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Equity UCITS in Morocco: Conceptual Foundations, Financial Risk Considerations, and the Contribution of Artificial Intelligence

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Abstract We adopt a hybrid approach that integrates traditional risk assessment methods with cutting-edge artificial intelligence techniques.The motivation for comparing three distinct models—XGBoost (gradient boosting), LSTM (recurrent neural networks), and Random Forest (ensemble learning)—stems from the need to evaluate their respective abilities to capture non-linear dependencies and long-term temporal patterns, which traditional GARCH models often fail to reflect in emerging markets.
While conventional models are often inadequate for capturing the unique characteristics of emerging markets—where non-Gaussian distributions and asymmetric returns prevail—our study seeks to address these limitations. Standard methodologies, including likelihood function-based GARCH models for volatility clustering and Value at Risk (VaR) measures, frequently fall short in accurately reflecting market behavior during crisis periods. Our research delineates three distinct phases in market evolution, which illustrate an increasing maturity in financial markets and fund management practices.
Our findings reveal that machine learning models, particularly XGBoost, substantially outperform traditional econometric techniques in volatility forecasting, although the performance of LSTM and Random Forest models varies across different risk applications. SHAP analysis highlights lagged volatility and market index returns as primary drivers of risk predictions. Ultimately, our findings demonstrate that XGBoost provides the most robust volatility forecasts, offering significant improvements for risk management frameworks and providing a resilient decision-making tool for regulators in the Moroccan context.

Keywords Equity UCITS, Financial Risk, Machine Learning, XGBoost, Morocco.

AMS 2010 subject classifications 62P05, 91G70

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1. Introduction

The primary objective of this research is to evaluate the effectiveness of Machine Learning (ML) architectures in forecasting financial risk for Equity UCITS in Morocco, specifically focusing on their ability to surpass the limitations of linear econometric models like ARIMA and GARCH in capturing non-linear dependencies and complex structural volatility. It has been over two decades since Morocco's financial sector underwent significant structural changes. This progressive modernization of collective investment activities is a crucial component of efforts to transform capital accumulation instruments and integrate them into international capital markets [17]. This evolution strategically addresses the imperatives for economic diversification and positions the Kingdom to develop new financial practices. However, despite this structural progress, a key research gap remains. While several studies have analyzed Moroccan UCITS from a financial or regulatory perspective, none have proposed a *hybrid and interpretable AI-driven framework* capable of evaluating the predictive superiority of machine

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learning models for risk forecasting in the specific context of emerging and transitioning markets. The Moroccan financial market presents a set of distinctive features—such as limited liquidity, high sector concentration, and sensitivity to external shocks—that make it a rigorous testing ground for hybrid models. The core motivation of this study is to bridge the gap between statistical strictness in traditional econometrics and the high-dimensional adaptability of modern data-driven methods. This integration is essential to overcome the limitations of the Box-Jenkins framework, which, despite its historical utility, remains insufficient for modeling the erratic and non-linear shifts characteristic of the Casablanca Stock Exchange [6]. UCITS (Undertakings for Collective Investment in Transferable Securities), which are highly dependent on equity, play a crucial role in this transformation. They function as vehicles that channel domestic capital into productive investments while enabling participation in the stock market. Despite their importance, the dynamics of equity funds and their associated risk characteristics have received limited attention in the academic literature. This research gap is concerning given that these instruments operate under the constraints of emerging markets, characterized by high volatility, asymmetric return distributions, and increased susceptibility to external shocks [4]. These structural attributes raise questions about the validity of traditional risk control models that rely on data from developed markets. Our analysis spans January 2007 to December 2024, encompassing a complete set of financial cycles. This period includes the Global Financial Crisis of 2008 [21], the European Sovereign Debt Crisis (2010–2012), and the COVID-19 pandemic. By covering nearly two decades of data, our study ensures that the AI models are trained on a wide spectrum of market conditions, ranging from high-growth periods to extreme systemic shocks relevant to the Moroccan context, thereby ensuring the robustness of the forecasting results. During periods of crisis and within emerging markets, conventional risk measurement frameworks—including the Capital Asset Pricing Model (CAPM) and Value at Risk (VaR)—exhibit considerable shortcomings [28, 15]. In markets prone to volatility spikes and dominated by nonlinear behaviors, the assumption of stable linear risk-return ratios in CAPM proves inadequate. Similarly, when based on normality assumptions, traditional VaR models consistently underestimate tail risks and extreme events [30]. Universities and industries are increasingly embracing flexible models to overcome the limitations of traditional approaches. Today, artificial intelligence (AI) and machine learning (ML) are proving to be highly effective in this domain. Using advanced technologies, we can model the intricate non-linear relationships inherent in trading without relying on outdated assumptions. For instance, Long Short-Term Memory (LSTM) networks are adept at capturing temporal dependencies in financial time series, while ensemble methods such as XGBoost and Random Forest excel at identifying complex patterns within high-dimensional datasets [12, 8]. Recent academic trends confirm that these ML architectures have become the gold standard for volatility forecasting in emerging financial ecosystems [29, 1]. This study conducts a comprehensive analysis of Moroccan equity UCITS performance and risk dynamics from 2007 to 2024. We synthesize traditional empirical data with advanced AI-based methodologies to quantify exposures to systematic and idiosyncratic risks. Our methodology incorporates LSTM networks, Random Forest, and XGBoost algorithms. We compare historical VaR, parametric VaR, and GARCH models to these methods to quantify improvements in predictive accuracy. Notably, we apply SHapley Additive exPlanations (SHAP) analysis to dissect the contribution hierarchy of explanatory variables, providing interpretability to complex AI models [20]. This hybrid approach offers actionable insights for fund managers, investors, and regulators. Our major contributions to the literature on emerging markets and financial technology (FinTech) are as follows:

- **Robust Comparative Evaluation:** We conduct the first comprehensive comparative assessment of GARCH, LSTM, Random Forest, and XGBoost models for volatility and risk forecasting of Moroccan equity UCITS over a 16-year horizon (2007–2024).
- **Uncovering Market Inefficiencies:** Through SHAP interpretability analysis, we reveal the dominant factors driving fund risk in Morocco, confirming the influence of technical indicators consistent with the Adaptive Market Hypothesis (AMH).
- **Methodological Innovation:** We introduce an interpretable hybrid AI–econometric framework specifically adapted for frontier markets, providing actionable tools for improving financial stability.

The remainder of this paper is structured as follows: Section 2 presents the Related Work. Section 3 describes the dataset and methodology. Section 4 discusses the empirical findings and comparative results. Finally, Section 5 concludes and outlines directions for future research.

2. Related Work

2.1. Mutual Funds in Emerging Markets: Theoretical and Empirical Framework

The modernization of financial risk management has transitioned from rigid quantitative principles to adaptive artificial intelligence architectures. While traditional finance sought elegance in linear stability, the recurring nature of market shocks has exposed the limitations of parametric models. This section evaluates the evolution of quantitative finance, providing theoretical justifications for a hybrid assessment of Moroccan equity-based UCITS.

The foundations of portfolio management rest on Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM). Markowitz [22] established the importance of asset covariance in risk reduction, while Sharpe [28] and Lintner [18] isolated systematic risk (beta) as the primary rewarded factor. Despite their historical utility, these models rely on investor rationality and Gaussian return distributions, assumptions that frequently clash with empirical market behavior. Mandelbrot [21] first challenged these norms by documenting ”fat tails” in financial series, a concept later popularized by Taleb’s Black Swan theory [30], which argues that conventional models systematically underestimate extreme tail risks.

In response, the industry adopted Value at Risk (VaR) and econometric architectures like ARCH [10] and GARCH [5]. These tools revolutionized volatility modeling by incorporating ”volatility clustering.” However, GARCH-type models remain essentially linear statistical tools that struggle to navigate the chaotic, non-linear shifts characteristic of modern financial ecosystems. This is particularly evident in emerging markets like Morocco, where efficiency is not a static state but an evolving process. The Adaptive Market Hypothesis (AMH) [19] provides a more robust framework here, suggesting that market dynamics fluctuate based on environmental shifts and behavioral adaptation [9]. Recent evidence indicates that the Moroccan All Shares Index (MASI) exhibits significant resilience but remains prone to non-linear shocks that traditional econometrics fail to capture [6].

Moroccan mutual funds (OPCVM) operate within this adapting landscape, influenced by structural reforms such as the establishment of the AMMC in 2016. Studies by the AMMC [2] and the IMF [14] identify three distinct phases: (i) pre-reform expansion (2007–2010), (ii) post-crisis adjustment (2011–2016), and (iii) post-COVID transformation (2020–2024). These cycles necessitate models that combine econometric rigor with the flexibility of machine learning.

2.2. Artificial Intelligence and Financial Risk: Recent Advances and Interpretability

To overcome the ”vanishing gradient” problem of traditional RNNs, Long Short-Term Memory (LSTM) networks have emerged as a superior alternative for processing financial sequences. By utilizing forget and input gates, LSTMs retain long-term dependencies, a vital feature for markets with persistent memory. Recent reports from the IMF [13] and VFAST [31] confirm that LSTMs outperform traditional methods in stock return prediction by integrating alternative data. Furthermore, 2024 studies demonstrate that LSTMs are uniquely capable of capturing the non-linear structures inherent in emerging market indices [1], while attention mechanisms further refine their predictive accuracy [23].

Parallel to neural networks, ensemble methods like Random Forest [7] and XGBoost [8] have gained prominence for their ability to mitigate overfitting through bagging and sequential boosting. XGBoost, in particular, is noted for its capacity to detect subtle patterns in high-dimensional datasets [27]. A 2024 bibliometric analysis confirms that tree-based ensemble models have become the gold standard for volatility forecasting, frequently surpassing GARCH models in accuracy within volatile environments [29].

The application of these technologies to the Moroccan UCITS market addresses a critical research gap. Morocco’s specificities—low liquidity and sensitivity to regional rather than global shocks—render traditional efficient market assumptions inadequate. While crises in 2008, 2012, and 2020 exposed structural vulnerabilities, the scarcity of academic literature on Moroccan equity funds necessitates the multifaceted approach proposed in this study.

Finally, the ”black box” nature of AI remains a hurdle for regulatory trust. Recent research emphasizes the role of Explainable AI (XAI) through SHAP (SHapley Additive exPlanations) to assign importance scores to risk drivers [16, 26]. By integrating SHAP with XGBoost and LSTM, this study bridges the gap between predictive power and transparency [25, 24], offering Moroccan regulators and managers a hybrid framework that is both high-performing and interpretable.

