis contingent on method and period

Table 3 collects the efficiency tests. Autocorrelation-based tests reject the random walk hypothesis: first-order autocorrelation is 0.1255, the Ljung-Box statistic reaches 32.97 at five lags, 40.24 at ten and 60.35 at twenty, with p-values below 0.0001, and the runs test gives 746 sequences against 827 expected, a statistic of -3.987 at $p = 0.0001$. Heteroskedasticity-robust variance ratios reject only at short horizons, at 2.385 for two sessions and 2.151 for four, falling to 1.500 and 1.118 at eight and sixteen.

A more decisive qualification emerges from the period control. Re-estimated on the 1,403 sessions after 2020, the robust variance ratios no longer reject at any horizon: the two-session statistic returns to 1.957 at $p = 0.0503$, exactly at the conventional threshold, then falls to 1.696, 1.380 and 0.620 at four, eight and sixteen sessions. The rejection on the full sample is therefore driven by the 2020 crisis. The proximity of the threshold calls for caution: outside the crisis the market is not statistically distinguishable from a random walk, without the converse being ruled out by a comfortable margin.

A third qualification comes from the control by index. Over the common period of 1,419 sessions, the broad MASI and the liquid-stock MASI 20 produce virtually identical results: first-order autocorrelations of 0.0907 and 0.0856, Ljung-Box p-values of 0.0010 and 0.0060, and robust variance ratio statistics of 1.885 and 1.819 at two sessions. Were non-synchronous trading materially affecting the broad index, a gap would appear here; it does not. One boundary applies: the MASI 20 series begins in December 2020, so the control covers the

ordinary regime but not the March 2020 crash, and only the post-crisis diagnosis is secured by this test.

The interpretation must be stated with care. What these tests establish is negative: the evidence against weak-form efficiency is not robust to the treatment of heteroskedasticity or to the exclusion of the 2020 crisis. Whether the autocorrelation is caused by volatility clustering cannot be settled here, since the robust variance ratio corrects the inference without identifying its source. The departure from the random walk is stable neither across methods nor across periods, and the coefficients are small, probably too small to be exploited net of transaction costs, although trading strategies and costs are not evaluated here. Concluding to inefficiency from autocorrelation tests alone would be an inferential error.

Table 3. Weak-form efficiency tests

Test	Statistic	p	Conclusion
Ljung-Box (5 lags)	32.97	< 0.0001	Rejection
Ljung-Box (10 lags)	40.24	< 0.0001	Rejection
Ljung-Box (20 lags)	60.35	< 0.0001	Rejection
Runs test	z = −3.987	0.0001	Rejection
Variance ratio q = 2 (homoskedastic)	z = +5.091	< 0.0001	Rejection
Variance ratio q = 2 (robust)	z* = +2.385	0.0171	Rejection
Variance ratio q = 4 (robust)	z* = +2.151	0.0315	Rejection
Variance ratio q = 8 (robust)	z* = +1.500	0.1335	No rejection
Variance ratio q = 16 (robust)	z* = +1.118	0.2634	No rejection
Variance ratio q = 2 (robust, excl. 2020)	z* = +1.957	0.0503	Borderline: no rejection
Variance ratio q = 4 (robust, excl. 2020)	z* = +1.696	0.0899	No rejection
Variance ratio q = 8 (robust, excl. 2020)	z* = +1.380	0.1677	No rejection
Variance ratio q = 16 (robust, excl. 2020)	z* = +0.620	0.5354	No rejection
Variance ratio q = 2 (robust, MASI 20)	z* = +1.819	0.0689	No rejection
Ljung-Box (5 lags, MASI 20)	16.34	0.0060	Rejection

Note. Source: authors' calculations. Unless stated otherwise, rows refer to the MASI over the full sample (1,652 sessions); z is the homoskedastic Lo–MacKinlay statistic and z its heteroskedasticity-robust counterpart, both asymptotically standard normal; p-values are two-sided and conclusions refer to the 5 percent level; Ljung-Box statistics are chi-squared with as many degrees of freedom as lags. First five autocorrelations of the MASI: +0.1255; +0.0586; -0.0162; -0.0003; -0.0220. Rows ten to thirteen are computed on the sample excluding the 2020 financial year, that is, 1,403 sessions from January 4, 2021 to August 31, 2026. The two-session result excluding 2020 (p = 0.0503) lies at the 5 percent threshold and is flagged as borderline. The last two rows report the MASI 20 control over the period common to both indices, that is, 1,419 sessions from December 10, 2020 to August 31, 2026. On that common period, the MASI itself gives a first-order autocorrelation of +0.0907, a Ljung-Box p-value of 0.0010 (against 0.0060 for the MASI 20) and a robust variance ratio z* = +1.885 (p = 0.0595) at q = 2.*

4.4. Conditional volatility and the leverage effect

ARCH effects are overwhelming. The Lagrange multiplier test at ten lags produces a statistic of 452.82, with a p-value of the order of 10^{-91}. The Ljung-Box test on squared returns rejects independence at the order of 10^{-176}.

