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BEHAVIORAL DYNAMICS AND MARKET ADAPTATION: CROSS-COUNTRY EMPIRICAL EVIDENCE OF THE ADAPTIVE MARKET HYPOTHESIS

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ABSTRACT- *This paper explores the Adaptive Market Hypothesis (AMH) across nine MENA-region markets, as well as, offering an empirical validation of market adaptability. While efficient market hypotheses posit constant market efficiency, AMH suggests that market efficiency is dynamic; evolving in response to economic shifts, investor learning, and market behavior. It employs an analytical framework to daily time-series data spanning 15 years from nine MENA-region financial markets, enabling a robust evaluation of market adaptability across varying economic cycles. It integrates Markov Switching Models (MSM) to detect regime shifts, Momentum Strategies to evaluate trend persistence, and Long Short-Term Memory (LSTM) neural networks to forecast price movements and validate market adaptability. The results revealed significant evidence of time-varying market efficiency across all nine markets, with observable regime-switching behavior detected through Markov Switching Models (MSM). These models successfully captured transitions between efficient and inefficient states, highlighting periods of volatility and stability that align with AMH predictions. Momentum Strategies, particularly the 250-day variant, outperformed the Buy & Hold strategy during specific market phases, suggesting exploitable inefficiencies. Furthermore, LSTM models, when adjusted for regime states identified by MSM, demonstrated enhanced predictive accuracy, capturing nonlinear dynamics and transitions reflective of adaptive market behavior. This paper contributes to the adaptive portfolio management, strategic trading, and policy formulation in emerging and frontier MENA markets. It introduces a structured, multi-layered analysis of market adaptability, empirically validates AMH in underexplored MENA markets, and sets the stage for adaptive investment models capable of real-time adjustments.*

Keywords-Adaptive Market Hypothesis, Markov Switching Models, Momentum Strategies, LSTM, Market Efficiency, MENA-region Markets, Regime Shifts, Forecasting.

1. INTRODUCTION

Financial markets are central to global economic systems, channeling capital through complex interactions between investors, institutions, and policymakers. Traditional financial theories often assume these markets are efficient, rational, and self-correcting. However, empirical anomalies such as the 2008 global financial crisis, the exponential rise of Bitcoin, and the GameStop short squeeze challenge this assumption. These events underscore the reality that markets are not consistently predictable and suggest that efficiency fluctuates based on behavioral and structural dynamics. This evolving nature of market behavior calls for theoretical frameworks capable of capturing adaptive mechanisms within financial systems.

Despite the foundational role of theories such as the Efficient Market Hypothesis (EMH) and the Capital Asset Pricing Model (CAPM), persistent market anomalies such as speculative bubbles, herding behavior, and momentum effects suggest that these models fall short in explaining real-world dynamics. The EMH posits that asset prices always reflect all available information, implying static market efficiency. However, empirical evidence increasingly shows that market efficiency is not constant, but evolves in response to shifts in behavior, competition, and macroeconomic forces. This disconnect highlights a critical research gap: most empirical validations of the Adaptive Market Hypothesis (AMH) have focused on developed markets and short-term periods, while emerging markets particularly in the MENA region remain underexplored. Understanding how these markets transition between efficient and inefficient states, and whether such transitions can be forecasted, remains a significant unanswered question in financial economics. Addressing this gap requires an integrated empirical framework capable of capturing temporal shifts in efficiency and the behavioral mechanisms that drive them.

This research aims to empirically validate the Adaptive Market Hypothesis (AMH) by investigating regime shifts and evolving efficiency across nine MENA-region financial markets. By integrating Markov Switching Models, momentum strategies, and LSTM neural networks, the study constructs a comprehensive framework that models dynamic market behavior. The findings are expected to demonstrate that financial markets do not exhibit static efficiency, but instead adjust over time in response to behavioral, structural, and informational factors.

This study contributes to financial literature by offering a structured empirical validation of the Adaptive Market Hypothesis (AMH) within the MENA region, an area where market efficiency remains insufficiently examined. By applying a combination of Markov Switching Models, momentum strategies, and Long Short-Term Memory (LSTM) neural networks, the research captures both the cyclical nature of efficiency and the role of behavioral adaptation. The findings provide practical insights for investors, analysts, and policymakers seeking to interpret shifting market conditions and design strategies responsive to time-varying efficiency.

The remainder of this paper is structured as follows: Section 2 presents the theoretical framework and prior research; Section 3 outlines the methodological approach; Section 4 reports the empirical results; and Section 5 offers conclusions and recommendations for future research.

2. THEORETICAL FRAMEWORK AND PRIOR RESEARCH

2.1. Evolution of Financial Market Theories

Over the past century, financial markets have evolved from fragmented, manually operated systems to complex, digitized infrastructures where trading is driven by algorithms, real-time data, and global connectivity. Earlier market structures were characterized by inefficiencies due to limited information access and slower communication. In contrast, modern markets operate with unprecedented speed and data integration, reshaping how prices form and how participants behave.

This evolution presents a challenge to static economic theories that assume homogenous agents and constant efficiency. Traditional models such as the Efficient Market Hypothesis (EMH) and the Capital Asset Pricing Model (CAPM), while foundational, often fall short in explaining persistent volatility, irrational investor behavior, and structural breaks. As a result, alternative frameworks like the Adaptive Market Hypothesis (AMH) have emerged, offering dynamic and behaviorally informed perspectives on how financial markets function.

2.2. Efficient Market Hypothesis (EMH)

The EMH, formalized by Eugene Fama in 1970, revolutionized financial economics. It posits that financial markets are informationally efficient, meaning that asset prices at any given time fully reflect all available information. EMH can be categorized into three forms:

- Weak-form efficiency: All past trading information, including prices and volume, is already reflected in current asset prices. Thus, technical analysis is deemed ineffective.
- Semi-strong efficiency: All publicly available information is reflected in asset prices, making fundamental analysis ineffective.
- Strong-form efficiency: Asset prices instantly and fully reflect even insider information, leaving no opportunity for excess returns through any informational advantage.

According to EMH, it is impossible to consistently achieve returns exceeding average market returns on a risk-adjusted basis, given that all relevant information is already incorporated into prices.

Alongside the development of EMH, the Capital Asset Pricing Model (CAPM) emerged, providing a framework for understanding the relationship between expected returns and systematic risk. Introduced by Sharpe (1964), Lintner (1965), and Mossin (1966), CAPM asserts that an asset's expected return is proportional to its beta, a measure of its sensitivity to market movements.

CAPM complements EMH by offering a quantitative approach to asset pricing under the assumption of efficient markets. If markets are efficient, CAPM should theoretically hold, as risk is the only driver of returns. Together, EMH and CAPM laid the foundation for modern portfolio theory, investment strategy design, and regulatory frameworks.

However, real-world market behaviors increasingly challenged these theories. If markets are fully efficient and asset prices always reflect all available information, why do recurring patterns like bubbles, crashes, and anomalies persist? Such empirical inconsistencies prompted the exploration of alternative frameworks that could better accommodate observed phenomena.

2.3. Empirical Challenges and Market Anomalies

While EMH offered an elegant theoretical framework, numerous empirical observations began to cast doubt on its validity:

- Momentum Effect: Stocks that performed well in the past tend to continue performing well in the short term, directly contradicting EMH's assertion that past price movements have no predictive power (Jegadeesh & Titman, 1993; Asness, Moskowitz, & Pedersen, 2015).
- Market Crashes and Bubbles: If markets were perfectly efficient, extreme mispricings leading to market crashes wouldn't exist. The 2008 financial crisis and the cryptocurrency boom of the 2010s exposed fundamental inefficiencies (Woolley, 2014).
- Herding Behavior: Investors often follow the crowd rather than acting rationally, leading to speculative bubbles and panic-driven sell-offs (Shleifer & Vishny, 1997).
- Overreaction and Underreaction: Psychological biases cause investors to overreact to news or underreact to important information, creating price momentum (Kahneman & Tversky, 1979).
- High-Frequency Trading (HFT): The rise of algorithmic trading, which exploits fleeting inefficiencies, suggests that price adjustments are not instantaneous and often create additional volatility (Meng & Li, 2021).

These empirical challenges implied that the classical depiction of financial markets as perfectly efficient, rational, and self-correcting was, at best, an idealization. They opened the door to alternative explanations that integrate human behavior, learning, and evolutionary dynamics into market analysis.

2.4. Behavioral Finance and Evolutionary Economics

As traditional theories like the Efficient Market Hypothesis (EMH) struggled to explain repeated market anomalies, Behavioral Finance emerged to offer a new perspective. Unlike classical finance, which assumes investors are perfectly rational and that markets are always efficient, Behavioral Finance shows that real-world investors often make decisions based on emotions, biases, and imperfect reasoning. Research by Kahneman and Tversky (1979), especially their work on Prospect Theory, revealed that people are more sensitive to losses than to gains, leading them to behave irrationally under risk.

Common biases such as overconfidence, where investors overestimate their knowledge; loss aversion, where they fear losses more than they value gains; anchoring, where they fixate on irrelevant information; and herding, where they follow the crowd, all contribute to market behavior that cannot be explained by traditional models. Instead of prices always reflecting true value, markets often overreact to news, underreact to important information, or sustain momentum trends for longer than rational models would predict.

Behavioral Finance made it clear that financial markets are frequently inefficient. Prices can deviate from intrinsic value for extended periods because of widespread psychological behaviors among investors. Events like financial bubbles, sudden crashes, and irrational trading patterns are not rare exceptions but natural outcomes of human behavior influencing markets.

Recognizing these realities created the need for new theories. Scholars and practitioners began to look for models that could better describe how markets truly work, focusing on markets as evolving, flexible systems rather than perfectly efficient machines.

2.5. Adaptive Market Hypothesis (AMH)

In response to the limitations of EMH, Andrew W. Lo (2004, 2005) proposed the Adaptive Market Hypothesis (AMH), offering a dynamic, evolutionary perspective on financial markets. Drawing heavily on principles from evolutionary biology, AMH conceptualizes markets as ecosystems where financial agents behave like species competing for survival and adapting to constantly changing environments. Instead of viewing markets as perpetually efficient or inefficient, AMH contends that market efficiency is conditional and varies over time depending on environmental pressures, competition, adaptation, and the evolving behavior of investors.

Drawing on Darwinian principles, AMH suggests that:

- Investors learn and adapt their strategies based on survival, competition, and past successes or failures.
- Different market environments favor different behaviors and strategies, similar to species adapting to ecological niches.
- Financial innovations, economic cycles, crises, and regulatory changes continuously reshape market dynamics.

Unlike EMH, which assumes rationality, AMH incorporates the behavioral realities of loss aversion, overconfidence, and herd mentality (Kahneman & Tversky, 1979; Shleifer & Vishny, 1997), recognizing that inefficiencies persist until arbitrage corrects them, only for new inefficiencies to emerge in an ongoing evolutionary cycle. Therefore, within the AMH framework, markets may appear efficient during stable periods, but they are prone to inefficiency during episodes of rapid change, structural shifts, or financial crises.

However, despite its theoretical appeal, the Adaptive Market Hypothesis has been criticized for lacking clear testable predictions and a formal mathematical structure. Unlike the Efficient Market Hypothesis, which allows for direct testing using statistical efficiency measures, AMH is often viewed as more descriptive than predictive (Campbell, 2008). It does not clearly define when or why markets become inefficient, nor does it offer a specific method to measure how investors "adapt" over time. As a result, researchers must often rely on additional models such as Markov Switching Models, rolling window tests, or time-varying regression techniques to capture the dynamic behavior that AMH proposes (Lo, 2012). Moreover, the concept of “adaptation” in AMH is somewhat abstract and is usually inferred from observed changes in market performance, which raises concerns about how reliably it can be measured. According to Chordia et al. (2014), although AMH helps explain why market efficiency may change over time, it requires the use of indirect indicators that may not fully reflect investor learning or competitive dynamics. Therefore, most empirical studies on AMH, including this one, adopt hybrid approaches that combine traditional econometric tools with behavioral or structural insights to test its assumptions more effectively.

2.6. Market Dynamics and Adaptations

Markets are complex adaptive systems that do not operate in a uniform or predictable manner. Rather than existing in a perpetual state of efficiency, financial markets move through efficiency cycles, where inefficiencies create opportunities for excess returns until they are gradually arbitraged away.

A cross-country analysis by Santos, Fávero, Brugni, and Serra (2023) examined how markets evolve over time and found that market efficiency follows a cyclical pattern rather than remaining constant. Their study revealed that financial markets experience phases of inefficiency, where arbitrage opportunities exist, followed by periods of increased efficiency, where those opportunities diminish.

This cyclical nature of market efficiency is influenced by multiple factors, including:

- Institutional structures and government regulations
- Economic shocks and financial crises
- Liquidity and capital flows
- Technological advancements

Their research also showed that markets in emerging economies tend to experience prolonged inefficiencies compared to developed markets, where efficiency adjusts more rapidly due to better infrastructure and transparency. This supports Lo's (2004) AMH framework, which emphasizes that market efficiency is highly context-dependent and varies across different regions and asset classes.

A similar study by Mandacı, Taşkın, and Ergün (2019) examined Borsa Istanbul (BIST) and found that market efficiency is not a binary state but fluctuates across different indices and investment periods. Using rolling window variance ratio tests and BDS tests, they found that:

- High liquidity and technological advancements lead to more efficient markets.
- Financial instability, speculative trading, and economic uncertainty create inefficiencies.

These findings provide further empirical support for AMH by demonstrating that market efficiency is conditional and constantly evolving rather than being a permanent feature of financial markets.

2.7. Empirical Evidence Supporting AMH

The Adaptive Market Hypothesis is backed by a growing body of empirical research that confirms market efficiency fluctuates based on external conditions.

- Urquhart & McGroarty (2016) found that market efficiency is not a fixed state but varies across time, particularly during economic downturns. Their study on the FTSE

100 and S&P 500 indices revealed that efficiency is higher in stable periods but declines in financially unstable environments, supporting AMH's view that markets evolve dynamically.

- Okorie & Lin (2021) studied the impact of COVID-19 on financial markets, showing that efficiency collapsed in the early months of the pandemic but recovered as investors adapted their trading behavior. This demonstrates how market efficiency responds to external shocks, a key prediction of AMH.
- Munir et al. (2022) examined South Asian stock markets and found that market anomalies, such as contrarian effects, exist during heightened uncertainty, further supporting AMH's claim that markets transition between efficient and inefficient states depending on prevailing conditions.

But if efficiency changes, how do we model these fluctuations? Markov Chains provide an answer.

2.8. Markov Chains

Markets constantly transition between different states, making it essential to use models that can capture these non-linear shifts. A Markov Chain is a probabilistic system in which the likelihood of moving from one state to another depends solely on the current state, without regard to the sequence of past events. This property of "memorylessness" makes Markov Chains highly effective for modeling regime changes, which often occur unpredictably.

