



Do Financial Markets Adapt Differently?

A Cross-Country Examination Using the Adaptive Market Hypothesis

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Do Financial Markets Adapt Differently? A Cross-Country Examination Using the Adaptive Market Hypothesis

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Abstract

- **Purpose:** This research aims to simultaneously examine different aspects of the Adaptive Market Hypothesis (AMH) in the global financial market context, a topic of significant interest and relevance. We seek to answer whether financial markets can adapt differently, a question that is particularly pertinent in today's dynamic financial landscape. A Cross-Country
- **Design/methodology/approach:** This research pioneers а comprehensive approach by combining multiple linear and non-linear tests for this study, thereby ensuring the robustness of our conclusion. We use the martingale difference hypothesis (MDH) or autocorrelation tests to detect linear and non-linear relationships in a time series, from which a conclusion regarding the validation of the AMH theory can be made. Our use of tests that use different techniques to overcome the drawbacks of each method showcases the thoroughness of our research methodology. This research goes further by conducting additional robust tests to enhance the examination of the AMH. The Markov Switching Model, a powerful tool for analyzing regime shifts that influence the behavior of the financial market, is employed. This method significantly strengthens our research, enabling us to capture changes in the structure of the market dynamics and provide a more comprehensive understanding of AMH.
- **Findings:** The predictability of stock returns is subject to fluctuations over time. Moreover, the efficiency of each market demonstrates a unique pattern of behavior over time. thereafter Markets have a cyclical pattern of efficiency and inefficiency. And the test results support the Adaptive Market Hypothesis (AMH).
- Originality/value: This research examines AMH in the global financial market setting and asks whether financial markets may respond differently. Cross-country strategy is key to AMH. The research tries to improve literature in numerous ways. The research aims to track and explain the evolution of developed, frontier, and emerging financial markets from various perspectives. Studying the AMH in these financial

markets is important because it allows us to generalize the theory across different settings and cultures.

Keywords:

Efficiency Market Hypothesis (EMH); Adaptive Market Hypothesis (AMH); Cross-Country analysis; Developed Markets; Emerging Markets; Frontier Markets; Martingale Difference Hypothesis (MDH); Markov Switching Model.

1. Introduction:

The complexity of financial markets arises as a function of the interactions between heterogeneous agents, leaping innovations, and different economic states (Arthur, 1999). These are the dynamics that help to create enormous profitability and growth in the financial industry. However, on the other hand they also have unintended outcomes in the form of financial bubbles, market crashes, and crises (Lo, 2004). The aggregate behavior from the actions of the various agents leads a system that grows in complexity over time to levels that may lie outside the scope of traditional market explanations. Consequently, our perspectives on markets cannot be confined within the limits of static models, rather, they must be dynamic, thus, our approach to financial systems must also evolve to reflect this.

Random walks, first established as a fundamental scientific concept, were later adopted in finance to describe the behavior of homogeneous participants in the market. This scenario evolved from the random walk theory, which resulted in the formulation of the Efficient Market Hypothesis (EMH) thereafter, which classifies the information impact on asset prices into strong, semi-strong, and weak forms, the weak-form version of market efficiency is the most examined form of the EMH in empirical studies. According to this form, stock returns are independent, and no one can predict future return based on past information. Therefore, profitable trading strategies using historical information do not exist. (Fama, 1965; Fama, 1970). However, these models remained largely unvalidated until the 1980s. With increasing skepticism about classical game theory, researchers started to spotlight perception and cognitive biases in financial decisions. This transition resulted in the formulation of prospect theory, introducing psychological and behavioral aspects into the financial and economic model (Kahneman & Tversky, 1979).

Market anomalies came in waves, leading behavioral economists, most notably (Tversky & Kahneman, 1974), to criticize the basic assumption of rational agents on which the EMH (Fama 1970; Fama 1991) was based. They highlighted the impact of cognitive biases (e.g. loss aversion, overconfidence, and herding), limiting human decision-making under bounded rationality response. Their research indicated when certainty is the norm, decision making can seem rational, however, financial decision making is typically characterized by complicated, dependent variables and nonlinear relationships. These intricacies allow for distortions in the information processing, leading to the magnification or attenuation of outcomes, greater uncertainty, and herding behaviors that reinforce irrationality.

This discourse was further enriched by empirical critiques that examined unexplained phenomena in the marketplace. Examples include (Shiller R. J., 1981) investigating market over volatility and (Thaler, 1985) studying psychological elements influencing choices. These criticisms were extended into economic theory via complexity economics, leading to re-imagining of markets as adaptable systems ruled by non-linear interaction and emergent properties (Arthur, 1999; Farmer, 2009). A plantation of these views demonstrates the limitations of traditional market theories in explaining inefficiencies, anomalies, and emergent dynamics, underscoring the importance of interdisciplinary and adaptive frameworks for understanding how financial markets operate.

Furthermore (Fama 1998) argues that EMH continues to hold true and that the anomalies detected in various studies are not consistently observable and tend to vanish when changes are introduced into the model, sample, or frequency of data. But more than mere methodology, (Fama 1998) argued, the persistent discussion about market efficiency may arise from the partial correctness of both EMH and behavioral finance. Market conditions evolve, they are not static, so it is important to adopt a flexible response that allows moving between these theoretical paradigms. As a result, it might be the case that the two viewpoints combined provide a fuller description of what we observe in the market. In this context, Lo (2004, 2005) develops a theoretical framework called the Adaptive Market Hypothesis (AMH) thereafter. Such is the groundwork laid for the AMH from an evolutionary stance of economic oddities, that logically, it is possible

and likely that both market efficiency and inefficiency may have evolved, and hence at any point in time efficiency is ever so dynamic and developing. This perspective embarks on the idea that market efficiency is an emergent evolutionary phenomenon that is driven by competitive pressures, mutation, adaptation, innovation and natural selection, which are factors affecting the effectiveness of trading strategies and the general efficiency of markets that evolve to cope with new market environments. The assumption that returns are ergodic implies that financial markets converge toward an ideal state of efficiency but (Lo 2005) argues that market equilibrium is not predetermined or guaranteed.

Lo also integrates derivative economics, framing markets as complex adaptive systems with non-linear dynamics and emergent behaviors (Farmer, 2009). AMH also notes that machine learning and big data will improve our ability to predict markets and capture changing dynamics (Lo, 2017).

By doing so, Lo connects EMH to behavioral and complex economics via AMH, creating an integrated framework for the analysis of actual marketplace actions, inefficiencies, and anomalies.