Table 4 reports both specifications, estimated with an AR(1) mean equation. The autoregressive term is significant ($\varphi = 0.127$, $p < 0.001$) and necessary: with a constant mean, the standardized residuals of the GJR-GARCH remain autocorrelated (Ljung-Box $p < 0.001$ at ten and twenty lags), whereas with the AR(1) mean they are not ($p = 0.069$ and 0.181; likelihood-ratio statistic of the AR(1) term 25.8, $p < 0.001$). The squared standardized residuals display no remaining ARCH effect ($p = 0.946$ and 0.996 at ten and twenty lags for the GJR-GARCH), and the Engle and Ng (1993) sign-bias tests, reported in Table 4, find no residual asymmetry in the GJR-GARCH model (joint $p = 0.888$). For the symmetric model the joint test does not reject either ($p = 0.152$), but the negative size-bias statistic is marginal ($p = 0.056$), consistent with the leverage effect that this specification omits. The symmetric GARCH(1,1) with Student innovations gives a shock reaction of 0.2575 and a memory coefficient of 0.7301, a persistence of 0.9876 implying a shock half-life of 55.5 sessions, about eleven weeks. The estimated degrees of freedom, 3.49, confirm extreme tail thickness, a value below 4 implying an infinite fourth moment. The implied long-run volatility of 30.29 percent should not be read literally, since near-unit persistence makes it highly sensitive to small parameter changes.

The asymmetric GJR-GARCH brings out what the symmetric model conceals. The asymmetry coefficient is 0.2556, significant at 1 percent with $p = 0.009$ (likelihood-ratio test of $\gamma = 0$: 16.9, $p < 0.001$), while the reaction to positive shocks falls to 0.1387: a negative shock raises conditional volatility about 2.8 times more than a positive one of equal size. The Akaike criterion falls from 3,358.0 to 3,343.2 and the Bayesian criterion from 3,390.5 to 3,381.0. Persistence under the GJR specification, measured by $\alpha + \gamma/2 + \beta$ (the factor 1/2 being the probability of a negative innovation under a symmetric distribution), is 0.9711 against 0.9876 for the symmetric model, which shortens the shock half-life from 55.5 to about 23.7 sessions, around five weeks. Conditional volatility ranges from 7.00 to 108.92 percent annualized, averaging 13.09 percent (Figure 2).

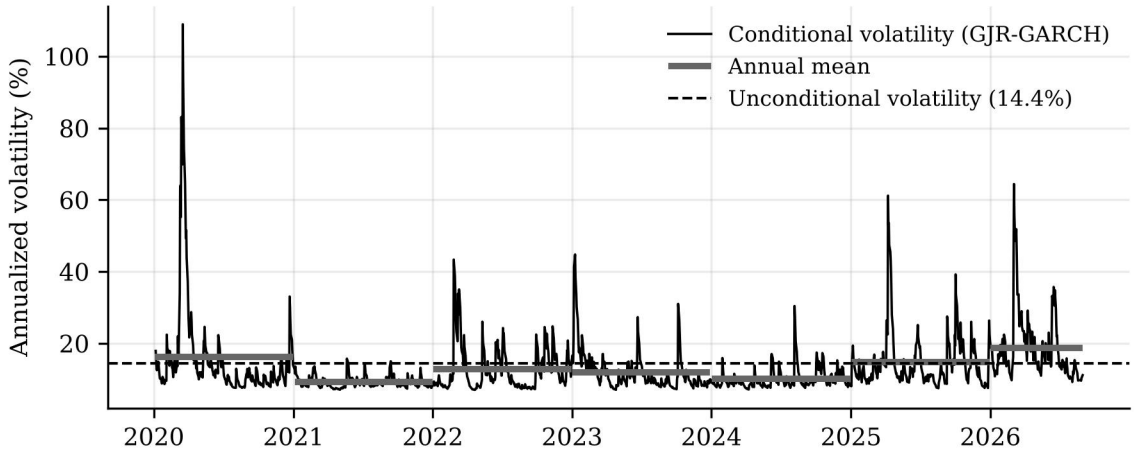
Table 4. Conditional volatility models (AR(1) mean, Student innovations)