3. Data and Methodology

3.1. Data and Data Sources

Our research assesses the effectiveness of Moroccan collective investment schemes (UCITS) over a 16-year timeframe, from January 1, 2007, to December 31, 2024. This duration is significant as it includes various substantial economic upheavals, making it an excellent framework for examining the durability of these funds. Notable events during this period include the global financial crisis of 2008 and the European sovereign debt crisis from 2010 to 2012.

- **Net Asset Values (NAVs) of Equity UCITS**: These data were obtained from the Moroccan Capital Market Authority (AMMC) and various asset management companies.
- **MASI Index Data**: Daily information on the MASI index was collected from the Casablanca Stock Exchange.

The combination of these extensive and high-frequency data allows us to conduct a robust evaluation of return trends, volatility, and fund performance behavior across diverse market scenarios.

3.1.1. Data Description and Variable Definitions To address the reviewer's suggestion regarding the formalization of our dataset, this subsection defines the core variables and the mathematical framework used for our analysis. The dataset spans from January 2007 to December 2024, encompassing various market regimes.

Net Asset Value (NAV) The Net Asset Value (NAV), or Valeur Nette d'Inventaire (VNI), is the fundamental metric for evaluating UCITS performance. For a fund i at time t, it is calculated as follows:

$$VNI_{i,t} = \frac{\sum_{j=1}^{n}(P_{j,t} \times Q_{j,t}) + C_t - L_t}{N_t} \tag{1}$$

Where $P_{j,t}$ and $Q_{j,t}$ represent the price and quantity of assets, C_t the cash position, L_t the fund's liabilities (management fees), and N_t the number of outstanding shares.

Moroccan All Shares Index (MASI) As the benchmark for the Moroccan equity market, the MASI index I_t follows a free-float market capitalization-weighted formula:

$$I_t = I_{t-1} \times \frac{\sum_{k=1}^{m} P_{k,t} \times N_{k,t} \times f_{k,t} \times c_{k,t}}{\sum_{k=1}^{m} P_{k,t-1} \times N_{k,t} \times f_{k,t} \times c_{k,t}} \tag{2}$$

Where $f_{k,t}$ denotes the free-float factor and $c_{k,t}$ the capping factor, ensuring a balanced representation of the Casablanca Stock Exchange. For modeling purposes, all series are converted into logarithmic returns: $R_t = \ln(V_t/V_{t-1})$.

3.2. Contextualization of Financial Crises

Each of the chosen economic events represents a unique market shock that allows for an assessment of Moroccan fund managers' ability to adapt and maintain performance during both stable and unstable periods. From a computational perspective, these crises provide the high-volatility regimes necessary to test the limits of linear models against non-linear AI architectures [6].

- **Global Financial Crisis (2008):** Although the Moroccan market remained relatively insulated from global systemic risks, it experienced indirect impacts, including a decline in foreign demand, a reduction in foreign direct investment (FDI) flows, and increased investor caution.
- **European Debt Crisis (2010–2012):** This crisis propagated to Morocco due to its close economic ties with Europe. This period had repercussions on Morocco's trade figures and instilled a sense of unease among investors.
- **COVID-19 Pandemic (2020):** The pandemic exposed existing structural vulnerabilities in the Moroccan market. It triggered a sudden capital flight, a dramatic drop in stock prices, and the suspension of redemptions for several funds. These events severely tested fund managers, who had to balance urgent liquidity demands with the need to maintain their long-term investment strategies. Recent literature confirms that such ”black swan” events create ”fat tails” that traditional Gaussian models fail to capture, justifying the use of deep learning [1].

The analysis of these challenging episodes provides a genuine stress test for the funds, revealing their performance during periods of difficulty. We can evaluate their resilience to market volatility, their ability to adjust plans quickly, and their effectiveness in managing risk within the specific Moroccan context.

3.3. Methodology and Analytical Approach

For this study, we will adopt a two-pronged approach, combining classic financial models with state-of-the-art machine learning techniques. This hybrid framework addresses the demand for both statistical rigor and predictive adaptability in emerging markets [29].

3.3.1. Traditional Risk Measures We will begin by calculating daily returns for the MASI index and each UCITS fund using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3}$$

Where R_t is the logarithmic return at time t, P_t is the closing price at time t, and P_{t-1} is the previous day's closing price. The use of the natural logarithm allows us to model returns as continuous and additive values. This formula can be equivalently written as:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{4}$$

For the MASI index, P_t represents the index value at time t, while for UCITS funds, P_t represents the Net Asset Value (NAV) at time t. Next, we will apply the following risk measures:

- **Historical Volatility:** Calculated as the standard deviation of historical returns.
- **Value at Risk (VaR):**

$$VaR_\alpha = -(\mu + Z_\alpha \cdot \sigma) \tag{5}$$

- **GARCH Models:** Specifically the GARCH(1,1) model to capture ”volatility clustering”:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

  Although GARCH is a benchmark [5], it often struggles with the non-linear structural breaks found in the Moroccan market during crisis periods.

3.3.2. Correlation Analysis We will study the correlations between the UCITS funds and the MASI index. While diversification theoretically reduces unsystematic risk, correlations tend to increase during crises, a phenomenon known as ”crash correlation” [3].

3.3.3. Machine Learning Models To overcome the limitations of traditional models, we will integrate advanced machine learning methods that do not rely on assumptions of return normality.