Recent empirical studies of AMH have issued tests of its explanatory power against that of the Efficient Market Hypothesis (EMH). Empirical evidence in favor of the AMH framework is provided by studies which have examined developed markets (Alvarez-Ramirez et al.,2012; Boya, 2019; Ito et al.,2016; Ito and Sugiyama, 2009; Kim et al., 2011; Lim et al., 2013) as well as equity markets in emerging countries (Abdmoulah, 2010; Charfeddine and Khediri, 2016; Kılıç, 2020; Phan Tran Trung and Pham Quang, 2019; Shahid et al., 2019; Smith, 2012; Todea et al., 2009; Tuyon and Ahmad, 2016). Moreover, evidence of AMH applicability has also been examined in non-stock markets such as the bond market (Charfeddine et al., 2018), foreign exchange market (Neely et al., 2009), cryptocurrency market (Chu et al., 2019), crude oil market (Ghazani and Ebrahimi, 2019), and lodging/resort real-estate investment trusts (REITs) (Almudhaf et al., 2020). In fact, these diverse financial markets have shown strong empirical evidence for AMH, strengthening its foundation as a model of the market behavior.

This research aims to simultaneously examine different aspects of AMH in the global financial market context and to answer such a question through the lens of whether financial markets can adapt differently. A Cross-Country which is a key point of the AMH (Lo, 2004). This study aims to contribute to literature in several ways. First, to the best of our knowledge, this is the first study to track and explain the evolution of the efficiency of the developed, frontier, and emerging financial markets using different perspectives. An insight into these markets could be additional relevant evidence for AMH because of the importance of the markets and their specificities. Thus, examining the AMH in these financial markets is relevant as assessing the AMH across different contexts and different cultures permits us to generalize the theory.

Secondly, this research tries to combine multiple linear and nonlinear tests for this study to mitigate the risk that spurious results from one test or just from linear tests affect the robustness of our conclusion. On the one hand, combine different linear tests to improve the robustness of the results. These are the martingale difference hypothesis (MDH), or autocorrelation tests detect linear and nonlinear relationships in a time series, from which a conclusion regarding the validation of the AMH theory can be made also employ tests that use different techniques to overcome the drawbacks of each method. First apply "Wild Bootstrapping Approach of Automatic variance ratio test", While for examining the autocorrelation I use the "Automatic Portmanteau test" as a robustness check for the results of the previous test and to ascertain that no positive and negative correlations are concealed. These tests are conducted with a rolling window approach. However, the rolling window tests face an empirical problem in selecting the optimal window length. To address this issue, use in addition the "non-Bayesian time-varying model approach (TV-AR), and an autoregressive model with the coefficients changing over time. This is a new testing method, which has been introduced in the work of (Ito et al. 2014, 2016) as this test could provide a more accurate measurement of market efficiency than statistical tests using the moving window method (Noda, 2016). On the other hand, it is shown that stock returns exhibit nonlinear dependency, which may be neglected by linear tests (Cont, 2001). The market psychology and the ubiquitous transaction costs are among the leading causes of non-linearity. Several studies have found these nonlinear dependencies (Almudhaf et al., 2020; Ghazani et Ebrahimi, 2019; Lim et Brooks, 2011; Ghazani et Araghi, 2014; Shahid et al., 2019). Therefore, adding a nonlinear test may provide more accurate results as the stock exchange exhibits nonlinear effects.

Finaly further robust tests are conducted to improve the examination of AMH in this research. With The Markov Switching Model, a powerful tool for analyzing regime shifts that influence the behavior of the financial market, is employed. This method significantly strengthens our research, enabling us to capture changes in the structure of the market dynamics and provide a more comprehensive understanding of AMH. Collectively, these tests provide a holistic indicator of market adaptivity, accommodating both the non-linearity and long-term dependencies introduced by the inherently flexible financial data.

The study analytically contributes by integrating adaptive and ecological perspectives, providing an integrated understanding of the dynamic nature of market efficiency in academic literature. The results also aim to inform others about investing strategies, policy making, and financial market development when it comes to understanding the characteristics of different types of markets. Using empirical evidence of time-varying efficiency and behavioral biases (Neely, 2009; Kim 2011), this analysis provides a detailed picture of financial markets globally.

The remainder of the research is organized as follows: Section 2 offers an extensive literature review; Section 3 describes the data and sample employed. The methodology is described in Section 4, and the empirical results are reported in Section 5. Finally, Section 6 wraps up with a summary of findings, implications, and possible directions for future research.

2. Literature review

2.1. Theoretical background

Central to modern financial economics, the Efficient Market Hypothesis (EMH) claims that asset prices incorporate all available information (Lo, Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis, 2005). This means that all markets are either efficient, or fully inefficient — and that this efficiency remains constant over time. This hard-edged, binary definition of market efficiency was challenged in 1980 by Grossman and Stiglitz (Grossman, 1980), who argued that there cannot be perfectly efficient markets. This led them to reason that if all information was already captured in prices, then traders would be better off not spending their wealth on obtaining costly data in the first place, a conclusion that entirely

undermines the efficiency described by the EMH. Aware of the limitations of full efficiency, (Campbell, 1997) Relative efficiency or efficiency relative to market defined posits comparisons of efficiency between the efficiency of markets each other. This led to research on the theory of evolving, or dynamic, market efficiency.

This raised some questions on market efficiency over intervals, which were later used by researchers. For instance, (Emerson, 1997) used Kalman filter process to track changes in efficiency status over time. In a similar work, (Zalewska-Mitura, 1999) introduced a time-varying autoregressive model to study the gradual learning that governs market efficiency. The use of rolling subsamples in the models is intended to identify structural breaks in the efficiency (Charles, 2009).

Simultaneously, a parallel stream of investigation developed around the behavioral elements of modern portfolio theory. This movement was initiated by (De Bondt, 1985), who showed that stock prices tend to overreact, indicating that markets are inefficient and affected by investors' psychological biases. (Daniel, 2001) built upon this idea to demonstrate that the rational behavior EMH presupposes is undermined by overconfidence and the self-attribution bias of investors. (Shiller R. J., 2003) goes on to build upon these concepts by calling for the rejection of EMH in favor of a behavioral finance framework focused on the role of human behavior in market behavior.

(Lo, 2004) extended earlier efforts by combining evolutionary principles with (Simon, 1955) bounded rationality to develop the Adaptive Market Hypothesis (AMH), which he believes could complement the EMH, (Lo, 2012) explains that investors, collectively, adapt over time to changing market dynamics through experience, Yet there are numerous empirical observations and evidence that indicate the infallibility of humans is false, including the continued existence of market anomalies and the existence of behavioral biases in the human population (Lo, 2005; Gu, 2023). Focusing on evolutionary dynamics rather than rational equilibrium, Andrew Lo's Adaptive Markets Hypothesis (AMH) has emerged as a strong contender: that the efficiency of markets is not a static phenomenon, but rather a process that unfolds over time under the influence of changing environmental conditions and adaptive.

The AMH states that asset prices reflect information under the current business dynamics of entry and exit by a rival firm within the same industry and the type and magnitude of profit opportunities (Lo, 2004). The AMH represents a conceptual and qualitative framework but is not carefully defined or formalized. However, it has practical implications for testing. First, that the relationship between risk and return is dynamic, not static. Second, arbitrage opportunities are temporary, implying that market efficiency is time varying. Third, changing business contexts change investment strategies and, hence, returns. Market players (investors) need to adjust to these shifting relegate to endure and perform.