Parameter	GARCH(1,1)	GJR-GARCH(1,1)	Interpretation
mu (constant)	0.0456 (0.0126)	0.0362 (0.0130)	Mean equation
phi (AR(1) term)	0.1244 (0.0296)	0.1268 (0.0281)	First-order autocorrelation
omega (constant)	0.0452 (0.0212)	0.0543 (0.0216)	Autonomous component
alpha (shock reaction)	0.2575 (0.0862)	0.1387 (0.0518)	Positive shocks
gamma (asymmetry)	–	0.2556 (0.0978)	Leverage effect
beta (memory)	0.7301 (0.0860)	0.7046 (0.0810)	Volatility inertia
Persistence	0.9876	0.9711	$\alpha + \beta$ (GARCH); $\alpha + \gamma/2 + \beta$ (GJR)
Half-life (sessions)	55.5	23.7	Decay of a volatility shock
Long-run volatility (annualized)	30.29%	21.78%	Not to be read literally
nu (degrees of freedom)	3.49 (0.33)	3.61 (0.34)	Very thick tails
Log-likelihood	−1,673.0	−1,664.6	Maximum likelihood
Akaike criterion	3,358.0	3,343.2	Asymmetric model dominates
Bayesian criterion	3,390.5	3,381.0	Asymmetric model dominates
Ljung-Box, residuals (10 lags), p	0.055	0.069	No residual autocorrelation
Ljung-Box, squared residuals (10 lags), p	0.933	0.946	No residual ARCH effect

Parameter	GARCH(1,1)	GJR-GARCH(1,1)	Interpretation
ARCH-LM test (10 lags), p	0.924	0.933	No residual ARCH effect
Ljung-Box, residuals (20 lags), p	0.152	0.181	No residual autocorrelation
Ljung-Box, squared residuals (20 lags), p	0.996	0.996	No residual ARCH effect
Engle–Ng sign bias test, p	0.138	0.487	No sign bias
Engle–Ng negative size bias test, p	0.056	0.719	No size bias
Engle–Ng positive size bias test, p	0.070	0.472	No size bias
Engle–Ng joint test, p	0.152	0.888	No residual asymmetry

Note. Source: authors' calculations. Maximum likelihood estimation on 1,652 returns. Standard errors are in parentheses and all coefficients are significant at the 5 percent level. The mean equation includes a constant and the first lag of the return. Persistence is α + β for the GARCH model and α + γ/2 + β for the GJR-GARCH model, and the half-life is ln(0.5)/ln(persistence), both computed from the unrounded estimates. The Engle–Ng tests regress the squared standardized residuals on the sign and size of the previous standardized residual (Engle & Ng, 1993). The two specifications yield distinct degrees of freedom, 3.49 and 3.61; the conditional value at risk of Section 4.6 is calibrated on the latter, while the Student value at risk of Table 5 uses the degrees of freedom estimated directly on the raw returns.

Figure 2. Annualized conditional volatility estimated by the GJR-GARCH model



Note. Source: authors' construction. Horizontal segments represent the annual mean; the dashed line is the unconditional volatility of the sample.

4.5. Value at risk: coverage and independence

Table 5 subjects three methods of computing one-day value at risk to two validation tests. The results carry two lessons of unequal weight.

Gaussian value at risk is rejected at both levels, for opposite reasons. At 95 percent it overstates risk: the threshold of -1.467 percent is breached 60 times, or 3.63 percent against 5 percent expected, with a Kupiec statistic of 7.16 at p = 0.007. At 99 percent it understates risk: -2.086 percent is breached 30 times, or 1.82 percent against 1 percent, with 8.95 at p = 0.003. This twofold error in opposite directions is the signature of a leptokurtic distribution handled with a normal law. The historical and Student approaches pass coverage, at 5.02 and 1.03 percent, and 5.39 and 1.21 percent. The Student threshold uses the degrees of freedom

estimated directly on the raw returns (ν = 2.25), not those of the conditional innovations (3.49), which describe standardized residuals rather than the unconditional distribution of returns.

The second lesson appears only in the independence test. None of the three methods passes it: p-values are below 0.001 in all six configurations. Exceedances cluster in bursts, which is consistent with volatility persistence. An unconditional measure, however well calibrated on average frequency, therefore leaves the institution exposed to sequences of consecutive losses it does not anticipate. Risk measurement on this market must be conditional.