While Markov Chains and their extensions, such as Markov Switching Models (MSM), are powerful in detecting regime changes, they also come with practical challenges. One major issue is their sensitivity to initial parameters, which can lead to convergence problems or local optima during estimation. Moreover, the choice of the number of regimes is often subjective and may influence model performance if not empirically validated. In emerging or thinly traded markets—such as several in the MENA region—low liquidity and data irregularities can lead to misclassification of regimes or unstable transition probabilities. Additionally, Markov models assume that regime transitions are driven by internal market dynamics, but in practice, external macroeconomic shocks or structural changes may influence market behavior in ways that violate the Markov property. These limitations necessitate careful interpretation and, in many cases, supplementary diagnostic testing or robustness checks when applying MSM to real-world financial data (Hamilton, 1990; Guidolin & Timmermann, 2007).

Unlike traditional financial models that assume linear relationships, Markov Chains accommodate dynamic, state-dependent adjustments, making them particularly useful for identifying when markets shift between:

- Bullish and bearish trends, helping investors adjust strategies accordingly.
- Stable and volatile conditions, enabling better risk management.

- Efficient and inefficient market phases, allowing traders to recognize opportunities for arbitrage.

By applying Markov Chains to market analysis, researchers and analysts can better understand how efficiency fluctuates, supporting the Adaptive Market Hypothesis (AMH), which argues that market efficiency is not fixed but evolves over time.

2.8.3. Applications of Markov Switching Models (MSM)

Empirical research has validated the effectiveness of Markov Switching Models (MSM) in identifying market regime shifts. Rodrigues do Carmo (2017) demonstrated that MSMs outperform traditional financial models in predicting market transitions, proving that financial markets do not follow a strict linear pattern but instead shift between different efficiency levels.

Further supporting this, Aronsson and Folkesson (2023) conducted an analysis of the Swedish OMXS30 index, finding that volatility clustering, where periods of high volatility are followed by further volatility, aligns with Markov Chain predictions. This finding confirms the Adaptive Market Hypothesis (AMH) assertion that market efficiency fluctuates rather than remains constant.

In another application, Kim, Shamsuddin, and Lim (2011) used Hidden Markov Models (HMMs) on U.S. stock market data, identifying distinct cycles between high and low efficiency states. Their findings reinforce the idea that market efficiency is an evolving feature shaped by investor behavior, external economic shocks, and technological advancements.

2.8.4. High-Frequency Trading (HFT)

A further dimension of market adaptation involves high-frequency trading (HFT), where advanced algorithms execute trades in milliseconds. Meng & Li (2021) explored the relationship between HFT and market efficiency, uncovering a dual effect:

- HFTs exploit short-term inefficiencies, taking advantage of momentary mispricings in the market.
- Over time, HFT activity contributes to overall market efficiency, as it forces price corrections faster than in traditional trading environments.
- However, in the short term, HFTs also introduce micro-level distortions, creating increased volatility and price dislocations that reduce stability.

This finding aligns with the core premise of AMH. Market efficiency is a dynamic process, and technological advancements like HFT can simultaneously disrupt and improve it depending on the phase and structure of the market.

2.8.5. Macroeconomic and Political Drivers of Efficiency Shifts

While internal market behavior plays a significant role in efficiency transitions, external economic and political factors also impact how markets adapt. Various studies have explored the role of macroeconomic events, trade wars, and financial instability in shaping market efficiency cycles.

A study on commodity markets by Rejeb and Boughrara (2013) demonstrated that periods of economic instability, global recessions, and trade wars lead to highly inefficient markets. Their findings showed that commodities such as gold, oil, and agricultural products are particularly vulnerable to inefficiencies during financial crises. This is largely due to speculative trading and investor sentiment overpowering fundamental valuation, reinforcing the need for adaptive financial models that account for these fluctuations.

Similarly, Ghazani & Araghi (2014) applied Markov Switching Models (MSM) to emerging markets, discovering that political risks and monetary policy shifts significantly impact market efficiency. Their research highlighted that:

- Currency fluctuations, interest rate changes, and inflation volatility affect the speed at which markets transition between high and low efficiency states.
- Periods of heightened political uncertainty contribute to prolonged inefficiencies, as investors become more cautious and reactive rather than following fundamental market indicators.

These studies demonstrate that financial markets do not function in isolation; they are influenced by macro-level economic and geopolitical developments, reinforcing AMH's premise that market efficiency is an ever-changing characteristic rather than a fixed state.

2.9. Momentum Strategies

Financial markets are like vast oceans, sometimes calm, sometimes stormy, but never truly still. Traders, much like skilled sailors, navigate through shifting conditions, adapting to the forces of supply, demand, sentiment, and information flow. Some ride the waves of momentum, taking advantage of trends that persist, while others anticipate reversals, waiting for inefficiencies to correct. Momentum investing is based on a straightforward idea: assets that have performed well recently will continue to do so in the short term.

This approach challenges the Efficient Market Hypothesis (EMH), which assumes prices instantly reflect all information, leaving no room for predictable trends. However, it fits perfectly with the Adaptive Market Hypothesis (AMH), which argues that markets are not always efficient but adapt as investors learn and compete.

2.9.1. Persistence of Momentum Effects

If markets were perfectly efficient, momentum would not exist, past performance would not predict future results. Yet, evidence shows it does, because price adjustments take time. Several factors explain this persistence:

- Slow Information Processing: Investors do not react to news, economic data, or earnings reports all at once. Some act quickly, while others take longer, causing prices to adjust gradually.
- Behavioral Influences (biases): Overconfidence leads traders to stick with winning assets, and herd behavior pulls others into the trend, strengthening momentum.

- Unequal Access to Information (Information asymmetry): Large institutional investors often move before smaller retail traders, extending trends until the market fully catches up. (Large institutional players often act before retail investors, allowing momentum effects to persist until the market fully adjusts.)

These forces create temporary inefficiencies, offering opportunities for traders who understand how and when markets adapt. Momentum is not an anomaly; it is a symptom of evolving efficiency, as AMH predicts.

2.9.2. Empirical Evidence on Momentum Anomalies

The evidence for momentum is not just anecdotal; it is robust, spanning decades and markets. In 1993, Jegadeesh and Titman cracked open the momentum puzzle, showing that stocks with strong past performance consistently outperformed over short horizons, a finding that shook the Efficient Market Hypothesis (EMH) to its core.
Fast forward to 2022, and Munir et al. uncovered a twist: momentum effects intensify during financial crises, aligning with the Adaptive Market Hypothesis (AMH) claim that market efficiency is conditional and evolves in response to economic turbulence. Their study revealed that during periods of uncertainty, investors rely more heavily on recent trends, making momentum-based strategies even more effective.
Akhter and Yong (2019) tied these findings to AMH by applying momentum models within its framework, confirming that momentum strategies remain profitable but are highly time-dependent. Their results suggest that momentum profits are not constant but fluctuate based on liquidity, volatility, and macroeconomic conditions, reinforcing the AMH's dynamic efficiency concept.

2.10. Digital Asset Markets

Cryptocurrency markets have defied every traditional economic model, behaving in ways that have left even the most experienced analysts struggling to keep up. Extreme price fluctuations, inefficient price discovery, and unpredictable investor behavior define this space. Yet, the evolution of the crypto market over the past decade provides one of the strongest real-world validations of the Adaptive Market Hypothesis (AMH).

2.10.1. Early-Stage Inefficiencies

In its early years, the Bitcoin market was comparable to a "wild west," characterized by thin trading volumes, high volatility, and rampant speculation. Prices were driven less by fundamentals and more by hype, misinformation, and manipulation. According to Chu et al. (2021) and Manahov et al. (2021), early crypto markets were highly inefficient, suffering from:

- Low liquidity, where large price swings occurred due to the lack of deep order books. With shallow order books, even small trades triggered massive price movements, leading to excessive volatility.

- Speculative trading, where prices were driven more by sentiment than by fundamental value.
- Lack of institutional investors, where, in the absence of stabilizing institutional players, retail speculation drove extreme price fluctuations and created short-term price distortions rather than rational market behavior.

2.10.2. Efficiency Transitions

Several studies have explored how cryptocurrency markets evolved over time, transitioning from extreme inefficiencies to more structured efficiency cycles:

- Chu et al. (2021) and Manahov et al. (2021) examined Bitcoin, Ethereum, and other digital assets, finding that market efficiency in the crypto sector is highly volatile. Their research showed that early-stage cryptocurrency markets were inefficient, but as institutional investors and algorithmic trading entered the space, efficiency gradually improved.
- Alvarez-Ramirez et al. (2018) used Markov models to track Bitcoin's efficiency cycles, revealing that cryptocurrency markets follow a similar efficiency pattern to traditional stock markets, with cyclical phases of inefficiency and efficiency. This further supports AMH's core argument that market efficiency is a dynamic property rather than a fixed state.

This pattern is precisely what AMH suggests: markets are never fully efficient or inefficient; they fluctuate based on competition, learning, and technological advancements.

2.11. Machine Learning Approaches

Traditional econometric models, such as Markov Switching Models and momentum strategies, have been instrumental in identifying structural breaks and persistent patterns in financial time series. However, the dynamic and nonlinear nature of financial markets, as posited by the Adaptive Market Hypothesis (AMH), necessitates more flexible and adaptive modeling techniques. Machine learning, particularly deep learning models like Long Short-Term Memory (LSTM) networks, has emerged as a promising approach to address these complexities.

2.11.1. LSTM Models

LSTM networks, a type of recurrent neural network introduced by Hochreiter and Schmidhuber (1997), are designed to capture long-term dependencies in sequential data. Their architecture allows for the retention of information over extended periods, making them well-suited for modeling financial time series characterized by volatility clustering and temporal dependencies. Studies have demonstrated the efficacy of LSTM models in forecasting stock prices and volatility, outperforming traditional models like ARIMA and Support Vector Machines in certain contexts.

Despite their advantages, LSTM models are not without limitations. They often require large training datasets, making them less suitable for smaller markets or shorter timeframes. They are also computationally intensive, demanding significant resources and fine-tuning to avoid overfitting. Moreover, LSTM models operate as "black boxes," offering little transparency into the causal relationships driving their forecasts, which complicates financial interpretation and limits their acceptance in policy or compliance contexts. In addition, LSTMs may not handle regime shifts or abrupt changes effectively unless adjusted with supplementary tools such as regime overlays, attention mechanisms, or hybrid frameworks. Their sensitivity to hyperparameters and initial conditions also poses challenges, as small changes can lead to significantly different outputs. For these reasons, researchers often integrate LSTM with econometric models such as ARIMA or Markov Switching Models to improve interpretability, resilience, and alignment with market structure (Bao et al., 2017; Fischer & Krauss, 2018).

In our study, we employed LSTM models in two distinct phases. Initially, we trained the model on a decade of historical data to forecast the subsequent five years, incorporating regime overlays for refinement. This approach yielded satisfactory forecasting accuracy, as evidenced by metrics such as RMSE. However, when the model was trained on the entire historical dataset to predict the next year without real-time feedback or adjustment, the forecasts became overly simplistic and failed to capture the complexities of market dynamics.

2.11.2. Hybrid LSTM Models and Adaptive Forecasting

To overcome the limitations of standalone LSTM models, researchers have increasingly turned to hybrid forecasting frameworks that combine LSTM with complementary techniques. These combinations are intended to improve accuracy, robustness, and adaptability, which are especially important under the assumptions of the Adaptive Market Hypothesis (AMH), where financial efficiency is considered dynamic and evolving.

One prominent class of hybrid models integrates wavelet transforms with LSTM networks. Wavelet decomposition allows the original financial time series to be separated into different frequency components. This process reduces noise and isolates patterns at multiple time scales. The decomposed signals are then fed into the LSTM architecture, improving learning efficiency and prediction accuracy. Zhang et al. (2024) developed a Wavelet-ARIMA-LSTM hybrid that successfully forecasted share price index futures. Similarly, Nguyen et al. (2019) demonstrated that a Wavelet-SVR-LSTM model could handle non-stationary stock series more effectively.

Another emerging architecture is the BiLSTM-Attention-CNN model. This framework combines Convolutional Neural Networks (CNN) for feature extraction, Bidirectional LSTM (BiLSTM) for learning temporal dependencies in both directions, and attention layers to dynamically weigh the most relevant parts of the sequence. Wang (2024) applied this model to stock price forecasting and found that it improved short-term trend capture and pattern recognition. Zhang et al. (2023) further validated its performance in highly volatile financial indices, showing that it outperformed conventional deep learning models in both accuracy and adaptability.

In addition, hybrid models that combine LSTM with classical econometric techniques, such as ARIMA, have shown promising results. These models, often referred to as LSTM-ARIMA, use ARIMA to model the linear component of the data and LSTM to capture the nonlinear behavior. Kashif and Ślepaczuk (2024) reported that their LSTM-ARIMA approach outperformed standalone models in the context of algorithmic trading strategies.

Recent developments have also introduced metaheuristic optimization algorithms to enhance the performance of LSTM models. Gülmez and Selçuklu (2024) presented a version of LSTM optimized using the Artificial Rabbits Optimization (ARO) algorithm. Their model delivered superior prediction accuracy across electricity and stock market datasets. These optimization methods address key challenges in LSTM such as sensitivity to initial weights and hyperparameter selection, leading to more stable and generalizable forecasting tools.

Collectively, these hybrid machine learning models represent an important evolution in forecasting methodologies. They allow researchers to better account for structural shifts, complex behavioral patterns, and market adaptability. Their ability to combine deep learning, signal processing, statistical modeling, and attention mechanisms makes them well suited for analyzing financial markets in alignment with the core principles of the Adaptive Market Hypothesis.

However, despite their flexibility and enhanced predictive power, hybrid models also present challenges. The integration of multiple modeling layers increases the risk of overfitting, especially in financial datasets with noise and structural breaks. Their complexity can reduce transparency and make model validation more difficult, particularly when combining machine learning with signal transformation or metaheuristic optimization. Additionally, the interpretability of results may suffer when several algorithms are stacked without a clear understanding of how each contributes to the final prediction. These issues become more pronounced when applying hybrid models to emerging markets, where data availability and quality are often limited. Therefore, while hybrid LSTM architectures hold strong potential, they must be implemented with careful tuning, cross-validation, and economic reasoning to avoid misleading or unstable outputs.