This specialist literature review provides an examination of AMH in the context of country-specific studies, reviewing empirical evidence from national markets, and analyzing the explanatory power of the hypothesis within different economic environments.

The AMH (Lo, 2005; Lo, 2004) - challenged by Andrew Lo - provides a synthesis of the EMH and behavioral finance. While the EMH assumes that actors are perfectly rational, the AMH considers investors to be intelligent, but fallible (Lo, 2012). Like others, they suffer from cognitive biases, rely on heuristics, and learn from experience (Lo, 2005). Most importantly, the AMH emphasizes that market efficiency is not constant; it changes over time and between markets (Lo, 2012; Dhankar, 2016). This variation needs to be analyzed due to multiple reasons such as changes in the competitive landscape, technological developments and the increasing sophistication of market participants (Lo, 2005). AMH takes an evolutionary approach to market dynamics, postulating that winning strategies are those that seminar with the ever-evolving characteristics of the market environment; like the process of natural selection in biological organisms (Lo, 2004; Santos, 2017). This means the market can be both efficient and inefficient at the same time, and which will dominate is dependent on the environment (Cruz-Hernndez, 2023).

2.2. Empirical studies.

Numerous studies have tested AMH using data from various national stock markets. These studies often employ different methodologies to assess market predictability and efficiency, including variance ratio tests, Brock-Dechert-Scheinkman tests, and generalized spectral tests (Cruz-Hernndez, 2023), (Ndubuisi, 2018), (Popović, 2013). Thereafter with review the empirical analysis in the Adaptive Market Hypothesis studies show that a classification based on the methodology used. First are return predictability as a Modified Standard Tests (Linear, nonlinear, and autocorrelation tests), second price–volume relationship.



Figure (1) Scopus Bibliographic Analysis

The results generally support AMH's central tenet of time-varying market efficiency, these studies will be classified based on country regions as (Americas, Europe, Asian, Africans and Middle East), but applied in the empirical analysis based on the MSCI Market Classification Framework classification as Developed, Emerging, and Frontier markets this market classification are uses three criteria to evaluate markets: economic development, size and liquidity requirements, and market accessibility, thereafter The growth trend of publications in the field of the Adaptive Market Hypothesis (AMH) was analyzed using bibliometric techniques to the identification of the areas with significant development and the orientations that have guided the research on Market Efficiency. This study extracted data from Scopus, and got the following results:

Developed markets, Americas, Europe, the Middle East and Africa (EMEA), and Asia-Pacific Countries (APAC) are 11%, 28%, and 8%, respectively, but in emerging markets there are 6%, 13%, and 26%, respectively. Finally, frontier markets for EMEA and APAC are 3% and 5%, respectively. From this, we can conclude the following: in developed and emerging markets, the EMEA region is more dominant than others. To study different European, African, and Middle Eastern markets to become more regulated and liquid, on the other hand, the frontier markets are dominant from APAC markets. All these indicators are mainly proof of these markets at different levels and with different economic factors and states, to the current inefficient state, with different transition levels in between some efficient to inefficient states.

2.2.1. Americas Markets Studies:

(Marco Aurélio dos Santos, 2024) Based on the adaptive markets hypothesis (AMH), the objective of this investigation was to determine the way numerous markets have evolved over time and the factors that have influenced this trend. In this regard, the authors believe that agents are motivated by the desire to generate anomalous returns to maintain their existence, and their environment has the potential to alter their decision-making processes and the market's efficacy. A daily closing-of-the-market index was compiled by authors from 50 countries between 1990 and 2022. The sample encompasses frontier markets, developed countries, and emergent countries. Following this, the authors conducted multilevel modeling with the Hurst exponent as an informational efficiency metric, which was estimated by two distinct moving windows: 500 and 1,250 observations (corresponding to approximately 2 and 5 years). The findings suggest that the efficacy of the markets is not consistent over time. Furthermore, the authors have determined that markets exhibit a cyclical pattern of efficiency and inefficiency, and they are presently in a phase of convergence to efficiency. This phenomenon may be attributed to the increase in computational capacity and the pace of the information available to agents.

Tiwari, Jena, Abakah, and SeongMin Yoon (Tiwari, 2023) used transfer entropy to quantify the flow of information between government bonds and equity markets across G7 countries (Canada, France, Germany, Italy, Japan, the UK and the US), to quantify the information flow and found that the markets were adaptive. Results showed that, although information flow from the equity dominates the flow from the bond market. However, during the period of market turbulence, the bond dominates the equity market.

Hany Fahmy (Fahmy, 2021) This research aims to empirically evaluate the viability of the Adaptive Markets Hypothesis by employing a smooth transition regression model with the market-to-book ratio as an exogenous threshold variable. The US Market (S&P500) are indeed ineffective most of the time and occasionally efficient, as evidenced by the results, which verify reconciliation.

Jae H. Kim, K. Lim, and Abul Shamsuddin (Kim J. H., 2011) provided evidence of time-varying return predictability in the Dow Jones Industrial Average from 1900 to 2009, consistent with AMH, using Automatic variance ratio, Automatic portmanteau, and Generalized spectral tests, and using AR(1), and GARCH(1,1) as an robustness check tests. Their findings showed that the return predictability was influenced by changing market conditions, with lower predictability during economic bubbles.

Samuel Tabot Enow (ENOW, 2022) explored AMH in five international markets (JSE, CAC 40, NASDAQ, JPX-NIKKEI, and DAX). The adaptive market hypothesis was investigated in this investigation from January 2017 to April 2022 using a variance ratio test. The conclusions indicated that adaptive markets were present in the CAC 40 and NASDAQ during the period under consideration. However, the JSE, JPX-NIKKEI, and DAX did not provide any statistical evidence to substantiate the adaptive concept.

Andrs R. Cruz-Hernández and Andrs Mora-Valencia (Cruz-Hernández, 2024) studied the AMH in five major Latin American stock exchanges. Three versions of the variance ratio test and the BrockDechert-Scheinkman test are implemented to evaluate nonlinear predictability. To assess the Martingale difference hypothesis, implement the Dominguez-Lobato and generalized spectral tests. And finally, implement a GARCH-M model to evaluate the risk-return relationship over time. According to the findings, the predictability of stock returns fluctuates over time. Moreover, the efficacy of each market exhibits a distinct pattern of behavior over time. The adaptive market hypothesis posits that market efficiency and market anomalies may coexist in capital markets, as evidenced by the toggling behavior between periods of efficiencies and inefficiencies in the analyzed emerging market indices.