Table 5. One-day value at risk, Kupiec coverage test and Christoffersen independence test

Method	Threshold	Exceedances	Frequency	Kupiec (p)	Christoffersen (p)
Historical 95%	−1.196%	83	5.02%	0.964	0.0002
Gaussian 95%	−1.467%	60	3.63%	0.007	< 0.0001
Student 95%	−1.178%	89	5.39%	0.475	0.0002
Historical 99%	−2.895%	17	1.03%	0.906	< 0.0001
Gaussian 99%	−2.086%	30	1.82%	0.003	0.0001
Student 99%	−2.661%	20	1.21%	0.405	< 0.0001

Note. Source: authors' calculations. Expected theoretical frequencies: 5.00 percent and 1.00 percent. The Student value at risk is calibrated on ν = 2.25, estimated by maximum likelihood on the raw returns (location-scale Student distribution); a value this low reflects the extreme tails of the sample. Calibrating instead on the conditional estimate of 3.49 gives thresholds of -1.293 and -2.387 percent, with 70 and 24 exceedances, and the same conclusions.

4.6. Conditional value at risk

The failure of the independence test condemns not risk measurement but measures treating volatility as constant. The appropriate measure is a conditional value at risk built on the volatility predicted by the GJR-GARCH model, its quantile calibrated on that model's 3.61 degrees of freedom rather than the 3.49 of the symmetric specification used in Table 4. The threshold then tightens in calm periods and widens after a shock.

In sample, the measure passes all three tests at both levels: 81 exceedances at 95 percent, or 4.90 percent, with p-values of 0.856, 0.303 and 0.579; and 18 at 99 percent, or 1.09 percent, with p-values of 0.718, 0.529 and 0.768. The conditional threshold at 99 percent averages -2.153 percent but ranges from -1.112 percent in calm periods to -19.375 percent at the height of the March 2020 crash, a breathing no unconditional measure reproduces. This extreme is consistent with Figure 2: on March 17, 2020 the conditional volatility reaches 108.92 percent annualized, or 6.86 percent per session; the 99 percent quantile of the standardized Student distribution (-2.66) turns it into a threshold of -18.24 percent, and the AR(1) mean, fed by the -9.23 percent session of March 16, adds -1.13 percent.

Since in-sample evaluation is favorable by construction, the measure was tested out of sample. The first 750 sessions serve as initialization, the model is re-estimated every 25 sessions on an expanding window, and each session's value at risk uses only prior information. The test period covers 902 sessions, from December 29, 2022 to August 31, 2026.

Table 6 and Figure 3 compare the conditional measure with unconditional measures re-estimated, like the conditional one, on an expanding window every 25 sessions over the same test period. At 99 percent the conditional measure passes all three tests: 8 exceedances, or 0.89 percent of sessions, with p-values of 0.728, 0.705 and 0.876. The sharpest result concerns their structure: none of the eight is immediately followed by another, whereas it is the succession of losses that places an institution in difficulty. At 95 percent the measure also

passes all three tests: 53 exceedances, or 5.88 percent, with p-values of 0.240, 0.558 and 0.422, so that modeling volatility corrects the clustering of moderate losses as well as that of extreme ones.

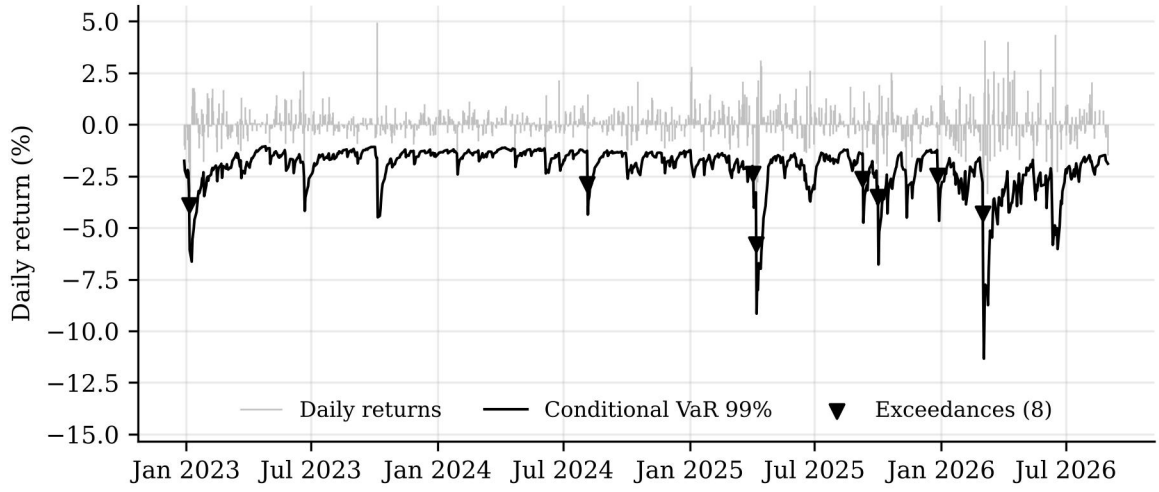
The comparison is unambiguous: none of the six unconditional measures passes the joint test, with p-values from 0.0068 to 0.019, and historical value at risk at 99 percent, which passes coverage at 1.11 percent of exceedances, is rejected on independence at 0.0034. The result is unchanged with a rolling window of 750 sessions (joint p-values from 0.0007 to 0.02). At 99 percent, the average loss on exceedance days is 3.49 percent for the conditional measure against 3.85 percent for the historical one.