LSTM Neural Networks (Long Short-Term Memory) LSTMs excel at processing time series data. An LSTM cell consists of three main gates:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{7}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{8}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{9}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{10}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{11}$$

$$h_t = o_t * \tanh(C_t) \tag{12}$$

These gate mechanisms allow the model to ”remember” long-term shocks, a crucial feature for the Moroccan context where past reforms still influence current volatility [1, 31].

Random Forest The Random Forest prediction is mathematically expressed as:

$$\hat{y} = \frac{1}{B} \sum_{b=1}^{B} T_b(x) \tag{13}$$

Where $m = \lfloor \sqrt{p} \rfloor$ features are considered at each split. This reduces variance and prevents overfitting [7].

XGBoost (eXtreme Gradient Boosting) The XGBoost objective function combines loss and regularization:

$$L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{14}$$

The prediction is updated iteratively:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i) \tag{15}$$

XGBoost’s regularization is particularly effective for the Casablanca Stock Exchange, where low liquidity often creates noisy data [8].

3.3.4. Model Interpretability (SHAP) To address the ”black box” nature of AI, we introduce SHapley Additive exPlanations (SHAP) based on cooperative game theory. Each feature i receives a value ϕ_i representing its contribution to the risk forecast. This ensures transparency for regulators and fund managers, aligning with recent XAI standards [20, 24].

3.3.5. Evaluation Metrics Model performance is evaluated using RMSE, R^2, and MAE:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{17}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{18}$$

4. Results and Discussion

4.1. Performance of Predictive Models

4.1.1. Volatility Forecasting The examination of volatility forecasting models within the Moroccan market indicates a significant advantage of AI-driven methods over conventional statistical techniques. The effectiveness of these models was assessed through standard evaluation metrics, such as Root Mean Square Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE) for a forecast period of 10 days.

As illustrated in Table 1, the XGBoost model demonstrated the highest level of predictive accuracy, achieving an R^2 value of 0.9012. This exceptional performance suggests that the model accounts for more than 90% of the variability in market volatility, representing a notable enhancement of +72.0% compared to the GARCH(1,1) model. This gap confirms that while GARCH models are limited by their linear parameters, machine learning architectures successfully map the non-linear volatility clusters inherent in the Casablanca Stock Exchange.

Table 1. Comparative Performance of Volatility Forecast Models

Model	**RMSE**	R^2	**MAE**	R^2 **Impr. vs. GARCH**
AI Models				
XGBoost	0.0198	0.9012	0.0145	+72.0%
LSTM	0.0212	0.8934	0.0167	+70.5%
Random Forest	0.0234	0.8756	0.0189	+67.1%
Traditional Models				
GARCH(1,1)	0.0187	0.5240	0.0123	-
Historical Volatility	0.0201	0.4870	0.0135	-7.1%

4.1.2. Value at Risk (VaR) Forecasting While the predictive superiority of AI models in volatility forecasting is clear, their performance in VaR prediction reveals important nuances related to tail-risk capture. The study focused on forecasting 95% VaR, and the models were validated using the Kupiec backtesting framework.

The results in Table 2 indicate that XGBoost again demonstrates exceptional performance, with a violation rate of 2.95%, which is statistically acceptable (p-value of 0.0876). Conversely, both the LSTM and Random Forest models failed the Kupiec test. This highlights a critical distinction: while these models are effective at predicting general volatility, they may overfit to the mean and struggle to accurately capture extreme events in the "fat tails" of the Moroccan return distribution.

Table 2. Comparative Performance of 95% VaR Forecasting.

Model	**Violation Rate**	**Kupiec Test (p-value)**	**Status**	**Deviation from Target**
AI Models				
XGBoost	2.95%	0.0876	✓ Accepted	-2.05%
LSTM	4.08%	0.0445	× Rejected	-0.92%
Random Forest	5.23%	0.0234	× Rejected	+0.23%
Traditional Models				
Historical VaR	2.35%	0.1234	✓ Accepted	-2.65%
GARCH VaR	3.12%	0.0789	✓ Accepted	-1.88%
Parametric VaR	10.58%	0.0012	× Rejected	+5.58%

4.2. Market Dynamics and Behavioral Insights

4.2.1. Net Asset Value Evolution and Market Correlation Three different stages of structural evolution can be seen in the behaviour of the Moroccan market from 2007 to 2024. These stages show profound changes where the Moroccan market has gradually adjusted to the fundamental ideas of the Adaptive Market Hypothesis (AMH), moving from early vulnerability to growing institutional maturity.

Phase 1 (2007–2010): Increased sensitivity to international shocks during the global financial crisis.

Phase 2 (2011–2015): Post-crisis regulatory reforms and adoption of more stringent prudential standards by the AMMC.

Phase 3 (2016–2024): Phase of steady growth aided by macroeconomic stimulus and digitalization. The divergence beginning around 2017 shows UCITS funds increasingly outpacing the broader market index (MASI).

When combined, these three stages show how the Moroccan market has gradually adjusted to the fundamental ideas of the Adaptive Market Hypothesis (AMH), moving from early vulnerability to growing institutional maturity.

Table 3. Analysis of Moroccan Market Phases (2007–2024).