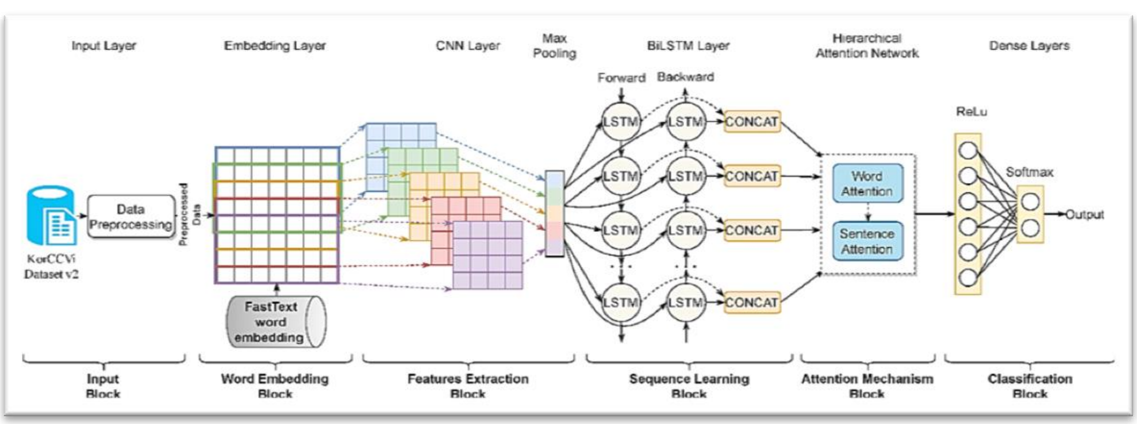

Figure 1: Architecture of the CNN–BiLSTM-Attention hybrid model.

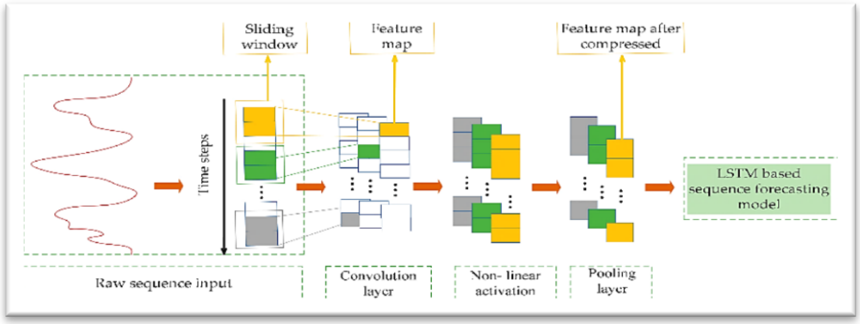

Figure 2: Structure of a Wavelet-LSTM hybrid forecasting model.

2.12. Research Gap and Hypothesis Development

Despite the substantial theoretical and empirical developments in understanding market efficiency through EMH and its alternatives, there remains a critical gap in the literature. While the Adaptive Market Hypothesis (AMH) has gained growing empirical support, most studies have focused on developed markets or applied limited time windows, failing to capture long-term and region-specific adaptive behavior. Few have employed dynamic, regime-sensitive models such as Markov Switching Models (MSM) to quantify the evolution of efficiency, especially in MENA-region markets. Additionally, the integration of machine learning techniques, particularly Long Short-Term Memory (LSTM) neural networks, with econometric frameworks to forecast market behavior under adaptive conditions remains underexplored. This study addresses this gap by combining Markov regime-switching models, momentum strategy testing, and LSTM forecasting on daily data across nine MENA markets. In doing so, it aims to provide a comprehensive, data-driven validation of AMH within a previously underrepresented regional and methodological context.

Several recent studies have attempted to explore aspects of AMH using localized or limited methodological tools. For example, Mandacı et al. (2019) examined time-varying efficiency in Borsa Istanbul using variance ratio and BDS tests, but did not incorporate forecasting or regime modeling. Similarly, Urquhart and McGroarty (2016) applied rolling window tests to major developed markets, confirming time variation but without structural modeling of efficiency phases. Munir et al. (2022) investigated contrarian effects in South Asia under AMH assumptions but lacked forecasting tools or hybrid models. These studies support the core ideas of AMH but leave unexplored the joint application of MSM and LSTM in emerging markets. Our study builds on this foundation by integrating regime-switching, momentum-based validation, and deep learning-based forecasting to analyze efficiency evolution over a longer timeframe. This integrated approach helps close the empirical gap, especially in the context of MENA markets, which are structurally different and more prone to behavioral dynamics and information asymmetry.

Based on the above, the research hypothesis is formulated as below:

H_0: There is no significant relationship between the dynamic shifts in market efficiency and the ability to generate abnormal returns.

This means that financial markets in the MENA region do not adapt in a manner consistent with the Adaptive Market Hypothesis.

3. METHODOLOGICAL FRAMEWORK

This section outlines the methodological framework adopted to empirically examine the Adaptive Market Hypothesis (AMH) across nine MENA-region financial markets using a combination of econometric and machine learning techniques. The approach integrates descriptive statistical analysis, stationarity testing, Markov Switching Models, momentum profitability strategies, and long-term forecasting via LSTM neural networks.

3.1. Research Design

This research adopts a quantitative, exploratory, and comparative design. It aims to test the hypothesis that financial market efficiency is dynamic and evolves over time, a core proposition of AMH. To achieve this, the study employs a dual-phased approach:

- Econometric Modeling using regime-based probabilistic tools (Markov Chains) and performance-based strategies (momentum).
- Machine Learning Forecasting using LSTM (Long Short-Term Memory) models to simulate and validate future efficiency dynamics.

3.2. Analytical Framework

The empirical framework integrates three components, each capturing a different dimension of market adaptability. Markov Switching Models are used to classify time-series data into efficient and inefficient regimes based on volatility structures. Momentum strategies test for the persistence of returns, revealing short-term inefficiencies consistent with behavioral biases. Finally, LSTM neural networks are employed to forecast future prices, with regime overlays applied to account for nonlinear and state-dependent behavior. This multi-method framework provides a robust structure for confirming AMH empirically. A simplified visualization of this analytical framework is shown in Figure 3 below.

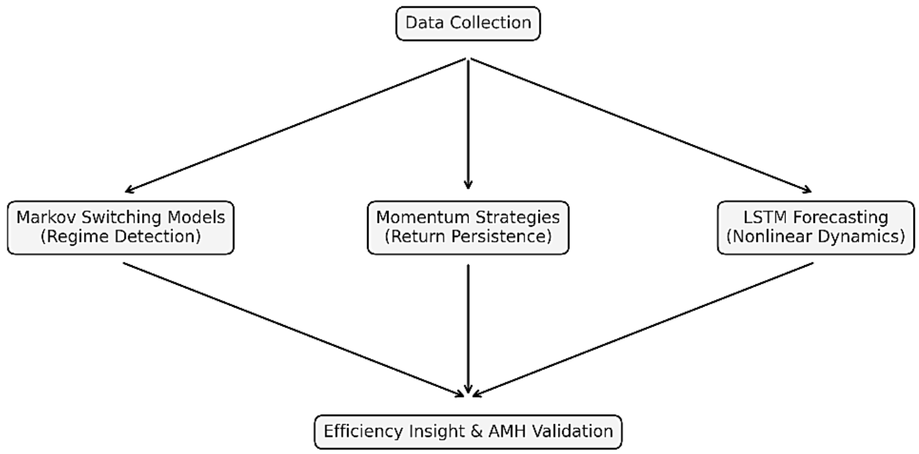

Figure 3. Data Collection

3.3. Data Collection Methods

Daily historical market data was collected for nine financial markets from different countries as shown in Table 1.

Table 1. Country Code Reference Table

Code	Country
DFMGI	United Arab Emirates
BKA	Kuwait
MASI	Morocco
EGX100	Egypt
TASI	Saudi Arabia
MSM30	Oman
AMMAN	Jordan
BAX	Bahrain
QSI	Qatar

The dataset includes over fifteen years of data for most indices, comprising the following variables: closing prices, daily returns, trading volume, and open-high-low-close (OHLC) information.

Data processing and statistical analyses were conducted using Python 3.12 (Python Software Foundation, 2023), utilizing the following libraries:

- LSTM modeling: TensorFlow (v2.15) with Keras API
- Markov switching models: statsmodels (v0.14) for regime detection
- Momentum analysis: pandas_ta (v0.3) for technical indicators
- Data processing and manipulation: Pandas (v2.1) and NumPy (v1.26)
- Scientific computing: SciPy (v1.11)

The computational environment was managed via conda to ensure reproducibility, package control, and version consistency across all analytical stages.

The Python environment provided a robust framework for calculating returns, running descriptive statistics, performing unit root and normality tests, applying Markov Switching Models, evaluating momentum strategy performance, and developing LSTM-based forecasting models. This ensured a consistent, reproducible, and efficient computational workflow throughout the research.

3.4. Sampling Strategy

The sampling strategy involved two distinct phases aligned with the dual objectives of the study:

1. *Phase 1: Econometric Analysis (Markov Models + Momentum Strategies)*

For each of the nine markets, the full available daily dataset was utilized to conduct:

– Log return computation
– Descriptive statistics
– Unit root and normality testing
– Markov regime classification
– Momentum profitability tests

This allowed us to observe long-run behavior across multiple market cycles, ensuring a robust examination of time-varying efficiency consistent with the Adaptive Market Hypothesis (AMH). No artificial truncation of the sample was applied, enabling each model to detect regime transitions and momentum patterns across the full historical span.

2. *Phase 2: Machine Learning Forecasting (LSTM Model)*

A temporal holdout method was adopted to train and validate the LSTM forecasting model:

– Training set: The first 10 years of historical data
– Testing set: The most recent 5 years, which were already observed

The model was trained to predict the test period and its output was compared with actual returns. Markov regime probabilities were then used to adjust the forecasts, enhancing interpretability and correcting potential inefficiencies.

This dual-phase sampling approach ensures the integrity of both retrospective (econometric) and predictive (machine learning) components of the research, allowing each to independently and jointly contribute to confirming AMH dynamics.

3.5. Analytical Approach

3.5.1. Descriptive and Preliminary Statistical Analysis

Each market's return series was converted into log returns to standardize volatility and improve statistical properties for modeling. This transformation also supports time-additivity and stabilizes variance. Descriptive statistics, including mean, standard deviation, skewness, and kurtosis, were computed for each return series to assess distributional characteristics. To evaluate normality, a key assumption in many econometric models, the Jarque-Bera test was applied. The full formula, test assumptions, and derivation of the Jarque-Bera statistic are provided in Appendix A to enhance clarity without overwhelming the main text. In addition to the test statistic, the p-value associated with the JB test was reported. The p-value indicates the probability of observing the given skewness and kurtosis under a normal distribution. A p-value less than 0.05 suggests a statistically significant deviation from normality, which supports the presence of potential inefficiencies in the return series.

3.5.2. Stationarity Tests

Before the application of time-series models, it was essential to test the stationarity of the log return series to ensure that their statistical properties, such as mean and variance, remained stable over time. Stationarity is a foundational requirement for valid application of econometric models such as Markov Switching Models and neural networks like Long Short-Term Memory (LSTM). To assess this, two complementary unit root tests were employed:

- Augmented Dickey-Fuller (ADF) Test
- Phillips-Perron (PP) Test

Both tests assess the null hypothesis that the return series contains a unit root, indicating non-stationarity. Rejection of the null supports the presence of stationarity, validating the use of regime-switching and forecasting models in the subsequent analysis.
The PP test differs from ADF by adjusting for serial correlation and heteroskedasticity using a non-parametric correction. This makes it more suitable when error terms may not be independently and identically distributed. Rejection of the null hypothesis in either test indicates stationarity, confirming that the return series is appropriate for modeling using Markov models and LSTM networks.

The Full equations and technical assumptions for the ADF and PP tests are detailed in Appendix A for reference.

3.6. Econometric Modeling: Markov Switching Models

To detect shifts in market efficiency and capture regime dynamics, two-state Markov Switching Models were employed. These models classified market behavior into:

- Regime 0: Low volatility, considered as the efficient state
- Regime 1: High volatility, representing the inefficient state

Each market's return series was analyzed to estimate:

- Transition probabilities between regimes
    - Variance within each regime
    - The persistence of efficiency and inefficiency across time

The models assume that returns alternate probabilistically between different regimes based on the Markov property, where the next state depends only on the current one. This memoryless structure aligns conceptually with the Adaptive Market Hypothesis, which posits that markets react to recent conditions rather than following deterministic patterns.

The full specification of the Markov Switching Model, including the regime-dependent mean-variance formulation and the transition probability matrix, is provided in Appendix B. This allows readers to consult the technical details while maintaining fluency and accessibility in the main methodological narrative.

3.7. Momentum Strategies: A Profitability-Based Test

To empirically evaluate market inefficiencies and complement the regime-based results, this study implemented two momentum strategies:

- Momentum 250-day
- Momentum 500-day

The selection of these time horizons is grounded in both empirical evidence and behavioral finance theory. The 250-day window approximates one calendar year and corresponds with institutional portfolio rebalancing cycles. It aligns with foundational research by Jegadeesh and Titman (1993), which documented momentum persistence over similar horizons. The 500-day window extends the analysis to a longer-term cycle, allowing for the detection of deeper structural inefficiencies and smoother trend effects.

These strategies are designed to exploit persistent trends in returns by generating trading signals based on lagged price comparisons. When the current asset price exceeds its level **n** days earlier, a long position is taken; otherwise, the strategy stays out of the market. Daily strategy returns are computed accordingly.

Their performance was benchmarked against a passive Buy-and-Hold strategy to evaluate relative profitability and to identify periods of exploitable inefficiency. Outperformance by momentum strategies would suggest that historical price patterns retained predictive power, consistent with the Adaptive Market Hypothesis, which views market efficiency as dynamic and evolving over time. Full strategy logic, signal criteria, and cumulative return formulas are presented in Appendix C for technical reference.

3.8. Machine Learning Forecasting: Long Short-Term Memory (LSTM)

To further investigate market adaptability and forecast future price behavior, the study employed Long Short-Term Memory (LSTM) neural networks. LSTM is a type of recurrent neural network capable of capturing nonlinear patterns and long-term dependencies in sequential financial data, which makes it particularly suitable for modeling the structural complexity described by the Adaptive Market Hypothesis.

The forecasting was conducted in two phases:

1) First, the LSTM model was trained on the initial 10 years of historical log return data to predict the subsequent 5-year period. The model's outputs were then adjusted using regime probabilities derived from the previously estimated Markov Switching Models. This hybrid structure allows the LSTM to produce regime-aware forecasts that reflect both temporal patterns and changes in efficiency states.

2) In the second application, the LSTM model was trained on the entire 15-year dataset to generate a full-year forecast for 2025. Unlike the first phase, this setup excluded any actual 2025 data, simulating a purely forward-looking prediction. Although initial forecasts reflected observed patterns, the model's long-range accuracy declined without real-time feedback, highlighting the limitations of static training in dynamic financial environments.