The second study carried out in the Latin American region was performed by Dacio Villarreal-Samaniego and Roberto J. Santillán (Villarreal-Samaniego, 2023); both studies also showed evidence for the AMH by confirming the Dayof-the-Week anomaly in Latin American stock markets. The purpose of this study is to investigate the Day-of-the-Week anomaly in the stock market indices of Argentina, Brazil, Chile, Colombia, Mexico, and Peru by applying the Adaptive Markets Hypothesis to various subperiods and market conditions. The Day-ofthe-Week effect is observed in three of the indices and is subject to fluctuations in the presence of the effect under varying market conditions, as indicated by the Autoregressive-Moving-Average, Generalized-Autoregressive-Conditional-Heteroskedasticity specifications, and Kruskal-Walli's test employed in the experiment. According to this empirical evidence, the Adaptive Markets Hypothesis is validated.

Dzung Phan Tran Trung and Hung Quang (Dzung & Quang, 2019) The purpose of this research is to evaluate the adaptive market hypothesis in the two primary Vietnamese stock exchanges, the Ho Chi Minh City Stock Exchange (HSX) and the Hanoi Stock Exchange (HNX), by examining the correlation between historical stock returns and current stock returns. The automatic variance ratio test ("AVR"), the automatic portmanteau test ("AP"), the generalized spectral test ("GS"), and the time-varying autoregressive (TV-AR) approach are the specific tests that are implemented. The empirical findings are consistent with the adaptive market hypothesis in the Vietnamese stock market. In addition, the findings indicate that the adaptive market hypothesis has been significantly influenced by the evolution of HSX.

2.2.2. Europe Markets Studies:

M. Rossi and A. Gunardi (Rossi, 2018) This research examines several of the most significant market anomalies in the stock exchange indexes of France, Germany, Italy, and Spain during the initial decade of the new millennium (2001-2010). The GARCH model and the OLS regression are employed in this investigation to confirm the distribution of the returns and their autocorrelation. The analysis fails to provide compelling evidence of comprehensive Calendar Anomalies. Some of these effects are country specific. In addition, the instability of these country-anomalies during the initial decade of the new millennium raises some skepticism regarding the importance of CAs.

Steve Sherlock (Sherlock, 2018) By examining how the risk-return tradeoff varies across various investment horizons and market conditions, a novel theory known as the Adaptive Markets theory (AMH) is applied to the Swedish stock market scenario. The OMXS30 index was used to quantify yearly returns and volatility in a variety of investment horizons between 1986 and 2017. Several distinct market environments are revealed through the sample observations. To evaluate the statistical significance of the risk-return relationship, regression analysis is implemented. The results indicate that risk is not a reliable explanatory variable for average returns, as evident by the feeble and fluctuating statistical relationship between risk and return. It has been demonstrated that the risk-return relationship is influenced by the market environment and the duration of the investment horizon. The AMH is substantiated by these OMXS30 index findings, which demonstrate that the risk-return relationship is dynamic and subject to modifications in a variety of market environments and investment horizons.

The study (Popović, 2013) conducted by S. Popovic, Ana Mugosa, and Andrija Đurović The adaptive markets hypothesis (AMH) was investigated in this research by utilizing three factors that we assumed to influence the weakform of market efficiency: the observation period, the time horizon depicted by rolling window sizes, and the data aggregation level. From 2004 to 2011, examined the market value weighted index MONEX20, which serves as a proxy for the Montenegrin equity market. Rolling window analysis is implemented to quantify the persistence of deviations from a random walk hypothesis (RWH) over time, with a fixed parameter in each window. Investigated whether short-range linear dependence is changing over time by employing the rolling sample approach. This method was implemented on the first-order serial autocorrelation coefficients (AC1) and on the runs test, as the non-normality properties of MONEX20 indicate that a non-parametric methodology should be implemented. The evidence revealed that the degree of weak-form Montenegro equity market efficiency is influenced by all three factors, which has significant long-term impact on profit opportunities in this market.

In another article, Mika Rönkkö, Joonas Holmi, Mervi Niskanen, and Markus Möttönen (Rönkkö, 2024) This research investigates whether the adaptive markets hypothesis (AMH) more accurately depicts the efficacy of the Finnish stock market than the efficient markets hypothesis (EMH). Furthermore, investigated the correlation between market volatility and return in the Finnish stock market and investigate the influence of market liberalization and small market size on its efficacy. Utilizing the rolling window analysis and subsample analysis, evaluated the efficacy of the OMXH25 index's daily returns and implemented three linear and two nonlinear predictability tests. The findings of the investigation provide substantial evidence in favor of AMH. In addition, they contend that a market's efficiency is not diminished by its small size alone; the efficiency of a market is enhanced after a delay when it is opened to foreign investors; and the correlation between market volatility and return in the Finnish stock market is typically negative and fluctuates over time. These results largely challenge the investing paradigm.

V.Aleknevičiūtė, Vaida Klasauskaitė, and Eglė Aleknevičiūtė (Aleknevičienė, 2021) The Adaptive Market Hypothesis (AMH) is examined in this study with respect to calendar anomalies in the Baltic stock markets. The analysis of existing calendar anomalies over time is conducted using sub-sample GARCH (1,1) regression, Kruskal–Walli's statistics, and rolling windows. In these markets, three calendar anomalies were verified: Friday, MoY (July and January), and ToM (turn-of-the-month). Baltic stock markets exhibited behavior that was in accordance with the AMH. It was determined that the opportunity to generate anomalous returns on investment strategies that were based on the Friday, July, and ToM effects was eliminated during the financial crisis of 2007– 9. The Friday and ToM effects exhibit a more time-varying pattern, whereas the July effect is less so.

2.2.3. Asian Markets Studies:

Ali Fayyaz Munir, Mohd Edil Abd. Sukor and Shahrin Saaid Shaharuddin (Munir, 2022) In order to verify the existence of the Adaptive Market Hypothesis (AMH) in South Asian emergent stock markets, analyze the impact of altered market conditions on time-varying contrarian profitability. According to the empirical results, there is a robust contrast in all emerging markets. Contrarian

returns are demonstrated to be more robust during periods of market downturns, increased volatility, and crises, particularly during the Asian financial crisis. According to the argument, the linkage is the result of structural and psychological disparities in emerging markets, which generate distinctive intuitions regarding stock market anomalies and returns. The study's overall findings regarding the time-varying contrarian returns offer partial support for AMH. Investors in South Asian emergent markets, like those in developed markets, could not adjust to changing market conditions, which is another noteworthy finding of this investigation. Consequently, contrarian profits are frequently observed, and persistent weak form market inefficiencies are prevalent in these markets.

Todea, Maria Ciupac-Ulici, and Simona Silaghi (Todea A. C.-U., 2009) The profitability of the moving average strategy on six Asian capital markets is examined in this research, with an emphasis on the intermittent nature of linear and/or nonlinear dependencies. The study spans the years 1997-2008. The most profitable strategy from 15,000 alternatives is chosen for each market. The primary finding is that the profitability of moving average strategies is not consistently consistent over time; rather, it is episodic, indicating the occurrence of sub-periods of linear and non-linear correlation. As a result, it is possible to assert that the degree of market efficiency fluctuates in a cyclical manner over time. These statistical characteristics are consistent with the Adaptive Markets Hypothesis (AMH).