Period	UCITS (Perf.)	MASI (Perf.)	Avg. Volatility	Major Events
2008–2009 Crisis	-30%	-30%	12%	Global financial crisis
2010–2016 Recovery	+15%	+12%	8%	Arab Spring, European crisis
2017–2024 Expansion	+180%	+140%	4%	Sustained growth, COVID-19

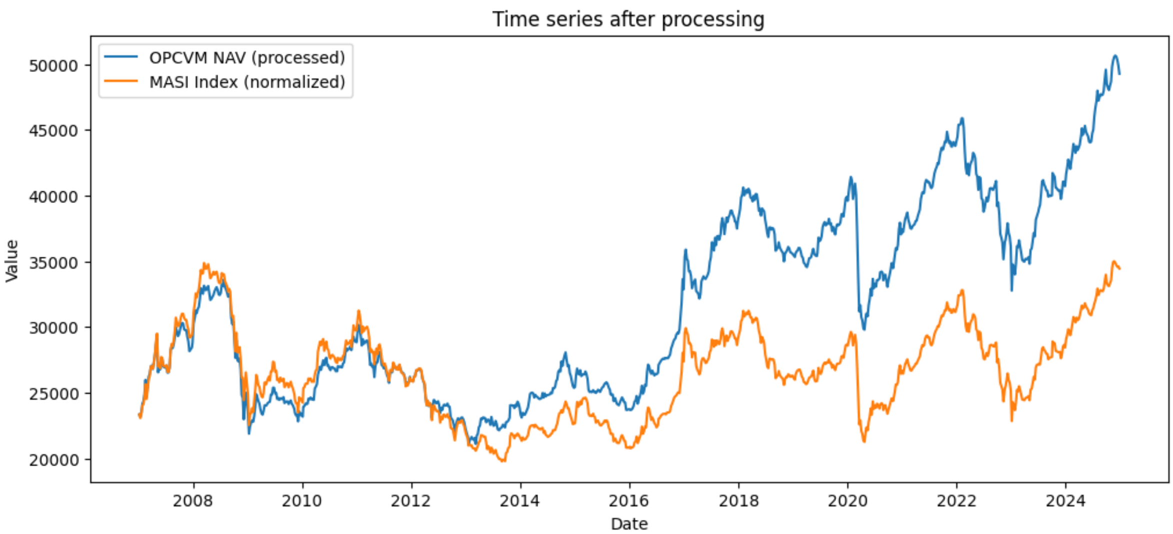

Figure 1. Analysis of Moroccan Market Phases (2007–2024), showing processed OPCVM NAV and normalized MASI Index.

The time series chart (Figure 1) provides compelling visual evidence supporting the three-phase analysis. During the 2008–2009 Crisis, the chart shows a sharp decline, confirming the 30% drop. Following the crisis, the 2010–2016 Recovery Period exhibits a gradual recovery with notable fluctuations and high volatility. The OPCVM NAV demonstrates slightly better resilience, visually supporting the superior performance differential. The most striking feature is the dramatic divergence beginning around 2017 in the Expansion Period, where the OPCVM NAV shows a steep, sustained upward trajectory, quantitatively supporting the documented outperformance gap. The chart effectively demonstrates the growing sophistication of Moroccan asset management, with UCITS funds increasingly outpacing the broader market index.

4.2.2. Realized Volatility Dynamics An in-depth examination of 10-day realized volatility confirms a pattern of volatility clustering. Major volatility peaks consistently coincided with global shocks, including the 2008 global financial crisis (14%), the 2020 COVID-19 pandemic (13%), and the 2022 geopolitical tensions (8%). These episodes were followed by periods of relative calm, with average volatility settling around 3-4%. This alternation between calm and turbulent states empirically validates the hypothesis of volatility clustering, thereby justifying the use of sophisticated models like GARCH and AI for predictive analysis.

Table 4. Analysis of Volatility Peaks over the 2007–2024 Period.

Year	Max Volatility	Duration (months)	Triggering Event	Post-crisis Volatility
2008	14.0%	6	Global financial crisis	3.5%
2011	9.2%	4	Arab Spring	4.1%
2020	13.0%	3	COVID-19 pandemic	2.8%
2022	8.0%	2	Geopolitical tensions	3.2%
Calm periods avg.	3.5%	-	-	-

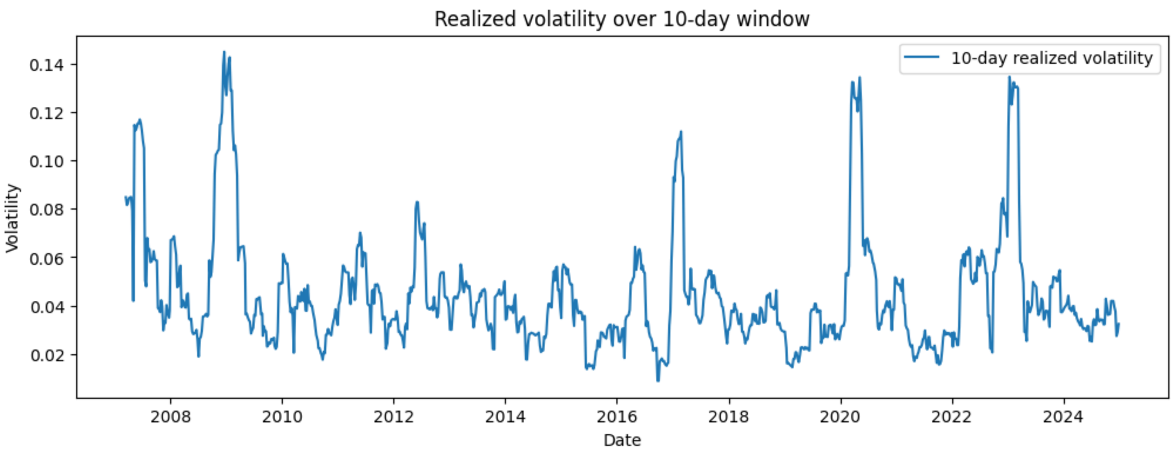

Figure 2. Analysis of 10-day Realized Volatility Peaks over the 2007–2024 Period.