Forecast accuracy was evaluated using Root Mean Squared Error (RMSE) to quantify deviations between predicted and actual values. To further strengthen the statistical rigor of model evaluation, future iterations of this research will incorporate the Diebold-Mariano (DM) test to formally compare the predictive performance of the LSTM-based model with benchmark alternatives. The DM test will allow us to determine whether observed forecast improvements are statistically significant, providing deeper insight into the value added by regime-aware machine learning techniques.

A detailed overview of the LSTM structure, input formatting, loss function, evaluation metrics, and regime correction formulas is included in Appendix D.

4. RESULTS AND ANALYSIS

This section presents the empirical findings obtained through a multi-method framework designed to evaluate the Adaptive Market Hypothesis (AMH) across nine MENA-region financial markets as follows:

4.1. Descriptive Statistics

The descriptive statistics presented in Table 2 show that daily returns across the nine MENA-region markets differ notably in terms of volatility, symmetry, and tail behavior. Mean returns are mostly close to zero, with some markets showing slightly negative averages, while standard deviations highlight moderate to high volatility, suggesting varied risk levels. Negative skewness is common, indicating a higher probability of extreme losses than gains. Additionally, the excess kurtosis in all markets reveals the presence of heavy tails, pointing to more frequent extreme price movements than would be expected under a normal distribution. These observations are supported by the Jarque-Bera test results, where most markets show significant deviations from normality (p-values < 0.05). Such statistical patterns challenge the assumptions of the Efficient Market Hypothesis and instead support the Adaptive Market Hypothesis, which acknowledges that market efficiency fluctuates due to behavioral, structural, and informational factors.

Table 2. Descriptive Statistics

Code	*country*	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera (JB)*	*JB P-value*
DFMGI	**UAE**	0.0004777	0.0105306	-1.0429881	14.186882	8088.206	0
BKA	**Kuwait**	0.0002486	0.0083725	-2.9828881	32.375758	54997.257	0
MASI	**Morocco**	0.0001791	0.0077072	-1.8710261	25.797292	33201.801	0
EGX100	**Egypt**	0.0010427	0.0004129	-1.3052475	4.7718189	604.292	0
TASI	**Saudia Arabia**	0.0003377	0.0002517	-1.2496848	11.8021202	5222.295	0
MSM30	**Oman**	0.0000370	0.0053737	-0.899026	11.5590019	8404.473	0
Amman	**Jordan**	0.000138	0.006664	-0.07	5.176911	1602.495	0
BAX	**Bahrain**	0.0002722	0.0053411	-1.2391734	19.295456	23243.557	0
QSI	**Qatar**	0.0000186	0.0088601	-1.1331086	13.822933	7616.504	0

4.2. Stationarity Tests (ADF and PP)

Table 3 presents the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests applied to the log return series to determine whether each market's return process is stationary, which is a critical assumption for regime-switching models and LSTM forecasting. The results of both ADF and PP tests revealed to the rejection of the null hypothesis of a unit root at conventional significance levels across all nine markets, confirming the stationarity of the log return series. This is a necessary precondition for applying both Markov regime-switching models and LSTM-based neural forecasting. The consistent rejection of non-stationarity also suggests that return dynamics can be modeled using lag-based and state-transition techniques, further supporting the methodological choices made in this study.

Table 3. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests

Exchange market (Variable)	*Test Equation*	*ADF unit root test*		*PP unit root test*	
		Levels	*1st Difference*	*Levels*	*1st Difference*
DFMGI					
	None	-2.566507	-2.566518	-2.566507	-2.566508
	Intercept only	-3.434508	-3.434540	-3.434508	-3.434511
	Intercept & Trend	-3.964182	-3.964228	-3.964182	-3.964186
BKA					
	None	-2.566538	-2.566552	-2.566538	-2.566539
	Intercept only	-3.434597	-3.434636	-3.434597	-3.434600
	Intercept & Trend	-3.964308	-3.964364	-3.964308	-3.964312
MASI					
	None	-2.566513	-2.566528	-2.566513	-2.566514
	Intercept only	-3.434526	-3.434567	-3.434526	-3.434528
	Intercept & Trend	-3.964207	-3.964265	-3.964207	-3.964211
EGX100					
	None	-2.566551	-2.566562	-2.566509	-2.566552
	Intercept only	-3.434633	-3.434664	-3.434633	-3.434636
	Intercept & Trend	-3.964360	-3.964403	-3.964360	-3.964364
TASI					
	None	-2.566509	-2.566523	-2.566509	-2.566510
	Intercept only	-3.434514	-3.434555	-3.434514	-3.434517
	Intercept & Trend	-3.964190	-3.964248	-3.964190	-3.964194
MSM30					
	None	-2.566533	-2.566547	-2.566533	-2.566534
	Intercept only	-3.434582	-3.434621	-3.434582	-3.434585
	Intercept & Trend	-3.964286	-3.964511	-3.964286	-3.964291
Amman					
	None	-2.566577	-2.566589	-2.566577	-2.566578
	Intercept only	-3.434705	-3.434740	-3.434705	-3.434708
	Intercept & Trend	-3.964461	-3.964511	-3.964461	-3.964466
BAX					
	None	-2.566533	-2.566544	-2.566533	-2.566534
	Intercept only	-3.434582	-3.434612	-3.434582	-3.434585
	Intercept & Trend	-3.964286	-3.964329	-3.964286	-3.964291
QSI					
	None	-2.566511	-2.566526	-2.566511	-2.566512
	Intercept only	-3.434520	-3.434564	-3.434520	-3.434523
	Intercept & Trend	-3.964198	-3.964261	-3.964198	-3.964203

4.3. Markov Regime Switching Analysis

This section presents the results of the two-state Markov Switching Model applied individually to each of the nine financial markets. For every market, a detailed table is included that outlines the estimated parameters for Regime 0 (interpreted as efficient) and Regime 1 (interpreted as inefficient). These parameters include the intercept values (const), regime-specific variances (sigma²), and their statistical significance($P > |z|$).

In addition to these core parameters, each table reports the regime transition probabilities, which describe the likelihood that a market remains in the same regime or shifts to the other. For example, $P[0 \rightarrow 0]$ reflects the probability that the market remains in the efficient regime, while $P[1 \rightarrow 0]$ reflects the probability that it switches from an inefficient to an efficient regime. These probabilities are critical for understanding each market's stability and adaptability over time, revealing not only how long it remains efficient but also how quickly it recovers from periods of inefficiency. To enhance the interpretation of regime dynamics, smoothed probability graphs are provided for each market. These graphs display, at each time point, the estimated probability of being in either Regime 0 (efficient) or Regime 1 (inefficient). Higher probabilities for Regime 0 indicate stable and efficient market conditions, while higher probabilities for Regime 1 reflect phases of heightened market inefficiency. This visual representation allows for a clearer understanding of market transitions and persistence across different economic cycles.

The following sections present the empirical results of the Markov Switching analysis for each of the nine MENA markets, illustrating the estimated parameters, regime-specific variances, and transition probabilities, along with the smoothed probability graphs for a comprehensive view of market dynamics.

UAE

Table 4. Table 4: UAE – Markov Switching Analysis

	Regime 0 parameters		***Regime 1 Parameters***		***Regime transition parameters***	
	Coef.	$\boldsymbol{P > \lvert Z \rvert}$	**Coef.**	$\boldsymbol{P > \lvert Z \rvert}$	**Coef.**	$\boldsymbol{P > \lvert Z \rvert}$
const	0.0008	0	-0.002	0.304		
sigma2	4.268E-05	0	0.0006	0		
$\boldsymbol{P\ [0 -> 0]}$					0.9757	0
$\boldsymbol{P\ [1 -> 0]}$					0.1760	0

The UAE market exhibited high persistence in the efficient regime, with a transition probability of 0.9757. The probability of moving from an inefficient to an efficient state was 0.1760, suggesting moderate adaptability. Volatility was significantly lower in Regime 0 (σ^2 = 4.268E-05) compared to Regime 1 (σ^2 = 0.0006), supporting the presence of dynamic shifts in market efficiency. The smoothed probability plot, presented in Figure 4, illustrates prolonged periods of stability interrupted by brief inefficiency phases, validating the Adaptive Market Hypothesis (AMH) in this market.

Notably, several regime switches align with regional economic events, such as the COVID-19-driven demand shock in 2020 and recovery phases linked to Expo 2020 in 2021–2022, both of which likely altered investor sentiment and risk pricing.

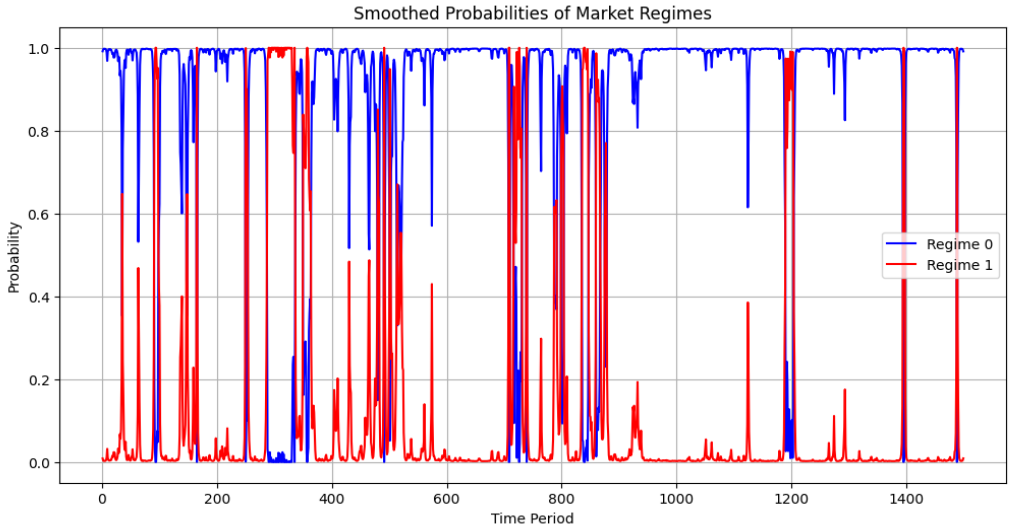

Figure 3: UAE's Smoothed Probability

Kuwait

Table 5. Kuwait – Markov Switching Analysis

	Regime 0 parameters		***Regime 1 Parameters***		***Regime transition parameters***	
	Coef.	$P > \|z\|$	**Coef.**	$P > \|z\|$	**Coef.**	$P > \|z\|$
const	0.0008	0	-0.0028	0.018		
sigma2	2.135E-05	0	0.0003	0		
$P[0->0]$					0.9747	0
$P[1->0]$					0.1295	0

Kuwait's market demonstrated strong regime persistence with a 0.9747 probability of remaining efficient, but a moderate 0.1295 chance of switching from inefficiency to efficiency. The large difference in volatility between the two regimes (2.135E-05 vs. 0.0003) underscores clear regime segmentation. The market's behavior supports the view that even highly efficient markets can occasionally exhibit inefficiencies before adapting back.

Periods of inefficiency coincide with geopolitical uncertainty in the Gulf region during 2020, as well as fluctuations in oil prices and subsidy reform discussions, which may have affected institutional investor behavior and triggered transitional volatility.

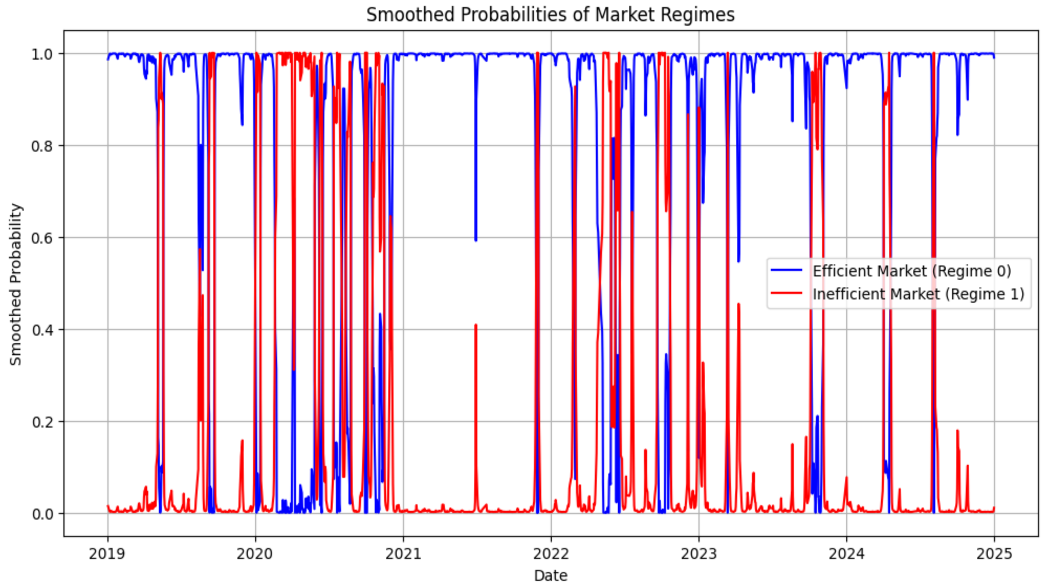

Figure 4: Kuwait's Smoothed Probability

Morocco

Table 6. Morocco – Markov Switching Analysis

	Regime 0 parameters		*Regime 1 Parameters*		*Regime transition parameters*	
	Coef.	$P > \|z\|$	**Coef.**	$P > \|z\|$	**Coef.**	$P > \|z\|$
const	0.0004	0	-0.0012	0.309		
sigma2	1.790E-05	1.55E-05	0.0003	0		
$P[0 -> 0]$					0.9507	0
$P[1 -> 0]$					0.2676	0

The Moroccan stock market showed relatively strong persistence in efficiency with a 0.9507 transition probability in Regime 0, and a higher tendency (0.2676) for returning from inefficiency back to efficiency. The volatility difference between regimes (1.79E-05 vs. 0.0003) further emphasizes adaptive behavior. The smoothed probability plot shows more frequent regime changes compared to the UAE, reflecting faster correction mechanisms typical in evolving markets.

These fluctuations may relate to domestic monetary tightening policies and global commodity pressures post-COVID-19, which introduced uncertainty to sectors like tourism and banking, driving brief periods of inefficiency.