Seema Rehman, Imran Umer Chhapra, Muhammad Kashif, and Raja Rehan (Rehman, 2018) This research has been primarily focused on determining whether share prices are a random walk process by utilizing a newly developed State Space Model, Runs Test, and multiple unit root tests. The empirical findings of the study are enough to support the weak form inefficient hypothesis that the stock prices of the KSE 100 Index, S & P BSE 500 Index, and CSE All Share Index are not a random walk process. The random walk concept is reviewed in this study with a focus on the stock markets, omitting the other asset markets. This research provides fascinating information regarding independent samples from Pakistan, India, and Bangladesh, and it enhances the current body of literature on emerging markets.

Ramede Khunnawannaphong (Khunnawannaphong, 2024) The study evaluates market efficacy for the ASEAN stock market across various time periods from March 2009 to March 2024 by employing sophisticated methodologies, such as the Multiple Variance Ratio (MV) and Wild Bootstrapped Variance Ratio (WBVR) tests, in conjunction with the Rolling Window technique. The potential impact of company size on market efficiency is investigated through the use of daily price data, which is segmented into the overall market and three sub-groups based on market capitalization. the analysis is conducted. According to the results, market efficiency is not constant; it fluctuates, particularly during periods of economic crises or significant events, when all market segments exhibit inefficiency, deviating from the Random Walk theory. The implication is that stock prices become more predictable during these periods, which is in direct opposition to the expectations of an efficient market. Furthermore, the investigation reveals that differences in market efficiency are uniform across various company sizes, indicating that efficiency is not substantially influenced by market or company size.

Gourishankar S. Hiremath and Jyoti Kumari (Hiremath, 2014) This research investigates whether the adaptive market hypothesis offers a more accurate representation of the behavior of emergent stock markets, such as India. Linear and nonlinear methodologies are implemented to empirically assess the hypothesis. The Indian stock market alternated between periods of efficiency and inefficiency, as indicated by the cyclical pattern in linear dependence observed in the linear tests. In contrast, the results of the nonlinear tests indicate a substantial degree of nonlinearity in the returns over the course of the sample period, with a slight decrease in the magnitude of nonlinear dependence in the most recent period. Based on the results, it appears that the Indian stock market is advancing toward efficiency. Additional insights regarding the correlation between inefficiency, financial crises, and foreign portfolio investments are offered by the findings.

Oktay Ozkan (Ozkan, 2020) This research analyzes the evolution of the return predictability (or market efficiency) degree for Mexico, Indonesia, South Korea, and Turkey (MIST) countries and determines whether the results are in accordance with the implications of the adaptive markets hypothesis (AMH").

The rolling sub-sample windows method is employed to analyze the monthly data from January 1993 to July 2020 to ascertain whether the capacity of inflation and trading volume to forecast stock market returns varies over time. The novel wild bootstrap likelihood ratio approach is employed for this purpose. The AMH's implications for all MIST countries are corroborated by empirical findings, which demonstrate that the return predictability (or market efficiency) is time-varying. The validity of this substantiation is further enhanced by the inclusion of additional predictor variables, including realized volatility and exchange rate. The efficient markets hypothesis is less effective in explaining true stock market behavior than AMH, as this research demonstrates.

In the context of the COVID-19 pandemic, Jinfang Tian, Xiaotong Yang, Xue Rui, and Wang Chen (Song, 2021) Using monthly panel data on recently listed Chinese businesses from October 2019 to June 2020, this research uses a Difference-in-Differences (DID) model to investigate how the coronavirus disease 2019 (COVID-19) epidemic affected investor sentiment in the Chinese financial market. According to the evidence, investor sentiment is adversely affected by the pandemic's onset. The pandemic has substantially impacted non-pharmaceutical sectors, while it has enhanced investor sentiment in the pharmaceutical sector, according to a prospective industry heterogeneity analysis. The pandemic has a detrimental effect on the private sector and foreign-invested sector in China, while it has a substantial positive impact on the state-owned sector. This investigation complements the current body of research that examines the extent to which investor sentiment is affected by public health emergencies.

(S Kumar, 2021) The daily return of the LIV-EX 50 index from 1/1/2010 to 12/6/2020 is employed to evaluate the character of feeble form informational efficiency in the wine market. Initially, incorporated a variety of statistical tests, such as the Hurst coefficient, linear and non-linear dependence tests, and variance ratio tests. Tests are conducted on the entire dataset and on four sub-samples of equal length that are non-overlapping. In terms of informational efficacy, the variance ratio experiments yield a mix. The return series exhibited evidence of non-linear dependence. The Hurst coefficient values verify the existence of long-term persistence in the wine market. The possible adaptive nature of the wine

market is evaluated considering the conflicting evidence. The degree of information inefficiency in the wine market at any given time is quantified using the recently proposed Adaptive Index (AI). According to research findings, the wine market is adaptive and alternates between phases of efficiency and inefficiency. The wine market has been found to be comparatively unaffected by the Covid-19-induced disturbance, which confirms the haven property of wine. Finally, AI is employed to determine the influence of a variety of macroeconomic and financial events on the efficacy of the wine market.

J.Karasiński (Karasiski, 2023) This investigation implements robust martingale difference hypothesis tests to evaluate the predictability of returns in a comprehensive sample of the 40 most capitalized cryptocurrency markets within the context of the adaptive market hypothesis. The rolling window method was employed to apply the tests to daily returns during the research period of May 1, 2013, to September 30, 2022. This study's findings indicate that the returns of most of the cryptocurrencies under investigation were largely unpredictable. Nevertheless, a significant number of them also experienced certain brief periods of weak-form inefficiency. Validation of the adaptive market hypothesis is supported by the results. Furthermore, this investigation enabled the identification of certain variations in the predictability of returns among the cryptocurrencies that were examined.

Hereafter, M. Bhatia (Bhatia, 2024) The research investigates the developments in the efficacy of Indian banks' stock markets from January 1, 2007, to June 30, 2022. In response to three significant events: the global financial crisis, the local banking crisis, and the pandemic crisis, the study also aims to examine the extent to which the stock market efficacy is influenced by the various crises. In order to account for the implications of the adaptive market hypothesis (AMH), the wild bootstrap automatic variance ratio (WBAVR) test is implemented via the rolling window method. The automatic portmanteau (AQ) test, which is also underpinned by a data-driven procedure, is implemented to ensure the analysis's robustness. The findings indicate that the market efficiency of Indian banks is not a binary phenomenon; rather, both efficiency and inefficiency co-exist simultaneously, with the Central Bank of India being identified as the most "inefficient" bank.