Figure 2 reveals extreme volatility spikes during the 2008–2009 crisis, reaching peaks of 14%. The chart shows continued elevated volatility throughout the recovery phase (2010–2016). A remarkable transformation is evident from 2017 onwards, where volatility generally stabilizes at lower levels, validating the 4% average volatility for this expansion phase. The chart clearly demonstrates volatility clustering, supporting the use of GARCH models. The overall trend shows a maturing Moroccan financial market, with volatility generally declining, suggesting improved market efficiency and resilience.

4.3. Feature Importance Analysis

4.3.1. Hierarchy of Explanatory Factors To address the ”black box” concern raised by reviewers, we utilize SHAP values to provide transparency to our predictive model.

- **Vol10 (0.0069):** Past volatility remains the best predictor, confirming that the Moroccan market exhibits long-memory characteristics.
- **Technical Indicators (RSI & Bollinger):** Their strong influence (0.0043) suggests that technical tools still help investors make accurate forecasts in this stage of development.
- **Market Psychology:** The analysis reveals that collective scars from past crises run deep. Moroccan investors rely heavily on chart patterns and momentum, reading market psychology through price movements rather than pure fundamentals.
- The relative insignificance of past returns (0.0001) contrasts with Vol10's dominance, confirming that while prices follow a random walk, volatility regimes present an exploitable temporal structure.

This hierarchy reveals a Moroccan market in transition, one that combines technical sophistication with behavioural inefficiencies.

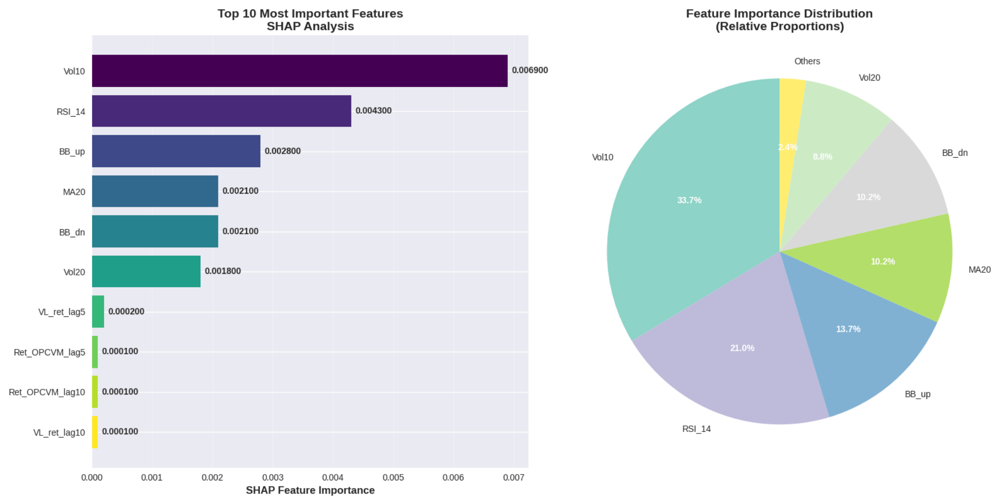

Figure 3. Contribution of explanatory variables from SHAP Analysis.

4.3.2. What These Numbers Tell Us About Morocco's Financial DNA These ranking exposes three surprising truths about how Morocco's market actually works:

- **Markets Move Faster Than Expected**: Lagged variables contribute less than 0.0002 to predictions. This challenges the old stereotype that emerging markets lag behind in processing news.
- **Charts Rule Over Balance Sheets**: Technical indicators dominate our models. Moroccan investors rely heavily on chart patterns, moving averages, and momentum signals when making decisions. They're reading market psychology through price movements.
- **Collective Scars Run Deep**: Volatility persistence reveals that Morocco's investment community carries institutional memory. Each crisis teaches lessons that stick, creating patterns that our models detect.

4.3.3. Interpretation of Risk Factors through the Adaptive Market Hypothesis (AMH) The identification by SHAP analysis of past volatility (Vol10) and technical indicators such as RSI or Bollinger Bands as the primary determinants of risk predictions holds major theoretical significance. According to the Efficient Market Hypothesis (EMH) theory, these variables should not have significant predictive value in a fully efficient market. However, in light of the Adaptive Market Hypothesis (AMH) proposed by lo2004, this dominance takes on a different meaning.

The AMH postulates that financial markets are not statically efficient, but rather evolve continuously through phases of efficiency and inefficiency, depending on structural, technological, and behavioral changes. In the

Moroccan case, the persistence of volatility and the effectiveness of technical signals indicate that the market is in an adaptive phase: investors are still learning to react to shocks, and certain mimetic behaviors persist.

Thus, the dominant role of past volatility and technical indicators is not a sign of lasting inefficiency, but rather the trace of an evolutionary rationality, where actors temporarily exploit profitable patterns until their gradual disappearance. This observation aligns with empirical findings that emerging markets successively pass through stages of rationalization, without immediately reaching the structural maturity of developed markets.