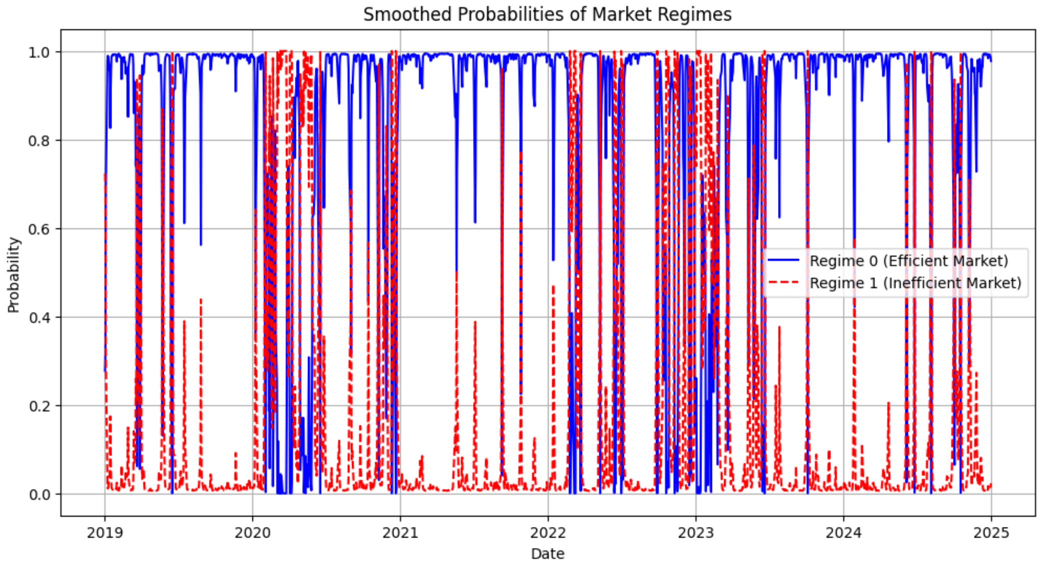

Figure 5: Morocco's Smoothed Probability

Egypt

Table 7. Egypt (EGX) – Markov Switching Analysis

	Regime 0 parameters		***Regime 1 parameters***		***Regime transition parameters***	
	Coef.	$P > \|z\|$	**Coef.**	$P > \|z\|$	**Coef.**	$P > \|z\|$
const	0.0031	0	-0.0075	0.001		
sigma2	0.0001	0	0.0007	0		
$P[0 -> 0]$					0.9587	0
$P[1 -> 0]$					0.1733	0

The EGX displayed notable adaptability, with a 0.9587 probability of remaining efficient and a 0.1733 probability of moving from inefficiency to efficiency. Volatility sharply increased between regimes (0.0001 to 0.0007), highlighting significant shifts during inefficient phases. The probability graphs confirm frequent fluctuations, consistent with Egypt's emerging market status and the AMH framework.

Several regime shifts observed between 2020 and 2023 likely coincide with key economic disruptions, including the COVID-19 pandemic's impact on capital markets, the 2022 Egyptian pound devaluation, and successive interest rate hikes driven by inflationary pressures. These events may have induced behavioral reactions, reduced investor confidence, and increased volatility, driving transitions into inefficient regimes as modeled by the Markov framework.

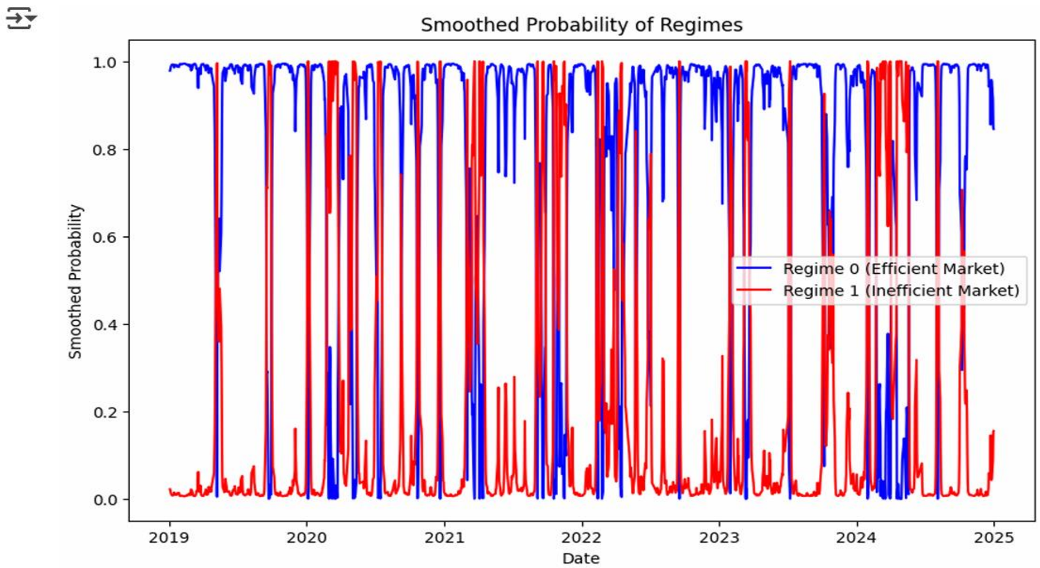

Figure 6: Egypt's Smoothed Probability

Saudi Arabia

Table 8. Saudi Arabia (Tadawul) – Markov Switching Analysis

	Regime 0 parameters		*Regime 1 parameters*		*Regime transition parameters*	
	Coef.	$P > \|z\|$	**Coef.**	$P > \|z\|$	**Coef.**	$P > \|z\|$
const	0.0009	0	-0.0023	0.044		
sigma2	4.22E-05	0	0.0003	0		
$P[0->0]$					0.9823	0
$P[1->0]$					0.0768	0

The Saudi Tadawul market demonstrated extremely high persistence in efficiency **(**0.9823**),** suggesting remarkable market stability. However, the probability of correcting from inefficiency was low **(**0.0768**),** implying that once inefficiency occurs, correction takes longer. Volatility shifts were also pronounced (4.22E-05 vs. 0.0003). This stability amid slow correction cycles mirrors the mixed behavior of developed markets.

Efficiency shifts may correspond to market reactions following the 2020 oil price crash, the 2021 Vision 2030 privatization announcements, or the 2022 Aramco dividend adjustments, all of which created episodes of investor repricing and regime persistence under varying volatility conditions.

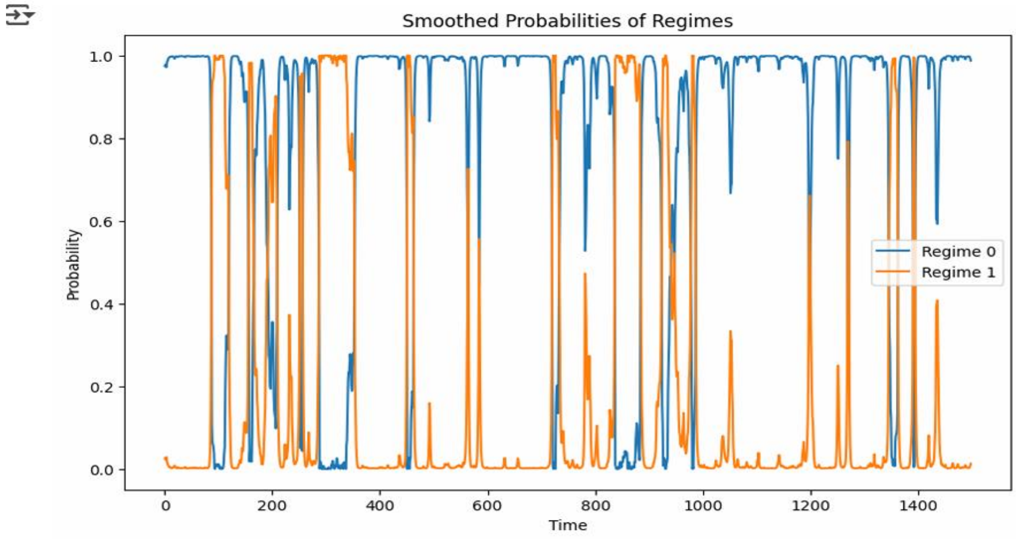

Figure 7: Saudi Arabia's Smoothed Probability

Oman

Table 9. Oman (MSM30) – Markov Switching Analysis

	Regime 0 parameters		*Regime 1 parameters*		*Regime transition parameters*	
	Coef.	$P > \|z\|$	**Coef.**	$P > \|z\|$	**Coef.**	$P > \|z\|$
const	-0.0002	0.232	0.0009	0.203		
sigma2	1.369E-05	0	9.928E-05	0		
$P[0 -> 0]$					0.9397	0
$P[1 -> 0]$					0.2826	0

The Omani MSM30 index showed a 0.9397 chance of remaining efficient and a 0.2826 probability of reverting from inefficiency, one of the higher reversion rates among the sample. The variance increase (1.369E-05 to 9.928E-05) signals considerable volatility shifts. Oman's market shows greater adaptive flexibility compared to larger MENA markets.

Volatility regimes in Oman appear responsive to fiscal reform efforts and public debt concerns during the COVID-19 recovery period, along with global rate hikes in 2022–2023 that may have influenced investor confidence and trading behavior.

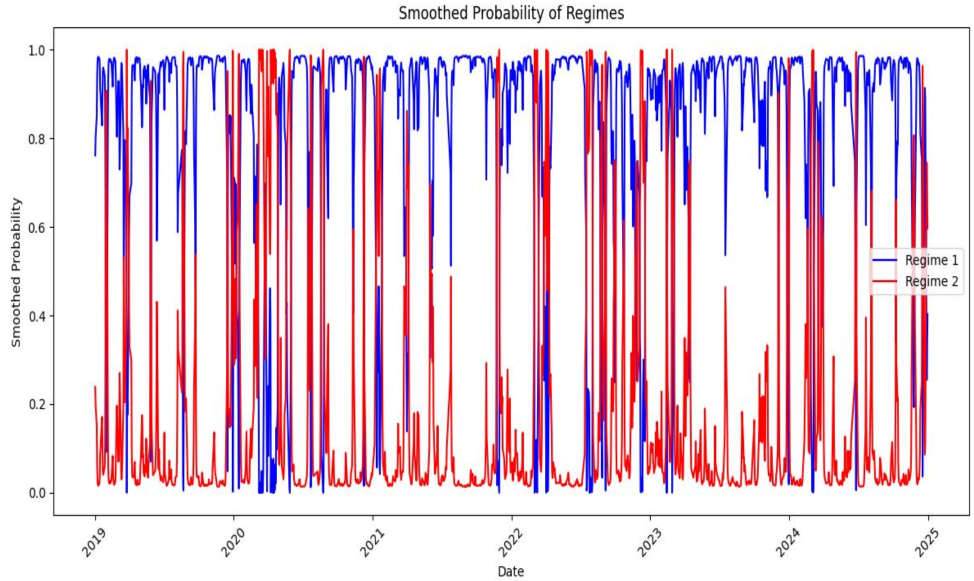

Figure 8: Oman's Smoothed Probability

<u>Jordan</u>

Table 10. Jordan (Amman All Share) – Markov Switching Analysis

	Regime 0 parameters		*Regime 1 parameters*		*Regime transition parameters*	
	Coef.	$P > \|z\|$	**Coef.**	$P > \|z\|$	**Coef.**	$P > \|z\|$
const	8.321E-05	0.521	0.0002	0.603		
sigma2	1.254E-05	0	0.0001	0		
$P[0->0]$					0.9690	0
$P[1->0]$					0.0561	0.002

Jordan's Amman All Share Index presented a 0.9690 probability of maintaining efficiency and a 0.0561 probability of returning to efficiency from an inefficient phase, which is one of the lowest reversion rates observed. The volatility jump between regimes (1.254E-05 to 0.0001) supports this observation. Jordan's market stability and occasional inefficiencies align closely with AMH predictions.

Episodes of inefficiency may correspond to macroeconomic pressures including rising debt levels, regional capital outflows, or political uncertainty during parliamentary cycles (2020), which affected liquidity and investor sentiment.

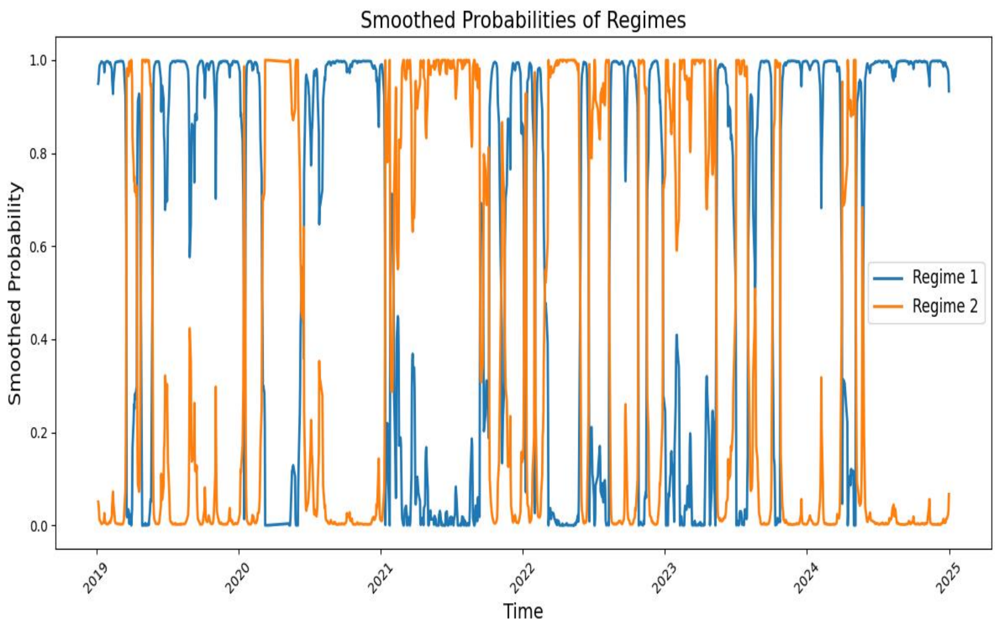

Figure 9: Jordan's Smoothed Probability

Bahrain

Table 11. Bahrain (BAX) – Markov Switching Analysis

	Regime 0 parameters		*Regime 1 parameters*		*Regime transition parameters*	
	Coef.	$P > \|Z\|$	**Coef.**	$P > \|Z\|$	**Coef.**	$P > \|Z\|$
const	0.0004	0	-5.056E-05	0.925		
sigma2	6.326E-06	0	9.612E-05	0		
$P[0->0]$					0.9349	0
$P[1->0]$					0.1999	0

Bahrain's market showed a 0.9349 probability of staying in the efficient regime and a 0.1999 probability of correcting from inefficiency. The variance between regimes (6.326E-06 vs. 9.612E-05) was substantial, indicating that inefficiencies are associated with significant volatility spikes. The smoothed probability graph reveals periodic inefficiencies followed by gradual stabilization phases.

Periods of inefficiency align with fiscal deficit concerns, restructuring plans in the banking sector, and shifts in GCC monetary policy. These events likely introduced uncertainty, leading to short-lived inefficiency phases before reversion.