Table 6. Out-of-sample backtesting: conditional value at risk and unconditional measures (902 sessions, December 29, 2022 to August 31, 2026)

Measure	Exceedances	Frequency	Kupiec (p)	Indep. (p)	Joint (p)
Conditional 99%	8	0.89%	0.728	0.705	0.876
Historical 99%	10	1.11%	0.747	0.0034	0.013
Gaussian 99%	17	1.88%	0.017	0.038	0.0068
Student 99%	13	1.44%	0.212	0.012	0.019
Conditional 95%	53	5.88%	0.240	0.558	0.422
Historical 95%	59	6.54%	0.042	0.040	0.016
Gaussian 95%	35	3.88%	0.109	0.0090	0.0091
Student 95%	61	6.76%	0.021	0.060	0.012

Note. Source: authors' calculations. The conditional measure is estimated on an expanding window re-estimated every 25 sessions, the one-session volatility forecast being built on prior information only. Unconditional measures are re-estimated every 25 sessions on the same expanding window (empirical quantile; Gaussian and Student distributions fitted by maximum likelihood). In sample, the conditional measure passes all three tests at both levels: p-values of 0.856, 0.303 and 0.579 at 95 percent, and of 0.718, 0.529 and 0.768 at 99 percent.

Figure 3. Conditional value at risk at 99 percent and realized returns over the out-of-sample test period



Note. Source: authors' construction. Triangles mark sessions where the realized loss exceeds the conditional value at risk.

4.7. A break in variance, not in trend

Comparing returns prior to 2026 with the current year reveals a break in variance, not in the mean. Annualized volatility rises from 13.5 to 21.09 percent, a variance ratio of 2.434, and the Levene test, which does not rely on normality, rejects equality of variances at p below 0.0001 (Brown–Forsythe variant: p below 0.0001); the Fisher test, whose normality assumption makes it less reliable on returns this heavy-tailed, reaches the same verdict. The difference in mean returns is not significant, at p = 0.738.

This qualifies the common reading, which presents the 2026 decline as a trend correction: the data point to a higher-volatility episode rather than a shift in mean return. The break date is set at the turn of the calendar year rather than estimated, and the tests used here do not by themselves establish a regime change. Over 158 sessions a cumulative fall of 1.03 percent is compatible with a statistically null mean return and a sharply increased variance. The distinction points towards risk management, revising exposures and reducing position sizes, rather than a directional bet on a reversal.

4.8. Comparison of the two indices

Table 7 sets the two indices side by side. Over the 1,419 common sessions the two indices behave alike: returns correlate at 0.980, annualized volatility is 13.10 against 14.05 percent and kurtosis 11.17 against 10.37. Performances nonetheless diverge recently: from 2021 to 2025 they track each other within about three percentage points, but in 2026 the MASI falls by 1.03 percent against 9.67 percent for the MASI 20. The gap suggests that the correction was concentrated in large capitalizations, the segment the contract is written on, although index returns are not decomposed by constituent here.

Table 7. Comparison of the MASI and MASI 20 indices over the common period (1,419 sessions)

Indicator	MASI	MASI 20	Reading
Annualized volatility	13.10%	14.05%	Slightly higher for large caps
Kurtosis	11.17	10.37	Comparable tail thickness
First-order autocorrelation	+0.0907	+0.0856	No liquidity artefact
Robust variance ratio, q = 2	z* = +1.885	z* = +1.819	Same diagnosis
2025 performance	+27.57%	+24.53%	Convergent
2026 performance (to Aug. 31)	−1.03%	−9.67%	Marked divergence

Note. Source: authors' calculations. Correlation of daily returns: 0.980. Regression coefficient of the MASI 20 on the MASI: 1.050 (R-squared 0.960).