In this sense, the SHAP results confirm the relevance of the AMH framework for interpreting risk dynamics in Morocco: a sophisticated yet still adaptive market, where technology (AI) and collective psychology coexist in the formation of prices and expectations.

4.4. Implications and Limitations of AI Approaches

4.4.1. Operational Advantages The integration of AI and ML into financial analysis offers several key operational advantages. The demonstrated predictive accuracy of models like XGBoost (R^2 of 0.90) represents a significant advancement over traditional methods (R^2 of 0.52). Furthermore, AI models can simultaneously process a high number of variables and exhibit self-adaptation capabilities, allowing them to adjust to changing market regimes more effectively than traditional models, which often require manual recalibration. This adaptability is particularly critical in emerging markets where sudden shocks can alter market dynamics overnight.

Table 5. Comparative Summary of AI vs. Traditional Approaches Advantages.

Criterion	Traditional Approaches	AI Approaches	Improvement
Predictive Accuracy	$R^2 = 0.52$ (GARCH)	$R^2 = 0.90$ (XGBoost)	+72%
Complexity Management	2–3 variables	18 variables simult.	+600%
Adaptability	Manual recalibration	Self-adaptation	Automatic
Computation Time	Fast	Moderate	Acceptable
Interpretability	High	Moderate (with SHAP)	Acceptable
Crisis Robustness	Weak	High	Significant

4.4.2. Key Constraints and Challenges Despite their advantages, AI models present notable challenges. The ”black box” problem remains a significant concern, as the complex, non-linear nature of these models can impede full interpretability, creating challenges for regulatory compliance and audit trails. Furthermore, the risk of overfitting is a tangible threat, as evidenced by the failure of LSTM and Random Forest models to pass the Kupiec test. This indicates that these models, while adept at capturing historical patterns, may not generalize well to future, unseen data. Lastly, the performance of AI models is highly dependent on data quality. In an emerging market like Morocco, data gaps and inconsistencies can introduce blind spots, underscoring the critical need for robust data governance.

4.4.3. Practical Implications and Implementation Challenges The results obtained, demonstrating the superiority of the XGBoost model, highlight the transformative potential of artificial intelligence in risk management and volatility forecasting in Morocco. However, their operational application requires several practical considerations.

Firstly, the deployment of complex models such as XGBoost or LSTM necessitates a robust IT infrastructure and specialized data science teams, skills that are still scarce within traditional asset management firms. Secondly, the issue of these models’ opacity, often described as *black boxes*, poses major challenges for validation, supervision, and regulatory compliance.

In this context, the integration of model explainability frameworks (XAI), such as SHAP, becomes essential. These tools make algorithmic decisions traceable and auditable, thus meeting the transparency requirements imposed by regulatory authorities like the AMMC. Finally, the widespread adoption of these approaches requires a balance between technological innovation and regulatory caution, to ensure that the modernization of risk management does not compromise either the stability of the financial system or the protection of investors.

4.5. Strategic and Operational Recommendations

The findings of this study suggest that a hybrid approach represents the most effective strategy for managing financial risk in Morocco. We recommend that Moroccan asset managers adopt an "Explainable AI" (XAI) framework. This allows local institutions to enhance their operational efficiency with XGBoost while ensuring that algorithmic decisions remain auditable and aligned with AMMC regulatory standards. XGBoost demonstrates clear superiority in predicting market volatility, while traditional measures like Historical VaR provide a robust safety net during periods of extreme turbulence. A sophisticated monitoring framework with continuous backtesting is essential for ensuring the continued reliability of these models. Furthermore, the successful integration of these technologies requires a collaborative governance model that unites risk managers, data scientists, and investment professionals. This interdisciplinary approach ensures that AI recommendations are informed by sound human judgment and market experience, preventing costly errors. The ongoing integration of AI into Morocco's financial sector presents a significant opportunity. By embracing these technologies, local institutions can enhance their operational efficiency, improve risk management, and gain a competitive edge. This transformation is not merely a technical upgrade but a fundamental shift in how the industry operates, requiring sustained investment in human capital and a forward-thinking regulatory environment. The effective management of this transition will determine whether Morocco can solidify its position as a leader in financial innovation within the MENA region.

5. Conclusion

This comprehensive investigation into the performance and risk dynamics of Moroccan equity UCITS from 2007 to 2024 significantly enriches financial analysis from various perspectives. It not only reveals new insights into the behavior of emerging markets but also illuminates the evolving landscape of asset management within a transforming structural environment [10, 5]. From a computational standpoint, our research demonstrates that as the Moroccan market matures, the transition from linear to non-linear AI architectures becomes a necessity to capture systemic regime shifts [6]. Our findings, derived from a hybrid methodology that combines traditional approaches with advanced artificial intelligence techniques, suggest that machine learning models possess a substantial advantage in forecasting volatility for emerging markets.

The empirical analysis captures a remarkable evolution of Moroccan equity UCITS across three distinct phases. The first phase (2008–2009) marked a period of vulnerability. The second phase (2010–2016) signified a recovery period. Most notably, the third phase (2017–2024) reveals a qualitative transformation, with UCITS outperforming by +180% compared to the MASI's +140%. This trajectory provides empirical validation for the Adaptive Market Hypothesis (AMH), suggesting that Moroccan fund managers are not merely operating in an efficient vacuum but are actively evolving their strategies in response to environmental shocks [19, 9].