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Hirayama Kenichi and Noda Akihiko (Hirayama, 2020) In the context of Fama's (1970) semi-strong form market efficiency, this research investigates the moment at which the financial market in prewar Japan lost its price formation function by employing a novel dataset. The relationship between the prewar Japanese financial market and various government policy interventions is the primary focus of our investigation into the evolution of semi-strong form market efficiency over time. To quantify the long-term effects of government policy interventions on the markets, we employ the generalized least squares-based time-varying vector autoregressive model of Ito et al. (2014; 2017) to measure the time-varying joint degree of market efficiency and the time-varying impulse responses. (1) The joint degree of market efficiency in the prewar Japanese financial market fluctuated over time as a result of external events such as policy changes and wars. (2) The semi-strong form EMH is almost supported in the prewar Japanese financial market. (3) Lo's (2004) adaptive market hypothesis is supported in the prewar Japanese financial market, even when public information affects the financial markets. (4) The prewar Japanese financial markets lost the price formation function in 1932, which was a turning point in the market. All of these findings are supported by the empirical results.

2.2.4. Africa and Middle east Markets Studies:

Paul Ndubuisi and K. Okere (Ndubuisi, 2018) The Adaptive Market Hypothesis is examined in this research by analyzing daily data from the Nigerian stock markets from 1987 to 2016. The results are as follows, as indicated by the use of four distinct sub-samples: although all four linear tests for the ASI indicate that the market is adaptive, the tests differ in their assessment of which subsamples are efficient and inefficient. Each of the nonlinear tests indicates that each market demonstrates a strong and significant nonlinear dependence, which suggests inefficiency. These results suggest that the ASI markets are linearly dependent; however, they are ineffective for each subsample due to their significant nonlinear dependence. The evidence of a transition to efficiency is also minimal. In summary, the linear tests provide substantial support for the AMH, while the nonlinear tests suggest a persistent, albeit time-varying, inefficiency.

Sermet Doan and Sinan Aytekin (Aytekin, 2023) The objective of this study is to examine the presence of the Adaptive Market Hypothesis in the Turkish stock market during events of global crisis. In order to achieve this objective, the major index (XU100) and selected sector indices (XBANK, XGIDA, XTEKS, XTRZM) of Borsa Istanbul were evaluated in the following crisis environments: the Asian Financial Crisis, the American "Dotcom" crisis, the Mortgage crisis, the European debt crisis, and the Covid-19 crisis. Wild Bootstrap Automatic Variance Ratio and Automatic Portmanteau tests were implemented in the investigation. All Borsa Istanbul indices within the scope of the research yielded findings that were consistent with the Adaptive Market Hypothesis, as indicated by the results achieved. It has been noted that market efficiency may fluctuate at varying frequencies and durations in accordance with the character of the crisis and the source of its output.

(Pinar Evrim Mandaci, 2019) To examine the effects of the Adaptive Market Hypothesis (AMH) on the indices of the Turkish stock exchange market (Borsa Istanbul) as a growing country. BIST-100, BIST-30, and BIST-All indices are examined for the period spanning January 2002 to April 2017. Design/Methodology/Approach: Linear methods (Variance Ratio Test) and nonlinear methods (BDS Test) were employed to calculate daily test values and two-year rolling windows in order to evaluate market efficiency. Results showed that The Variance Ratio Test findings indicate that index returns are unexpected, suggesting market efficiency, however the nonlinear analysis results reveal the presence of the adaptive market hypothesis. Specifically, the 2013-2016 period indicated that all three indices exhibited efficiency, suggesting that returns were unpredictable during this time. In Borsa Istanbul, the adaptive market hypothesis is supported by the results of the non-linear analysis, which demonstrate that the market is occasionally efficient and occasionally deviates from efficiency.

(Mostafa Lekhal, 2020) The Moroccan financial market from January 1992 to September 2019 is examined in this research using a variety of methodologies to examine various aspects of the Adaptive Market Hypothesis (AMH). The evolution of efficiency degree is assessed using linear and nonlinear tests with a rotating window, which are based on the daily returns on the MASI index. Profit opportunities occur intermittently, contingent upon market efficacy and market conditions, which is one of the practical implications of the AMH. To

explore this implication, monitor the changing performance of momentum-based trading strategies and the degree to which this performance is influenced by the degree of market efficiency and specific market conditions. The linear and nonlinear experiments indicate that the efficiency degree is time-varying. In addition, the momentum test reveals that profit opportunities emerge intermittently and vanish once they are capitalized on. Interestingly, the momentum profits are contingent upon both the level of market efficiency and specific market conditions. In general, results are in accordance with the AMH framework, which has been demonstrated to be a more comprehensive explanation of the behavior of emerging markets than the Efficiency Market Hypothesis (EMH).

Based on the above discussion, this research extends the previous literature, where it attempts to close the gap on the ground that: (i). The sample period will be as long as 14 years with different window operations (500 observations), affected by different shocks in the sample of exchange market indexes (political, economic, and pandemic), (ii). The sample data is semi-high frequency data with daily observations, with statistical characteristics to explain daily variations in market and asset returns, (iii). The empirical investigation uses linear, nonlinear, and autocorrelation tests a hypothesis, and applied further robustness check tests using state space models, and the long-term memory and persistence in market trends, and (iv). Applied to the different main indexes for Developed, Emerging, and Frontier exchange markets.

3. Sample Selection and Data Collection:

The sample period covers the closing trading days of the market index from 26 countries, from June 1, 2010, till June 30, 2024, comprising 3,523 trading days for every market index. A long-time window is selected to consider different market phases of the main indexes as a cross country analysis, sample includes developed countries (e.g. United States, Canda, United Kingdom, Germany, Netherlands, France, Australia, and Japan) emerging countries (e.g. Brazil, Colombia, Mexico, Egypt, Kuwait, Qatar, Saudi Arabia, United Arab Emirates, China, India, and South Korea), the so-called frontier markets (e.g. Bahrain, Oman, Morocco, Jordan, Tunis, Pakistan, and Vietnam), as shown in figure (2). The time varying subperiods as rolling operations (window) are for every 500 observations (2years approximately).



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The individual index log returns are calculated as follows:

$$r_{l,t} = \operatorname{Ln}\left(\frac{P_{i,t}}{P_{i,t-1}}\right) = \ln\left(Pt\right) - \ln\left(Pt-1\right)$$
(1)

Where $P_{i,t}$ the ending price for asset i in time t, $P_{i,t-1}$ the beginning price of the same asset i in time t.

Table (1) shows the descriptive statistics for the overall average daily log returns is 0.000, with the highest standard deviations is Jordan (AMMAN Index) with 0.029. that main signaling great heterogeneity between countries. The lowest average in the period in panel (B.1) for Colombia (COLCAP index), and in panel (C.1) for both Jordan (AMMAN Index) and Oman (MSX30 Index) with -0.000, and the highest average is in Panel (C.2) for Pakistan (KSI Index), Egypt (EGX100 Index), and United States (S&P500 Index) with 0.000574, 0.000553, and 0.000473, returns oscillate as Minimum and Maximum for Panel (A) in between -0.13176 and 0.112945, Panel (B) in between -0.15993 and 0.130223, and Panel (C) in between -1.16154 and 1.163145, The density function's left tail is larger than its right tail, as indicated by the negative skewness thereof. The data distribution's tail is larger than the normal distribution, as indicated by the excessively high Kurtosis. This is supported by the Jarque-Bera test, which confirms that the data is not normally distributed. Rather, the data distribution is leptokurtic, a characteristic that is widely observed in sock returns. In order to conduct our experiments, the data needed to be stationary. The ADF-GLS test of Elliott et al. (1992), which is specified in Table (3), is implemented to verify this condition. At the 5% significance level, the null hypothesis that the variables contain a unit root is rejected by the test. Consequently, the time series is stationary.