4.9. Discussion and implications

4.9.1. For the nascent futures market

The results converge on an operational warning for the futures market. High volatility persistence (0.988 under the symmetric model, 0.971 under the GJR-GARCH), degrees of freedom of 3.49, a significant leverage effect and extreme sessions seven times more frequent than the Gaussian prediction imply that calibrating initial margins on normality would expose the clearing house to substantial risk. The empirical threshold established here, a daily loss of 2.90 percent exceeded one session in a hundred, is a more reliable benchmark than its Gaussian equivalent of 2.09 percent. The rejection of the independence test identifies the remedy: margins should track conditional rather than average historical volatility, since with a

shock half-life of about 24 sessions under the GJR-GARCH (56 under the symmetric model) an unconditional model would leave the clearing house under-covered for weeks after each episode of tension.

The parameters adopted at launch sharpen the diagnosis. The initial margin of 1,000 dirhams on a notional near 13,000 dirhams is about 7.7 percent of notional, or 3.6 times the average conditional value at risk at 99 percent. Across 1,652 sessions only one daily variation exceeded that threshold, on March 16, 2020. But conditional value at risk at 99 percent exceeded the margin on 25 sessions, or 1.51 percent of the sample, in five episodes: March 2020, February 2022, January 2023, April 2025 and March 2026. A fixed margin therefore protects less precisely when risk materializes. Two qualifications apply: the comparison is an indicative order of magnitude rather than an assessment of regulatory adequacy, since margins follow their own methodology and longer liquidation horizons; and these magnitudes come from the broad index, marginally less volatile than the underlying at 13.10 against 14.05 percent. The same exercise on the MASI 20 itself, over its 1,419 sessions, confirms the order of magnitude: no daily variation exceeds the margin, the margin is 3.5 times the average conditional value at risk at 99 percent (-2.22 percent), and that value at risk exceeds the margin on 14 sessions, or 0.99 percent of the sample, in five episodes (February 2022, January 2023, April 2025, October 2025 and March 2026), the worst reaching -12.86 percent in March 2026.

4.9.2. For portfolio management

The non-rejection of weak-form efficiency outside crisis periods calls for caution towards strategies based on price series alone, as does the concentration of performance: most of the cumulative return disappears without the ten best sessions. The leverage effect further suggests putting downside protection in place before episodes of tension rather than during them. These findings align with the heterogeneity documented across African markets by Magnusson and Wydick (2002), Appiah-Kusi and Menyah (2003) and Jefferis and Smith (2005), and are consistent with Casablanca behaving, outside crisis episodes, like the more efficient African markets in that literature; a comparison with developed markets lies beyond the scope of this study.

5. Conclusion

This article has documented the risk dynamics of the Moroccan equity market over 1,652 sessions, as the Casablanca exchange acquires its first futures market. That risk is poorly described by Gaussian models: kurtosis reaches 18.07, extreme sessions are seven times more frequent than under normality, the leverage effect is significant, and Gaussian value at risk is rejected at both conventional levels. Volatility is strongly persistent, and the transition from 2025 to 2026 is statistically a break in variance rather than in trend.

Two results extend beyond the Moroccan case. The evidence against weak-form efficiency proves not robust, surviving neither the correction for heteroskedasticity nor the exclusion of the crisis year. And the three unconditional risk measures fail the independence test, so validation by exceedance frequency alone accepts unsuitable models, whereas the conditional measure passes every test at both the 95 and 99 percent levels, including out of sample. On this market, what can be predicted is not the direction of returns but their magnitude.

This study has four limitations. The observation period opens on a crisis and covers no complete ordinary cycle. The absence of volume data precludes a joint analysis of risk and liquidity, the MASI 20 control ruling out the non-synchronous trading artefact without substituting for a direct liquidity measure. The out-of-sample evaluation of the 99 percent measure rests on eight exceedances, which limits the power of the tests. Finally, the one-session horizon cannot be scaled by the square root of time given such persistence.

These limitations point to directions for future research: regime-switching (Hamilton, 1989) and quantile-based (Engle & Manganelli, 2004) specifications as alternatives to the GJR-GARCH specification; expected shortfall (Artzner et al., 1999), which now governs prudential market risk capital; backtesting at multi-day horizons relevant to margin calls; and, as trading history accumulates, the direct study of futures contract returns, volume and basis.

Declarations

Funding: The authors received no financial support for the research, authorship or publication of this article.

Conflict of interest: The authors declare that they have no competing interests.