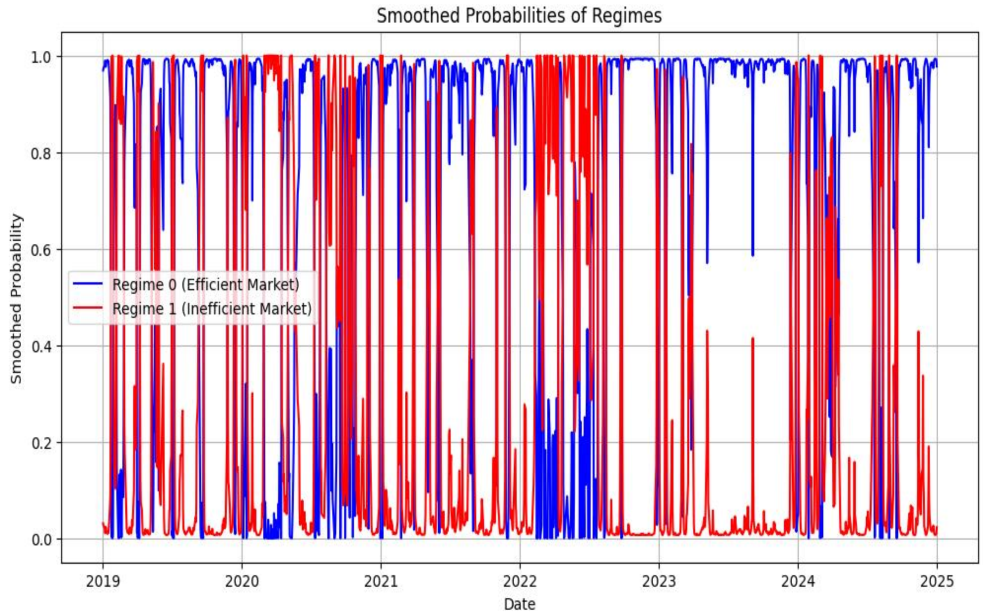

Figure 10: Bahrain's Smoothed Probability

Qatar

Table 12. Qatar (QSI) – Markov Switching Analysis

	Regime 0 parameters		*Regime 1 parameters*		*Regime transition parameters*	
	Coef.	$P > \|Z\|$	**Coef.**	$P > \|Z\|$	**Coef.**	$P > \|Z\|$
const	0.0004	0.065	-0.0008	0.247		
sigma2	2.988E-05	0	0.0002	0		
$P[0 -> 0]$					0.9563	0
$P[1 -> 0]$					0.1036	0.001

Qatar displayed strong persistence in efficiency (0.9563) and a lower tendency to correct from inefficiency (0.1036). Volatility surged during inefficient phases (from 2.988E-05 to 0.0002), consistent with periods of market instability. Smoothed probabilities suggest brief inefficient episodes, supporting the AMH's idea of markets adapting after disruption.

These shifts likely coincide with global LNG price volatility and investor repositioning surrounding FIFA World Cup 2022 infrastructure spending, as well as post-event capital flow adjustments that triggered brief inefficiencies in late 2022 and early 2023.

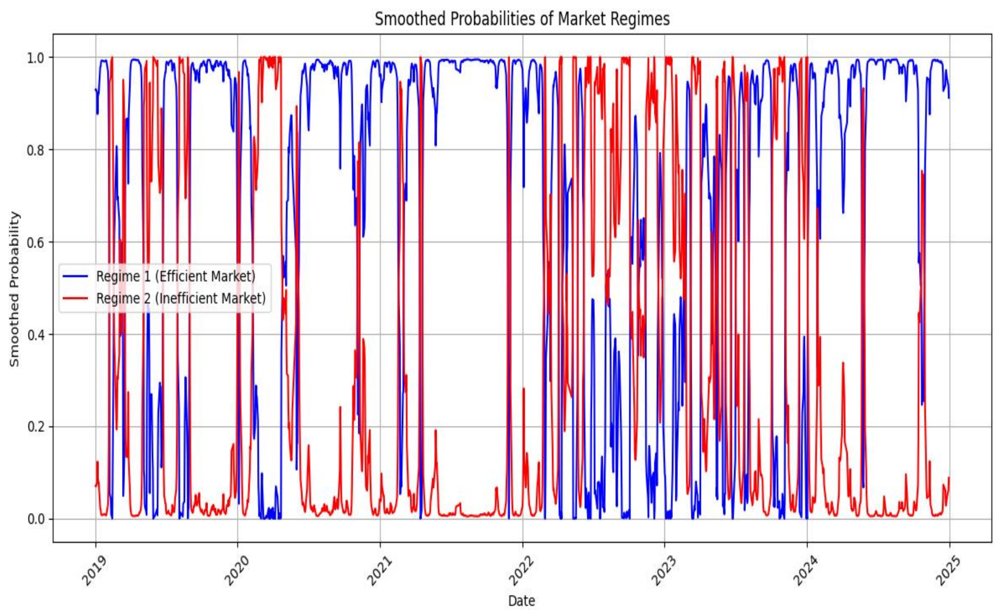

Figure 11: Qatar's Smoothed Probability

4.4. Momentum Strategy Performance

4.4.1. Cumulative Return Results

Table 13 presents the final cumulative returns of the momentum strategies (250-day and 500-day windows) alongside the Buy & Hold benchmark across the nine MENA-region financial markets. The results reveal varying momentum effectiveness depending on market conditions. In most markets, Buy & Hold outperformed both momentum strategies. This includes Egypt, UAE, Kuwait, Morocco, Bahrain, and Oman, suggesting that during the sample period, consistent upward trends favored passive investment. These findings are consistent with relatively efficient or trending markets where long-term holding strategies captured broader movements more effectively.

Table 13. Cumulative returns for all countries.

Code	*Country*	*Buy & Hold*	*Momentum 250*	*Momentum 500*
DFMGI	United Arab Emirates	2.05	1.65	1.62
BKA	Kuwait	1.44	0.73	1.23
MASI	Morocco	1.31	1.04	0.85
EGX100	Egypt	4.57	3.75	3.36
TASI	Saudi Arabia	1.54	1.55	1.5
MSM30	Oman	1.06	1.04	0.93
AMMAN	Jordan	1.22	1.56	0.98
BAX	Bahrain	1.49	1.11	1.33
QSI	Qatar	1.03	1.11	0.87

However, in markets such as Jordan, Qatar, and Saudi Arabia, momentum strategies, especially the 250-day variant, delivered superior cumulative returns. This indicates the presence of exploitable short- to medium-term inefficiencies, which supports the Adaptive Market Hypothesis (AMH). According to AMH, market efficiency is not fixed and may vary over time based on behavioral patterns, investor learning, and structural conditions. Overall, the mixed performance highlights the non-static nature of market efficiency across the region. This variation confirms the usefulness of momentum strategies as a tool for detecting time-varying inefficiency in line with the AMH framework.

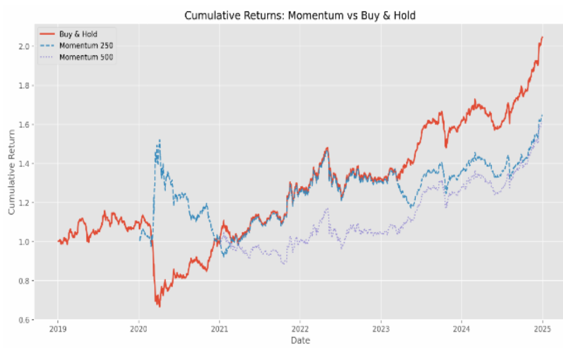

Figure 13: UAE's Cumulative Returns: Momentum VS Buy & Hold

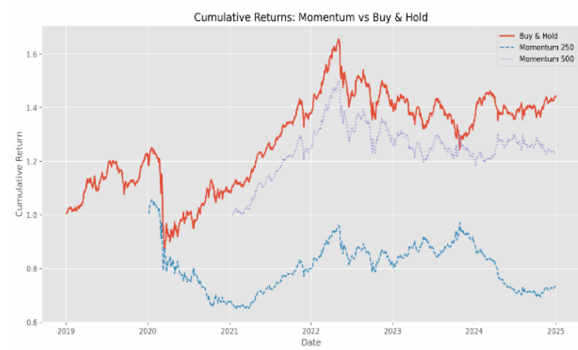

Figure 12: Kuwait's Cumulative Returns: Momentum VS Buy & Hold

4.4.2. Graphical Comparison of Strategies

The performance of the momentum strategies is further illustrated in the figures above, which present the cumulative return plots for each market under the three strategies: Buy & Hold, Momentum 250, and Momentum 500.

The graphs provide a visual confirmation of the table results. In markets such as Saudi Arabia and Jordan, the Momentum 250 strategy consistently surpassed the passive strategy for extended periods, capturing strong trend-following behavior. In contrast, markets like Egypt and UAE exhibit long-term upward movement, where Buy & Hold maintained dominance throughout, reinforcing the observation that those markets were in more persistent efficient regimes. Additionally, the divergence in performance between Momentum 250 and 500 highlights the importance of strategy horizon selection. Momentum 250 generally performed better in more adaptive markets with shorter-term trends, while Momentum 500 occasionally lagged due to over-smoothing or delayed response.

These graphical insights support the interpretation that market behavior varies significantly across countries and timeframes. Such heterogeneity reinforces the core premise of the Adaptive Market Hypothesis (AMH), which holds that financial markets adapt over time and are influenced by evolving investor dynamics, competition, and informational flow.

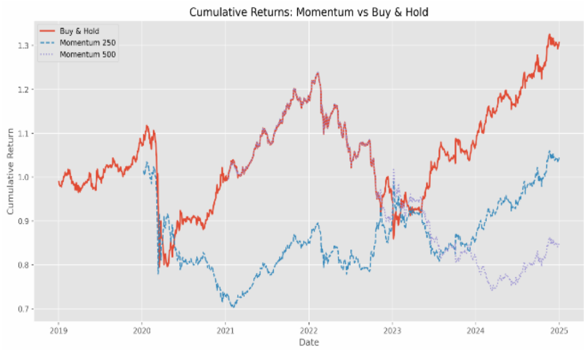

Figure 14: Morocco's Cumulative Returns: Momentum VS Buy & Hold

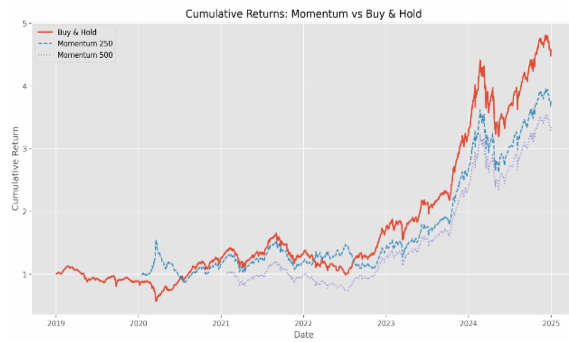

Figure 15: Egypt's Cumulative Returns: Momentum VS Buy & Hold

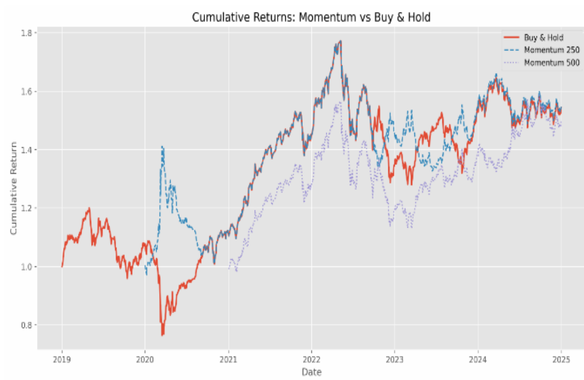

Figure 16: Saudi Arabia's Cumulative Returns: Momentum VS Buy & Hold

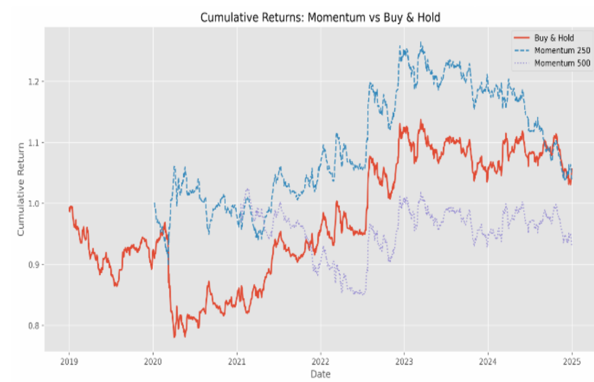

Figure 17: Oman's Cumulative Returns: Momentum VS Buy & Hold

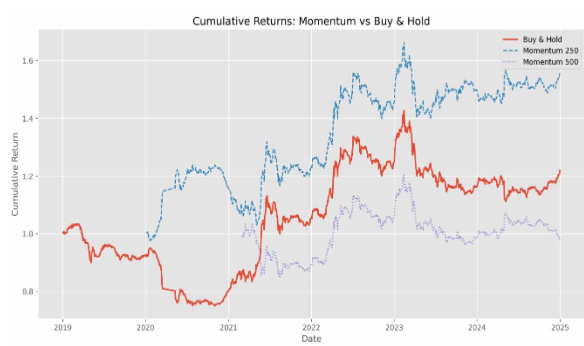

Figure 18: Jordan's Cumulative Returns: Momentum VS Buy & Hold

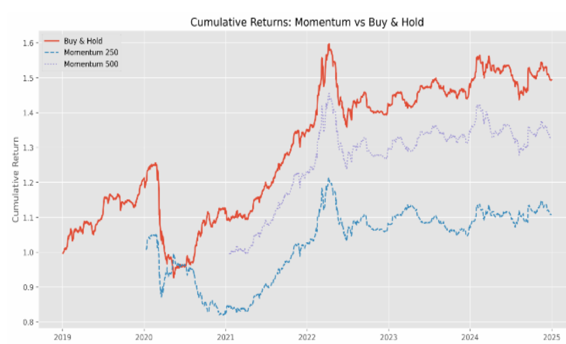

Figure 19: Bahrain's Cumulative Returns: Momentum VS Buy & Hold

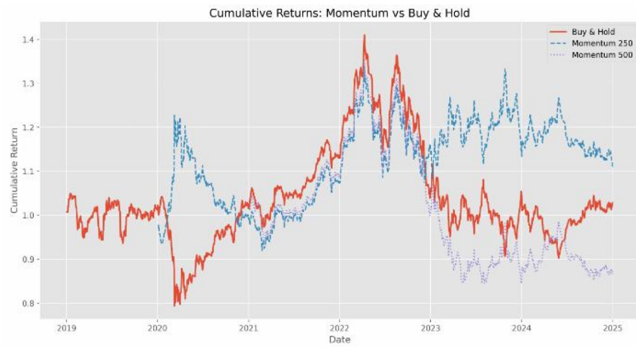

Figure 20: Qatar's Cumulative Returns: Momentum VS Buy & Hold

4.5. LSTM Forecasting and Prediction Analysis

This section presents the results of the Long Short-Term Memory (LSTM) neural network models applied to four selected markets: EGX, MSM30, Tadawul, and QSI. Two forecasting approaches were tested. The first involved forecasting based on historical data and validating against actual market returns, with predictions adjusted using Markov regime classification. The second involved training the model on the full historical dataset and forecasting the entire year of 2025 without access to real-time data, incorporating both regime probabilities and trend pattern structures. Each experiment is presented separately below.