Table (1): Descriptive statistics for market index return, Crosscountry Analysis

| Code | Country | Mean | Std Dev | Min | Max | Skewness | Kurtosis | Jarque-Bera | | ADE Stat |
|---|-------------------|-----------|----------|----------|----------|----------|----------|-------------|---------|----------|
| | | | | | | | | Stat | p-value | ADF Stat |
| Panel (A.1): Developed Markets (Americas) | | | | | | | | | | |
| S&P500 | United States | 0.000473 | 0.010875 | -0.12766 | 0.089671 | -0.74925 | 17.05097 | 29302.33 | 0 | -12.9504 |
| S&P/TSX | Canda | 0.000188 | 0.009219 | -0.13176 | 0.112945 | -1.35181 | 37.08843 | 1711120 | 0 | -12.578 |
| Panel (A.2): | Developed Markets | | | | | | | | | |
| FTSE100 | United Kingdom | 0.000143 | 0.009956 | -0.11512 | 0.086668 | -0.73435 | 13.30218 | 15946.01 | 0 | -14.5864 |
| DAX | Germany | 0.000314 | 0.012379 | -0.13055 | 0.104143 | -0.48131 | 10.93148 | 9458.215 | 0 | -17.6193 |
| AEX | Netherlands | 0.000298 | 0.010874 | -0.11376 | 0.085907 | -0.56806 | 10.11384 | 7754.343 | 0 | -21.7146 |
| CAC | France | 0.000246 | 0.011440 | -0.12421 | 0.079407 | -0.61527 | 11.26302 | 10433.87 | 0 | -21.951 |
| Panel (A.3): Developed Markets (APAC) | | | | | | | | | | |
| S&P/ASX | Australia | 0.000161 | 0.009335 | -0.10178 | 0.066358 | -0.88107 | 13.19492 | 16212.33 | 0 | -16.704 |
| Nikkei 225 | Japan | 0.000417 | 0.012833 | -0.10576 | 0.077314 | -0.3885 | 7.844609 | 3463.642 | 0 | -30.379 |
| Panel (B.1): Emerging Markets (Americas) | | | | | | | | | | |
| Bovespa | Brazil | 0.000205 | 0.015088 | -0.15993 | 0.130223 | -0.79529 | 14.99047 | 21140.52 | 0 | -21.7176 |
| COLCAP | Colombia | -1.74E-05 | 0.011211 | -0.1629 | 0.124697 | -1.13278 | 31.45332 | 115928.5 | 0 | -15.666 |
| MXX | Mexico | 0.000148 | 0.009735 | -0.06638 | 0.047439 | -0.42375 | 6.799092 | 2224.724 | 0 | -36.4379 |
| Panel (B.2): I | Emerging Markets | | | | | | | | | |
| EGX100 | Egypt | 0.000553 | 0.015976 | -0.15811 | 0.087638 | -1.15743 | 10.10385 | 7833.854 | 0 | -29.725 |
| BKP | Kuwait | 4.10E-05 | 0.009313 | -0.29356 | 0.061446 | -10.6433 | 306.6166 | 13378206 | 0 | -18.3461 |
| TASI | Saudi Arabia | 0.000186 | 0.010462 | -0.08685 | 0.085475 | -0.96248 | 14.66109 | 20388.42 | 0 | -22.6908 |
| DFMGI | Emirates | 0.000289 | 0.012532 | -0.08658 | 0.122045 | -0.23838 | 13.54643 | 16277.01 | 0 | -53.4438 |
| QSI | Qatar | 0.000105 | 0.009470 | -0.10208 | 0.073095 | -0.60541 | 13.60402 | 16607.32 | 0 | -18.7889 |
| Panel (B.3): Emerging Markets (APAC) | | | | | | | | | | |
| KS11 | South Korea | 0.000145 | 0.010395 | -0.08767 | 0.082513 | -0.26495 | 9.234835 | 5633.276 | 0 | -22.3406 |
| NSEI | India | 0.000435 | 0.010619 | -0.13904 | 0.084003 | -0.9761 | 14.31748 | 30104.97 | 0 | -16.6773 |
| SSEC | China | 6.26E-05 | 0.012605 | -0.08873 | 0.056036 | -0.89574 | 6.755783 | 6899.684 | 0 | -10.9417 |
| Panel (C.1): Frontier Markets (EMEA) | | | | | | | | | | |
| AMMAN | Jordan | -4.45E-05 | 0.029799 | -1.16154 | 1.163145 | 0.081162 | 1372.500 | 2.65E+08 | 0 | -27.6259 |
| BAX | Bahrain | 0.000108 | 0.004888 | -0.06001 | 0.034233 | -0.91993 | 12.77530 | 23921.66 | 0 | -10.1384 |
| MSX30 | Oman | -7.42E-05 | 0.005930 | -0.06413 | 0.053696 | -0.96159 | 16.05453 | 37554.32 | 0 | -21.0321 |
| MASI | Morocco | 3.50E-05 | 0.006791 | -0.09232 | 0.053054 | -1.02356 | 19.37836 | 55018.25 | 0 | -13.5896 |
| Tunindex | Tunis | 0.000196 | 0.005022 | -0.04186 | 0.041086 | -0.88556 | 13.88344 | 28373.18 | 0 | -11.2221 |
| Panel (C.2): Frontier Markets (APAC) | | | | | | | | | | |
| VNI | Vietnam | 0.000257 | 0.011734 | -0.06908 | 0.0486 | -0.75156 | 3.388592 | 1993.272 | 0 | -38.2618 |
| KSI | Pakistan | 0.000574 | 0.009091 | -0.05798 | 0.051031 | -0.50404 | 3.530025 | 1938.146 | 0 | -51.5743 |
| Source(s): Research data | | | | | | | | | | |

Note: This table reports descriptive statistics of daily market Index log returns $(R_{i,t})$ for the period

from 2010-2024.

4. Methodology:

4.1. Econometrics Models:

This research explores the evolution of market efficiency by applying the Martingale Difference Hypothesis (MDH) alongside linear and nonlinear autocorrelation tests. If these experiments exhibit return autocorrelation, it will be possible to forecast future stock prices using historical data. This approach could significantly enhance the understanding of market dynamics and assist investors in making informed decisions. Ultimately, the findings may challenge traditional notions of market efficiency and suggest the presence of predictable patterns within seemingly random price movements.

- Martingale difference hypothesis (MDH) with Linear Models: The Wild Bootstrapping Approach of Automatic Variance Ratio Test, the Automatic Portmanteau Test, The Time-Varying Autoregressive Model Approach of Ito et al. (2014, 2016),

- Martingale difference hypothesis (MDH) with Nonlinear Models: the Mcleod-Li Test.