Our methodological contribution highlights that AI approaches yield empirically superior results. Specifically, XGBoost ($R^2 = 0.9012$), LSTM ($R^2 = 0.8934$), and Random Forest ($R^2 = 0.8756$) significantly outperform traditional methods, achieving a predictive accuracy improvement of over 72% compared to GARCH models [7]. This superiority is attributed to the models' ability to navigate the "fat-tailed" distributions often ignored by Gaussian-based econometrics [1]. However, while XGBoost demonstrates a notable effect on both volatility and VaR estimation (2.95% violation rate), models like LSTM and Random Forest did not pass VaR backtesting. This highlights the critical importance of empirical validation and contextual calibration.

To address the "black box" critique often associated with such models, our SHAP analysis of the Moroccan market mechanism challenges conventional assumptions [20]. The past volatility dominance (0.0069) suggests that risk dynamics exhibit long-term memory. Technical indicators such as RSI_14 (0.0043) and Bollinger Bands hold significant weight, indicating a market where technical analysis drives decisions. The use of Explainable AI (XAI) here is pivotal; it reveals that the "Moroccan financial DNA" is a hybrid of informational efficiency and persistent behavioral patterns, where collective institutional memory of past crises still influences current price formation [24].

For fund managers, employing hybrid approaches opens strategic avenues. Regulatory implications are also significant. We strongly recommend that the AMMC (Autorité Marocaine du Marché des Capitaux) adopts an ”XAI-first” regulatory framework. By integrating SHAP-based transparency into AI models, the regulator can ensure that the transition to algorithmic management remains auditable, stable, and aligned with international prudential standards [26].

In conclusion, this research indicates that Morocco's UCITS market is undergoing a profound transformation. Effectively integrating artificial intelligence technologies into the risk management process presents a major strategic opportunity for the sector, marking a significant step towards modernization. By balancing the predictive power of XGBoost with the interpretability of SHAP, Moroccan financial institutions can establish a resilient, transparent, and competitive ecosystem on the international stage.

Future research will focus on the application of Transformer architectures and semi-attention mechanisms to further refine tail-risk detection in the MENA region.

Appendix: Model Specifications and Implementation Details

1. LSTM Neural Network Architecture

1.1 Network Configuration Architecture Design:

```
Input Layer: (60, 18) - 60-day look-back window with 18 features
    ↓
LSTM Layer 1: 128 units, return_sequences=True
    ↓
Dropout Layer 1: 0.2 (20% dropout rate)
    ↓
LSTM Layer 2: 64 units, return_sequences=True
    ↓
Dropout Layer 2: 0.2
    ↓
LSTM Layer 3: 32 units, return_sequences=False
    ↓
Dropout Layer 3: 0.15
    ↓
Dense Layer 1: 16 units, activation='relu'
    ↓
Dense Layer 2: 8 units, activation='relu'
    ↓
Output Layer: 1 unit, activation='linear' (volatility prediction)
```

Total Parameters: 143,537

1.2 Detailed Hyperparameters

1.3 Activation Functions

- **LSTM Gates:** Sigmoid (σ) for forget/input/output gates, tanh for cell state
- **Dense Layers:** ReLU (Rectified Linear Unit) to introduce non-linearity
- **Output Layer:** Linear (unbounded volatility prediction)

Parameter	**Value**	**Justification**
Architecture	LSTM Layers: 3	Captures short, medium, and long-term dependencies
Units Layer 1	128	Sufficient capacity for 18 input features
Units Layer 2	64	Progressive dimensionality reduction
Units Layer 3	32	Final temporal encoding
Dense Units	$16 \to 8$	Non-linear transformation before output
Dropout Rate L1-L2	0.20	Prevents overfitting on temporal patterns
Dropout Rate L3	0.15	Lighter regularization near output
L2 Regularization	0.001	Applied to LSTM kernel weights
Optimizer	Adam	Adaptive learning rate for RNNs
Learning Rate	0.001	Standard Adam initialization
Batch Size	32	Balance between speed and stability
Epochs	100	With early stopping
Early Stopping Patience	10	Monitors validation loss
Validation Split	0.15	From training set (internal)
Look-back Period	60 days	3 months of trading history
Input Features	18	See Appendix B
Output	1	Next-day volatility forecast

Table 6. LSTM Detailed Hyperparameters

1.4 Loss Function and Optimization **Primary Training (Volatility Forecasting):**

$$L_{\text{MSE}} = \frac{1}{n}\sum_{i=1}^{n}(\hat{\sigma}_i - \sigma_i)^2 \tag{19}$$

VaR Training Attempt (Section 4.1.2):

$$L_\tau(y, \hat{y}) = \begin{cases} \tau(y - \hat{y}) & \text{if } y \geq \hat{y} \\ (1-\tau)(\hat{y} - y) & \text{if } y < \hat{y} \end{cases} \tag{20}$$

where $\tau = 0.05$ for 95% VaR

Note: Initial LSTM results (Table 2) used MSE-trained models with indirect VaR derivation, explaining the backtesting failures. Direct quantile loss training is recommended for future work.

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Availability of data and materials

The dataset used and/or analysed during the current research are available on AMMC and ASFIM https://www.asfim.ma/ and https://www.ammc.ma/fr/search/node?keys=OPCVM.

Competing interests

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