4.5.1. LSTM + Markov: Forecasting with Observed Validation

In this approach, the LSTM model was trained on historical data from 2009 to 2019 and used to forecast prices for 2020–2024. The results were directly compared to actual return data, and Markov regime probabilities were applied to adjust the forecasts for enhanced realism.

Table 14 Table 14: EGX – LSTM Forecasting Analysis

Date	Actual Price	LSTM Prediction	Markov Corrected
12/18/2024	11538.76	11855.25977	11791.35742
12/19/2024	11532.93	11800.44824	11642.19727
12/20/2024	11558.99	11743.02637	11609.2666
2/21/2024	11298.43	11698.74805	11606.73047
12/22/2024	11251.98	11598.79688	11398.6377
12/23/2024	11275.97	11497.68066	11324.27344
12/24/2024	11269.09	11420.99902	11310.14453
12/25/2024	11181.23	11367.30566	11291.35156
12/26/2024	10993.7	11314.87793	11221.83984
12/27/2024	11217.62	11232.37695	11071.78809

Model	RMSE
LSTM only	129.5042851
LSTM + Markov	93.70995537

The LSTM model applied to the EGX market produced an RMSE of 129.50, reflecting strong predictive accuracy. After adjusting the forecasts using Markov regime-switching probabilities, the RMSE further decreased to 93.71, suggesting that accounting for dynamic efficiency changes enhances forecast reliability in adaptive market environments.

Table 15: MSM30 – LSTM Forecasting Analysis

Date	Actual Price	LSTM Prediction	Markov Corrected
12/18/2024	4470.39	4532.630371	4532.009277
12/19/2024	4508.73	4519.702148	4488.581543
12/20/2024	4488.4	4514.669434	4509.183594
12/21/2024	4492.84	4507.674316	4494.539551
12/22/2024	4485.54	4502.96582	4495.548828
12/23/2024	4479.95	4498.342773	4489.629883
12/24/2024	4468.19	4493.814941	4484.618652
12/25/2024	4516	4487.993652	4475.181152
12/26/2024	4544.96	4492.527344	4506.530273
12/27/2024	4576.6	4504.484863	4530.701172

Model	RMSE
LSTM only	42.89465866
LSTM + Markov	27.06209264

In the case of the MSM30 market, the LSTM network demonstrated reasonable forecasting precision, as shown by an RMSE of 42.89. Implementing Markov corrections to account for regime shifts led to an improved RMSE of 27.06, demonstrating the model's ability to adjust to shifting market regimes and structural changes over time.

The Tadawul market's LSTM model achieved an RMSE of 141.56, indicating a satisfactory level of predictive performance. Following the application of Markov-based adjustments, the RMSE improved to 102.84, confirming that recognizing efficiency state changes contributes positively to forecast precision.

Table 16: TASI– LSTM Forecasting Analysis

Date	Actual Price	LSTM Prediction	Markov Corrected
12/18/2024	11961.05	12058.83594	11972.7832
12/19/2024	11892.44	12006.79492	11957.90234
12/22/2024	11849.37	11957.91406	11900.73633
12/23/2024	11948.79	11914.65625	11860.38477
12/24/2024	11913.95	11920.66699	11937.73438
12/25/2024	11892.32	11939.95215	11936.59277
12/26/2024	11859.47	11952.56348	11928.74707
12/29/2024	11892.75	11946.13965	11899.59375
12/30/2024	12000.92	11940.48145	11913.78613
12/31/2024	12036.5	11969.31445	11999.53418

Model	RMSE
LSTM only	141.5625368
LSTM + Markov	102.8366755

Table 17: QSI– LSTM Forecasting Analysis

Date	Actual Price	LSTM Prediction	Markov Corrected
12/1/2024	10392.65	10409.83887	10414.84473
12/2/2024	10391.15	10409.20313	10400.60938
12/3/2024	10389.09	10408.61133	10399.58496
12/4/2024	10337.59	10407.73633	10397.97559
12/5/2024	10391.75	10396.4375	10361.36523
12/8/2024	10361.46	10394.90234	10392.55762
12/9/2024	10421.36	10389.44922	10372.72754
12/10/2024	10496.32	10396.78125	10412.7373
12/11/2024	10510.88	10421.9541	10471.72363
12/12/2024	10528.65	10452.50977	10496.97266

Model	RMSE
LSTM only	158.2606392
LSTM + Markov	107.1603051

For the QSI index, the LSTM model produced a baseline RMSE of 158.26, capturing general market movements effectively. After incorporating Markov regime information, the adjusted RMSE reduced to 107.16, demonstrating enhanced model robustness. This improvement reflects the model's ability to better account for structural shifts in efficiency and reinforces the importance of adaptive mechanisms in forecasting frameworks.

Overall, the results across the four markets show that LSTM neural networks are capable of capturing and predicting market behavior patterns over multiple years. Although a full 2025 forecast could not be realized due to resource constraints, the initial modeling demonstrates strong potential. Future work will focus on extending the forecast horizon and integrating Markov regime analysis into the LSTM predictions to provide dynamic investment recommendations, aligning with the evolving efficiency postulated by the AMH.

4.5.2. LSTM + Markov + Trend Patterns: Full-Year Forecast for 2025

In this second application, the LSTM model was trained on the entire 15-year dataset to forecast market performance for the full year of 2025. This time, the model did not receive any actual price data from 2025, making it a purely forward-looking forecast. To enhance prediction quality, the model architecture incorporated both Markov regime probabilities and trend pattern structures extracted from prior market cycles, allowing it to learn recurring behaviors and long-term directional tendencies.

This experiment was conducted on two selected markets: Qatar Stock Index (QSI) and Oman Stock Market (MSM30), both of which provided rich historical data with distinguishable cyclical characteristics.

1. **QSI Forecast Results**

The following graph presents the forecasted daily prices for the Qatar Stock Index (QSI) for the year 2025.

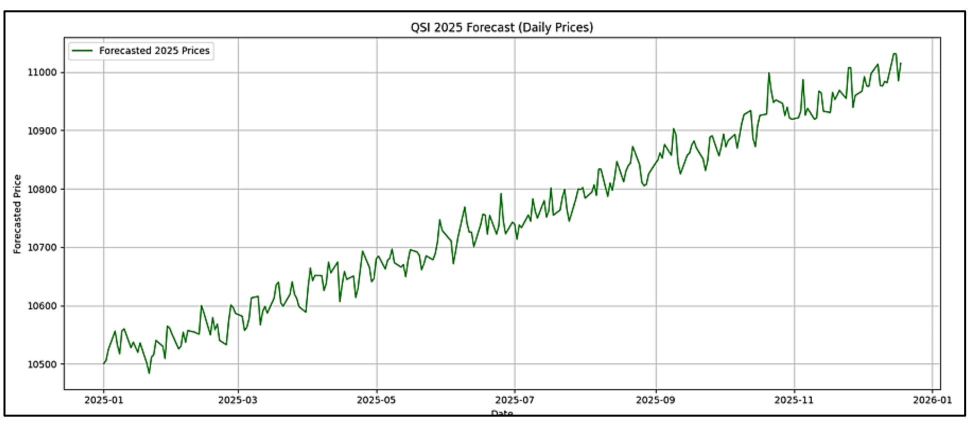

Figure 21: Forecasted daily prices for the Qatar Stock Index (QSI) for the year 2025.

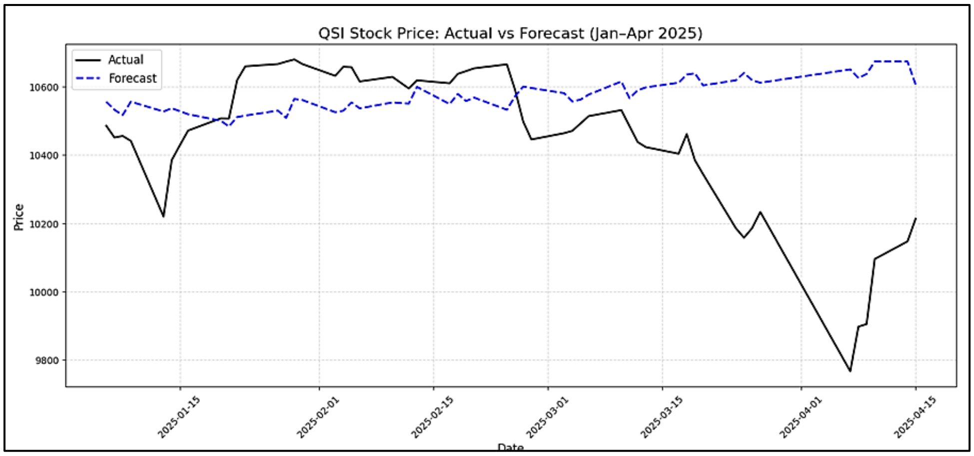

Figure 22: Forecasted vs. Actual Daily Prices for QSI – 2025

The first graph shows the forecasted QSI daily prices for 2025, reflecting predicted trends and volatility based on the model's output, while the second graph compares actual QSI stock prices with forecasted values from January to April 2025. It highlights deviations between predicted and actual data, helping assess the accuracy of the forecasting model.

2. MSM30 Forecast Results

The figure below displays the model's forecast for the MSM30 index using the same hybrid setup.

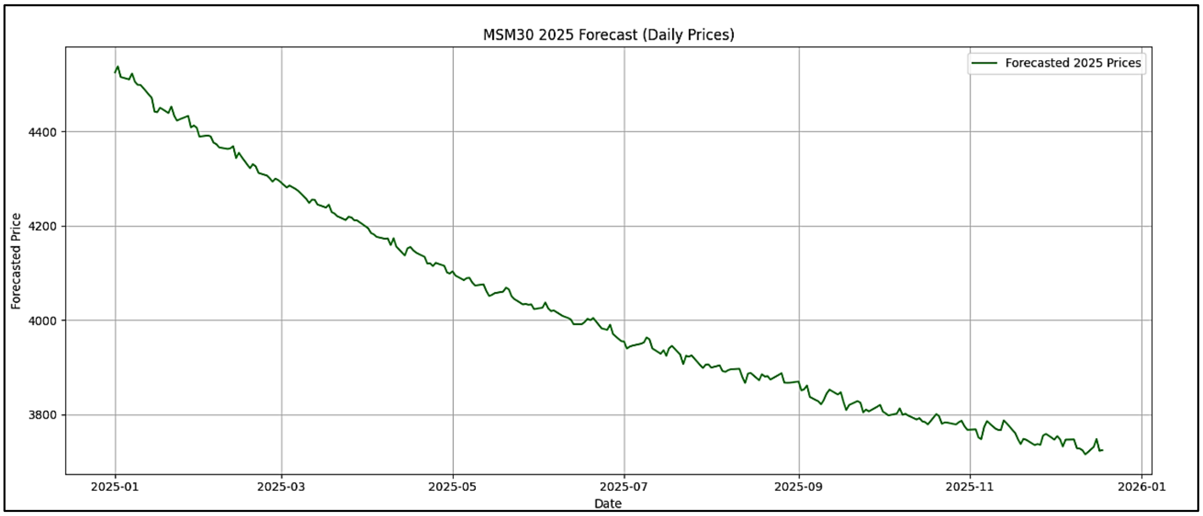

Figure 23: Forecasted daily prices for the MSM30 index for the year 2025.

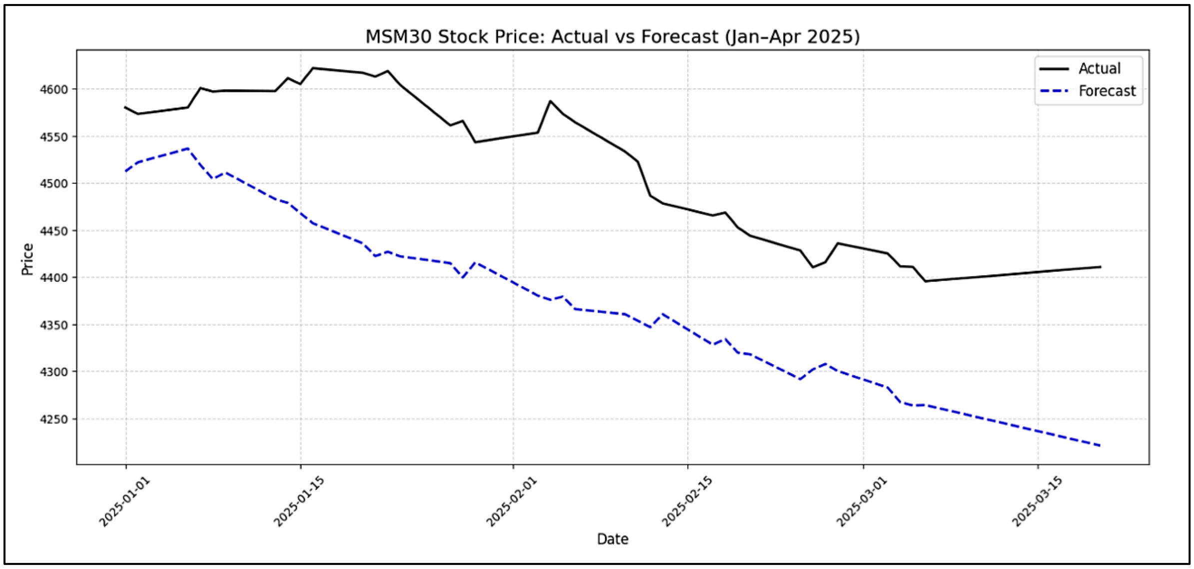

Figure 24: Forecasted vs. Actual Daily Prices for QSI – 2025

The first graph presents the forecasted daily prices of the MSM30 index for the full year 2025, generated by the LSTM model. The forecast reveals a steady downward trend from early January to December, suggesting either a reflection of macroeconomic expectations or a structural bias in the model. The smooth curve indicates that the model captures overall direction and long-term patterns, though it appears to underrepresent short-term volatility. The second graph compares the forecasted values with actual MSM30 prices from January to April 2025. While the model tracks the general downward movement, it consistently underestimates actual values. Although the directional trend is similar, the gap in magnitude highlights the need for further model refinement, possibly through the inclusion of additional inputs or updated training data. This comparison is important for assessing forecast reliability and guiding improvements in future applications.