Data availability: The daily index series analyzed in this study are publicly available from the historical database of Investing.com. The processed datasets (daily closing prices and returns of the MASI and MASI 20) and the Python code reproducing every table and figure are provided as supplementary material with this revision and will be deposited in a public repository (Zenodo) upon acceptance, subject to the data provider's terms of use.

Ethics approval: This study does not involve human participants or animals and required no ethics approval.

References

Aggarwal, R., Inclan, C., & Leal, R. (1999). Volatility in emerging stock markets. *Journal of Financial and Quantitative Analysis*, *34*(1), 33–55. https://doi.org/10.2307/2676245

Alagidede, P., & Panagiotidis, T. (2009). Modeling stock returns in Africa's emerging equity markets. *International Review of Financial Analysis*, *18*(1–2), 1–11. https://doi.org/10.1016/j.irfa.2009.02.001

Angelidis, T., Benos, A., & Degiannakis, S. (2004). The use of GARCH models in VaR estimation. *Statistical Methodology*, *1*(1–2), 105–128. https://doi.org/10.1016/j.stamet.2004.08.004

Appiah-Kusi, J., & Menyah, K. (2003). Return predictability in African stock markets. *Review of Financial Economics*, *12*(3), 247–270. https://doi.org/10.1016/S1058-3300(02)00073-3

Artzner, P., Delbaen, F., Eber, J.-M., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, *9*(3), 203–228. https://doi.org/10.1111/1467-9965.00068

Basel Committee on Banking Supervision. (2019). *Minimum capital requirements for market risk*. Bank for International Settlements. https://www.bis.org/bcbs/publ/d457.htm

Bekaert, G., & Harvey, C. R. (1995). Time-varying world market integration. *The Journal of Finance*, *50*(2), 403–444. https://doi.org/10.1111/j.1540-6261.1995.tb04790.x

Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial Economics*, *43*(1), 29–77. https://doi.org/10.1016/S0304-405X(96)00889-6

Bekaert, G., & Harvey, C. R. (2003). Emerging markets finance. *Journal of Empirical Finance*, *10*(1–2), 3–55. https://doi.org/10.1016/S0927-5398(02)00054-3

Berkowitz, J., & O'Brien, J. (2002). How accurate are value at risk models at commercial banks? *The Journal of Finance*, *57*(3), 1093–1111. https://doi.org/10.1111/1540-6261.00455

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. *The Review of Economics and Statistics*, *69*(3), 542–547. https://doi.org/10.2307/1925546

Bourse News. (2026, August 31). *Bourse de Casablanca : clôture du 31 août 2026* [Market report]. https://boursenews.ma/article/marches/bourse-casablanca-cloture-du-31-aout-2026

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The econometrics of financial markets*. Princeton University Press.

Casablanca Stock Exchange. (2026). *Index composition and history; market statistics*. https://www.casablanca-bourse.com

Chow, K. V., & Denning, K. C. (1993). A simple multiple variance ratio test. *Journal of Econometrics*, *58*(3), 385–401. https://doi.org/10.1016/0304-4076(93)90051-6

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics*, *10*(4), 407–432. https://doi.org/10.1016/0304-405X(82)90018-6

Christoffersen, P. F. (1998). Evaluating interval forecasts. *International Economic Review*, *39*(4), 841–862. https://doi.org/10.2307/2527341

Christoffersen, P. F., & Pelletier, D. (2004). Backtesting value at risk: A duration-based approach. *Journal of Financial Econometrics*, *2*(1), 84–108. https://doi.org/10.1093/jjfinec/nbh004

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, *50*(4), 987–1007. https://doi.org/10.2307/1912773

Engle, R. F. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives*, *15*(4), 157–168. https://doi.org/10.1257/jep.15.4.157

Engle, R. F., & Bollerslev, T. (1986). Modeling the persistence of conditional variances. *Econometric Reviews*, *5*(1), 1–50. https://doi.org/10.1080/07474938608800095

Engle, R. F., & Manganelli, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic Statistics*, *22*(4), 367–381. https://doi.org/10.1198/073500104000000370

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance*, *48*(5), 1749–1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Futures Market Coordination Body. (2026, April 6). *Institutional portal*. Bank Al-Maghrib; Moroccan Capital Market Authority.

Giot, P., & Laurent, S. (2003). Value-at-risk for long and short trading positions. *Journal of Applied Econometrics*, *18*(6), 641–663. https://doi.org/10.1002/jae.710

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, *48*(5), 1779–1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, *57*(2), 357–384. https://doi.org/10.2307/1912559

Hamilton, J. D., & Susmel, R. (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics*, *64*(1–2), 307–333. https://doi.org/10.1016/0304-4076(94)90067-1

Hamou, O., Oudgou, M., & Boudhar, A. (2025). Analysis of the effectiveness of classical models in forecasting volatility and market dynamics: Insights from the MASI and MASI ESG indices in Morocco. *Journal of Risk and Financial Management*, *18*(7), Article 370. https://doi.org/10.3390/jrfm18070370

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: does anything beat a GARCH(1,1)? *Journal of Applied Econometrics*, *20*(7), 873–889. https://doi.org/10.1002/jae.800

Harvey, C. R. (1995). Predictable risk and returns in emerging markets. *The Review of Financial Studies*, *8*(3), 773–816. https://doi.org/10.1093/rfs/8.3.773

Investing.com. (2026). *MASI and MASI 20 historical data* [Data set]. Fusion Media Limited. https://www.investing.com

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255–259. https://doi.org/10.1016/0165-1765(80)90024-5

Jefferis, K., & Smith, G. (2005). The changing efficiency of African stock markets. *South African Journal of Economics*, *73*(1), 54–67. https://doi.org/10.1111/j.1813-6982.2005.00004.x

Jorion, P. (2007). *Value at risk: The new benchmark for managing financial risk* (3rd ed.). McGraw-Hill.

Kingdom of Morocco. (2014). *Law No. 42-12 on the market for financial futures instruments, promulgated by Dahir No. 1-14-96 of May 20, 2014*. Official Bulletin.

Kuester, K., Mittnik, S., & Paolella, M. S. (2006). Value-at-risk prediction: A comparison of alternative strategies. *Journal of Financial Econometrics*, *4*(1), 53–89. https://doi.org/10.1093/jjfinec/nbj002

Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives*, *3*(2), 73–84. https://doi.org/10.3905/jod.1995.407942

Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics*, *8*(2), 225–234. https://doi.org/10.1080/07350015.1990.10509794

Ljung, G. M., & Box, G. E. P. (1978). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297–303. https://doi.org/10.1093/biomet/65.2.297

Lo, A. W. (2004). The adaptive markets hypothesis. *The Journal of Portfolio Management*, *30*(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, *1*(1), 41–66. https://doi.org/10.1093/rfs/1.1.41

Lo, A. W., & MacKinlay, A. C. (1990). An econometric analysis of nonsynchronous trading. *Journal of Econometrics*, *45*(1–2), 181–211. https://doi.org/10.1016/0304-4076(90)90098-E

Magnusson, M. A., & Wydick, B. (2002). How efficient are Africa's emerging stock markets? *The Journal of Development Studies*, *38*(4), 141–156. https://doi.org/10.1080/00220380412331322441

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, *36*(4), 394–419. https://doi.org/10.1086/294632

McNeil, A. J., & Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: An extreme value approach. *Journal of Empirical Finance*, *7*(3–4), 271–300. https://doi.org/10.1016/S0927-5398(00)00012-8

Moroccan Capital Market Authority. (2026). *Annual report*. https://www.ammc.ma

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, *59*(2), 347–370. https://doi.org/10.2307/2938260

Smith, G., & Ryoo, H.-J. (2003). Variance ratio tests of the random walk hypothesis for European emerging stock markets. *The European Journal of Finance*, *9*(3), 290–300. https://doi.org/10.1080/1351847021000025777

Wright, J. H. (2000). Alternative variance-ratio tests using ranks and signs. *Journal of Business & Economic Statistics*, *18*(1), 1–9. https://doi.org/10.1080/07350015.2000.10524842

Appendix. Methodological note

The main dataset comprises 1,653 daily closing prices of the MASI index (1,652 log returns) from January 2, 2020 to August 31, 2026; the secondary dataset comprises 1,420 prices of the MASI 20 index from December 9, 2020. Both come from Investing.com. Volatilities are annualized by the square root of 252 and the runs test uses crossings of the median return. Variance ratios follow Lo and MacKinlay (1988), the robust version using the heteroskedasticity-consistent asymptotic variance. Both volatility models are estimated by maximum likelihood with Student innovations and an AR(1) mean equation. Kupiec is a likelihood ratio test on exceedance frequency; Christoffersen tests their independence through a first-order Markov chain; the joint test sums the two statistics. Conditional value at risk is the conditional mean plus predicted volatility times the quantile of the normalized Student distribution with 3.61 degrees of freedom. The out-of-sample exercise initializes on 750 sessions, re-estimates every twenty-five sessions on an expanding window and forecasts one session ahead; the unconditional measures follow the same schedule. Data and code are available from the authors on request.