These two applications highlight the strengths and limitations of LSTM-based forecasting in financial market analysis. When combined with regime classification and validated against known data, the model demonstrates strong alignment with actual market behavior. However, in forward-looking scenarios without real-time input or exogenous context, its predictive performance declines. This underperformance stems from the model's overreliance on historical trend continuation in the absence of feedback loops, leading to unrealistic directional biases. The forecasts lacked response to mid-year shocks or nonlinear disruptions, such as unexpected policy shifts, inflation surges, or global economic spillovers, which typically influence adaptive investor behavior. Moreover, the model failed to incorporate macroeconomic signals, trading volume dynamics, or cross-asset interactions, elements essential for capturing regime changes under AMH. This underscores the importance of enhancing LSTM models with hybrid architectures that incorporate external variables, dynamic retraining, or complementary analytical layers to improve adaptability and reliability in evolving market conditions.

5. DISCUSSION, CONCLUSION & RECOMMENDATIONS

5.1. Discussion

The results of our multi-method empirical investigation offer robust support for the Adaptive Market Hypothesis (AMH), emphasizing the dynamic and evolving nature of financial market efficiency. The integration of statistical tests, regime-switching models, momentum profitability strategies, and machine learning forecasts allowed for a comprehensive understanding of how different markets behave under varying economic and informational conditions. These findings support the study's hypothesis (H_0), which posits a significant relationship between the dynamic shifts in market efficiency and the ability to generate abnormal returns. The observed regime transitions, time-dependent momentum returns, and LSTM-based predictive gains demonstrate that MENA markets exhibit adaptive behavior over time in ways consistent with AMH.

The Markov Switching Models provided strong empirical evidence of non-linear shifts between efficient and inefficient regimes across the nine MENA-region markets. These transitions were not random but followed probabilistic patterns that could be quantified and tracked over time. Notably, markets such as Kuwait, Qatar, and Bahrain exhibited more frequent regime changes, suggesting higher sensitivity to external shocks or structural inefficiencies, while others like the UAE and Morocco showed greater persistence in efficiency. This regime-based evidence suggests a potential role for adaptive regulatory mechanisms in MENA markets, ones that adjust oversight intensity or disclosure requirements in response to detected market states, particularly during periods of inefficiency or volatility.

Momentum strategy outcomes further supported AMH. In several markets, notably Jordan and Qatar, the 250-day momentum strategy outperformed Buy-and-Hold, indicating that price trends could be exploited within certain market phases. These temporary inefficiencies challenge the assumptions of the Efficient Market Hypothesis and align with AMH’s view that investor learning and behavioral biases often delay full price adjustment. Such patterns lend additional empirical weight to the study's hypothesis by showing that shifts in efficiency are not only detectable but also exploitable, reinforcing the view that markets adapt rather than behave randomly or uniformly.

The integration of LSTM models into our forecasting framework introduced a forward-looking, nonlinear modeling component aimed at capturing evolving market dynamics. In the first application, we developed a hybrid framework that combined LSTM forecasting with Markov regime classification. The model was trained on the first 10 years of historical data and tested on the following 5 years, during which actual return data was available. This allowed us to directly compare the forecasted values with real outcomes and apply regime-based adjustments using Markov probabilities. The resulting forecasts were not only statistically accurate but also behaviorally consistent with observed market movements, successfully capturing nonlinear patterns and shifts in efficiency states. However, the interpretability of the LSTM model remains limited due to its “black box” structure. While it captures temporal patterns, it does not readily reveal which factors drive predictions. This raises concerns about transparency for decision-makers and constrains the model’s usefulness in policy settings. Additionally, the generalizability of the findings may be restricted, as the model's accuracy is conditioned on the availability of structured historical data and may degrade in more volatile or thinly traded markets not represented in the current dataset.

In the second application, the model was trained on the entire 15-year dataset to forecast the full year of 2025. This time, the hybrid approach included both Markov regime probabilities and embedded trend pattern recognition based on the structure of previous market cycles. Although the model initially produced outputs that resembled actual market behavior in early 2025, its forecasts for the remaining months became overly simplistic and directionally biased. The model projected extended upward or downward trends without capturing mid-term corrections, volatility changes, or regime reversals. This behavior reflects a fundamental limitation of LSTM architectures when applied in isolation from real-time economic signals. Without continuous feedback or external data like economic news or policy changes, the model relies too much on past trends. As a result, it cannot adjust to sudden changes in the market. This makes forward-looking forecasts less reliable and highlights the importance of using hybrid models that combine LSTM with economic, policy, or sentiment data to improve accuracy.

These findings support the conclusion that while LSTM is a powerful tool for learning temporal dependencies, it requires further enhancement to perform reliably in adaptive financial settings. Our experience confirms that hybrid forecasting architectures are essential for capturing market behavior under the AMH framework, where efficiency is conditional and continuously evolving. These results align with recent studies that recommend combining LSTM with methods such as signal decomposition, attention mechanisms, or macroeconomic variable integration to improve flexibility and forecasting performance.

5.2. Limitations of the Study

While the results of this study are encouraging and offer valuable insights, several limitations must be acknowledged. Recognizing these limitations helps put the findings in context and provides direction for future improvements. However, there are some limitations as follows: (i) *Limited Time Coverage***;** the data used in this research covers the period from 2010 to 2024. Although this includes important events like the COVID-19 pandemic and recent inflationary pressures, it may not reflect longer-term structural changes. For example, deeper financial reforms or slow-moving technological trends may influence efficiency in ways not captured here, (ii) *Incomplete Evaluation of Future Forecasts*; the LSTM model was used to forecast market behavior for the full year of 2025. However, at the time of the study, complete 2025 data was not yet available. This means the model's accuracy for that period could not be fully tested, which limits the conclusions that can be drawn from those forecasts, (iii) *Black-Box Nature of the LSTM Model*; one of the key issues with LSTM models is that they do not clearly explain how decisions are made. Unlike traditional statistical models, it is difficult to interpret which variables had the most influence on predictions. This can be a problem for financial institutions or policymakers who need to understand and justify their decisions, (v) *Missing External Factors in the Model*; the model only used historical price data as input. Important external factors like central bank decisions, oil price shocks, or investor sentiment were not included. These events often play a significant role in real-world market behavior and could help improve the accuracy of the model, and (vi) *Results Are Limited to MENA Markets*; the findings of this study apply only to the MENA-region financial markets. These markets share certain characteristics, such as strong links to oil revenues or regional political developments. As such, the results may not be directly transferable to other regions without additional testing and model adjustments.

5.3. Conclusion

This research provides clear empirical evidence supporting the Adaptive Market Hypothesis, demonstrating that financial market efficiency is not constant but changes over time in response to varying conditions. By applying a combination of regime-based modeling, momentum performance strategies, and deep learning forecasting, the study was able to capture and interpret these adaptive dynamics effectively. These findings confirm the central hypothesis (H_0), which asserts a significant relationship between shifts in market efficiency and the potential to generate abnormal returns. The observed regime transitions and strategic profitability across different time horizons illustrate that MENA financial markets adapt in ways that depart from static efficiency models and align with the evolutionary principles of AMH.

Markov Switching Models revealed that market behavior alternates between different regimes of efficiency, following identifiable probabilistic patterns. Momentum strategy outcomes showed that certain return trends could be exploited during inefficient phases, offering further support for the time-varying nature of efficiency proposed by AMH. These findings confirm that traditional assumptions of market equilibrium do not always hold in real-world settings. This has implications for both financial institutions and regulatory authorities in the MENA region, who may benefit from incorporating regime-based indicators into their market oversight frameworks. Adaptive supervision, especially during phases of volatility or behavioral bias, could improve resilience, transparency, and investor protection in these evolving markets.

The integration of LSTM forecasting added a predictive layer to the analysis, illustrating both the strengths and weaknesses of deep learning in financial modeling. When supported by observed data and adjusted using regime probabilities, the LSTM model produced reliable forecasts. However, when used without feedback or contextual inputs, its predictions lost precision, underscoring the need for hybrid systems that combine machine learning with economic logic.

This study not only validates AMH through multiple empirical lenses but also offers a practical direction for future applications. The modeling framework developed here can be expanded into a decision-support system that helps investors anticipate market shifts and adjust strategies accordingly. With continued development and the inclusion of real-time variables, such systems could contribute meaningfully to adaptive portfolio management.

5.4. Recommendations and Future Research

Based on the empirical confirmation of the Adaptive Market Hypothesis (AMH) across nine MENA-region markets, and the performance of the hybrid modeling approach that combines Markov regime-switching and LSTM forecasting, the following practical recommendations are proposed. These suggestions aim to improve decision-making among investors, institutions, and regulators in environments where market efficiency changes over time.

- Create Investment Tools Based on Market Efficiency States; financial institutions are encouraged to develop digital platforms or systems that use the combination of LSTM forecasts and Markov regime analysis. These tools could help investors make better decisions by identifying whether the market is likely to be in an efficient or inefficient state. This approach would support portfolio strategies that respond to changing market behavior.
- Use Regime Forecasting in Portfolio Strategy, investors should consider adjusting their strategies depending on the expected regime. Long-term investments are more suitable in markets that are forecasted to remain efficient, while short-term or tactical strategies may be more effective during periods of predicted inefficiency. This allows portfolios to be more flexible and better adapted to current market conditions.
- Apply Cross-Market Comparisons to Allocate Capital More Wisely, investors and fund managers should not only look at individual market trends but also compare multiple MENA markets. By identifying which markets are likely to become more efficient or inefficient, capital can be shifted accordingly to take advantage of opportunities or reduce exposure to risk.
- Use Regime Information in Financial Supervision; regulators can benefit from monitoring regime shifts in real time. If a market begins to show signs of moving toward inefficiency or instability, regulators can consider issuing warnings, adjusting policy tools, or taking temporary measures to reduce potential disruptions. Early identification of regime changes could also support stronger market oversight.
- Educate Investors on Market Adaptability and Risk Behavior; since market behavior does not stay constant over time, educational programs should be updated to include the idea that market efficiency can shift. Teaching both retail and institutional investors about AMH, momentum strategies, and regime changes can reduce panic-driven reactions and improve decision-making, especially during periods of uncertainty or volatility.

However, directions for future research aims to build on the current findings and address the limitations discussed above, the following future research directions are proposed. These ideas aim to improve both the model and its practical use in academic and financial environments.

- Use More Advanced Forecasting Models; future studies could explore the use of more advanced models, such as stacked LSTM layers, GRU (Gated Recurrent Units), or transformer-based architectures. These models may be able to capture deeper relationships in the data and improve forecasting performance, especially in highly volatile markets.
- Add External and Behavioral Variables to the Model, including external data like interest rates, inflation figures, policy news, or even social media sentiment could help the model better reflect actual market behavior. This would allow forecasts to respond to real-world conditions, not just past price patterns.
- Test the Model on Other Asset Types, researchers may expand the current model to apply it to other asset classes, such as commodities, sector indices (e.g., banking or energy stocks), or cryptocurrencies. These markets often behave differently from traditional stock indices and may show different patterns of efficiency.
- Develop a Real-Time Regime Alert System, one of the most useful future applications would be a real-time tool that continuously monitors market regimes and sends alerts when a change is likely to occur. This could help investors take action more quickly and also assist regulators in preparing for market disruptions.
- Improve Model Transparency and Explainability, there is a growing need to make complex models more transparent. Future work should focus on integrating explainable AI techniques (e.g., SHAP values or attention mechanisms) into forecasting systems. This would make it easier for decision-makers to understand why the model makes certain predictions and to trust its recommendations.

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Appendices – Formula References

Appendix A: Statistical Test Equations

1. **Jarque-Bera Test:**

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

Where:

- n : number of observations
- S : skewness
- K : kurtosis

2. **Augmented Dickey-Fuller (ADF) Test:**

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta y_{t-i} + \varepsilon_t$$

Where:

- $\Delta y_t = y_t - y_{t-1}$: the first difference
- α : constant
- βt : trend component
- γ : coefficient testing for unit root (if $\gamma = 0$, unit root exists)
- δ_i : lag coefficients to address autocorrelation
- ε_t : error term

3. **Phillips-Perron (PP) Test:**
Similar to ADF but adjusts for serial correlation and heteroskedasticity using non-parametric techniques.

Appendix B: Markov Switching Model Formulation

1. **Return Equation:**

$$r_t = \mu_{S_t} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma^2{}_{S_t})$$

Where:

- r_t is the return at time t
- $S_t \in \{0, 1\}$ is the unobserved (hidden) state variable representing the regime
- μ_{S_t} is the mean return in regime S_t
- $\sigma^2{}_{S_t}$ is the variance of returns in regime S_t
- ε_t is a normally distributed error term with regime-dependent variance

2. **Transition Probability Matrix:**

$$P = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix}$$

Where:

- $P_{ij} = \mathbb{P}(S_t = j \mid S_t - 1 = i)$
- P_{00} : probability of staying in Regime 0 (efficient)
- P_{11} : probability of staying in Regime 1 (inefficient)
- $P_{01} = 1 - P_{00}$: probability of switching from efficient to inefficient
- $P_{10} = 1 - P_{11}$: probability of switching from inefficient to efficient

Appendix C: Momentum Strategy Formulas

1. **Signal Generation:**

$$Signal_t = \begin{cases} 1, & \text{if } P_t > P_{t-n} \\ 0, & \text{otherwise} \end{cases} \quad \text{with } n = 250, 500$$

Where:

- P_t : current closing price
- P_{t-n} : closing price n days ago
- $Signal_t$: trading position at time t (1 = invested, 0 = not invested)

2. **Strategy Return:**

$$R_t^{momentum} = Signal_t . r_t$$

Where:

- r_t : log return at time t
- $R_t^{momentum}$: strategy return at time t

3. **Cumulative Return:**

$$CR_t = \prod_{i=1}^{t} (1 + R_i^{momentum}) - 1$$

Where:

- CR_t : cumulative return of the momentum strategy

4. **Buy-and-Hold Return:**

$$CR_t^{BH} = \prod_{i=1}^{t}(1 + r_i) - 1$$

Where:

- CR_t^{BH} : cumulative return of a passive investment (holding the asset)

Appendix D: LSTM Forecasting Model Details

1. **Input:** Sequences of past log returns:

$$X_t = [r_{t-k+1}, r_{t-k+2}, \dots, r_t]$$

where $k = 60$ days (look-back window), and r_t is the log return at time t.

2. **Prediction:**

$$\hat{r}_{t+1} = f_{LSTM}(X_t)$$

3. **Loss Function: Mean Squared Error (MSE):**

$$\text{MSE} = \frac{1}{n}\sum_{t-1}^{n}(r_t - \hat{r}_t)^2$$

4. **Evaluation Metrics:**
   - Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t-1}^{n}(r_t - \hat{r}_t)^2}$$

5. Regime Adjustment:

$$\hat{r}_t^{adjusted} = \hat{r}_t \cdot \mathbb{P}(S_t = 0)$$