Although conditional heteroscedasticity is a prevalent characteristic of stock market returns, these tests are resilient to it. All tests are computed using the rolling window method (500 observations, 2 years Approximately).

4.1.1. Linear Models:

4.1.1.1. The Wild Bootstrapping Approach of Automatic Variance Ratio Test (WAVR):

Lo and MacKinlay (1988) initially introduced the variance ratio test, which has since become the most frequently used test for the testing of The Random Walk Hypothesis (RWH). The RWH posits that asset prices evolve through a stochastic process in which price changes are arbitrary and unaffected by historical movements. A test of this hypothesis is necessary to ascertain the efficacy of financial markets and the potential for return predictability. Markets should be efficient if price movements are unpredictable. In the alternative, any systematic patterns or correlations in return may suggest market inefficiencies that investors may exploit. The need for thorough statistical approaches for certifying RWH is emphasized by the persistent discourse on market efficiency.

This test examines the relationship between the variation of returns over prolonged holding periods and the variance of returns during shorter intervals. If the null hypothesis posits that a time series adheres to a random walk, the variance of q-period returns should equal q times the variance of one-period returns. This assumption relies on the concept that the variability of returns should rise linearly with the investment horizon if they are stochastic and uncorrelated.

The null hypothesis of the Variance Ratio Test is that the returns follow a random walk, which implies that the variance ratio $\theta(k)$ should be equal to 1 for all k. Deviations from this null hypothesis suggest the presence of predictable components in the returns. For instance, if $\theta(k) < 1$, it indicates negative serial correlation, a phenomenon often associated with mean reversion, where returns tend to be followed by reversals. Conversely, if $\theta(k) > 1$, it suggests positive serial correlation, which is consistent with momentum, where returns tend to be followed by further returns in the same direction. The magnitude and direction of the deviation from unity in the variance ratio provide insights into the nature of the predictability in the time series.

Any divergence from this linear scaling indicates the presence of serial correlation in returns, implying a deviation from random walk behavior. Standard Variance Ratio Tests possess limits, especially when used for financial time series, which often display traits that violate the test's foundational assumptions, notwithstanding their prevalent application. The reliance on asymptotic distributions for statistical inference is a significant constraint, since they may be erroneous in limited samples.

Moreover, heteroscedasticity is a common trait of financial data, signifying that return volatility varies across time. Standard variance ratio tests often presume homoscedasticity (constant variance), and the existence of heteroscedasticity may lead to erroneous test results. A further challenge is the arbitrary choosing of the number of delays (or holding periods) to be included in the test. An inappropriate choice of delays may result in a failure to identify genuine deviations from the random walk hypothesis or, conversely, the identification of spurious patterns.

The Automatic Variance Ratio Test (Kim J. H., 2009) is a revolutionary development that employs data-driven methodologies to determine the most suitable number of delays for the test. This method can improve the test's capacity to identify predictability by allowing the data to drive the selection of the number of delays. The integration of Wild Bootstrapping with the Automatic Variance Ratio Test provides a robust and adaptable framework for evaluating the random walk hypothesis amid authentic financial data attributes. In addition, the development of more rigorous methodologies has been undertaken to overcome these limitations. A method for statistical inference that is resistant to heteroscedasticity is provided by the Wild Bootstrapping approach (Kim J., 2009). Bootstrapping is a resampling technique that, in general, enables the estimation of a statistic's sampling distribution without the presence of strong distributional assumptions. Wild Bootstrapping is a particular form of bootstrap that is specifically designed to address situations in which heteroscedasticity may be prevalent. The wild bootstrap for $AVR(\widehat{K})$ can be conducted as given by equation (2) below:

$$AVR(\widehat{K}) = \sqrt{\frac{T}{\widehat{K}}} \frac{VR(\widehat{K}) - 1}{\sqrt{2}} \sim N(0, 1)$$
⁽²⁾

4.1.1.2. the Automatic Portmanteau Test (AP):

The Automatic Portmanteau test is a more sophisticated variant of the Portmanteau test. (J. Carlos Escanciano, 2009) introduced this test, which employs an entirely data-dependent procedure to ascertain the optimal value of p. The test is given by equation (3):

$$AQ = Q_p^* = T \sum_{i=1}^p \hat{P}_i^2 \qquad AQ \sim X^2$$
(3)

Akaike's information criterion (AIC) and Bayesian information criterion (BIC) are used to determine the optimal delayed order, \hat{P} . The test statistics are distributed according to the Chi-squared distribution, with one degree of freedom.

4.1.1.3. The Time-Varying Autoregressive Model Approach (TV-AR):

The time-varying autoregressive model is derived from the simple autoregressive model. The linear relationship in time series data has been evaluated for a long time using the straightforward autoregressive model. However, the basic model is unable to manage time series data with structural gaps, such as stock returns, due to the fact that the coefficients are fixed. This is a significant drawback of the model. Ito et al. (2014) proposed the time-varying

autoregressive model as a remedy for the limitation. The following is a detailed explanation of how to implement the model in the AMH testing. Initially, the BIC was employed to determine the optimal latency order for each series. Subsequently, a regression analysis based on the TV-AR model is performed, using the theoretical framework detailed below. The TV-AR model is articulated as a set of equations, predicated on the notion that parameter dynamics constrain the parameters.

The TV-AR model is presented in the form of an equation system as follows (with the assumption that parameter dynamics restrict the parameters):

$$X_t = \alpha_0 + \alpha_{1,t} x_{t-1} + \alpha_{2,t} x_{t-2} + \dots + \alpha_{q,t} x_{q-1} + u_t$$

(1)

$$\alpha_{i,t} = \alpha_{i,t-1} + \nu_{i,t} (i = 1, 2, ..., q)$$

(2)

$$E(u_t) = E(u_t^2) = E(u_t u_{t-m}) = 0 \forall m$$
$$E(v_{i,t}) = E(v_{i,t}^2) = E(v_{i,t} v_{t-m}) = 0 \forall m$$

where x_t represents the stock return at time t, α_i is the time-varying coefficients, u_t and v_t are the residuals of the model. (1) and (2) form a system of simultaneous equations for the model. Denotation of matrices are deployed as follows:

$$X_{t-1} = \begin{bmatrix} X_{t-1} \\ X_{t-2} \\ \vdots \\ X_{t-q} \end{bmatrix}; A_t = \begin{bmatrix} \alpha_{1,t} & \alpha_{2,t} & \dots & \alpha_{q,t} \end{bmatrix}; I_q \text{ is an identity}$$

matrix of order q.

Equation (1) can be rewritten accordingly:

$$X_t = \alpha_0 + x_{t-1}^T \times A_t^T + u_t$$

where x_{t-1}^T , A_t^T are the transpose of X_{t-1} , A_t correspondingly

Assign a range of values (from 1 to *T*) to the parameter t to obtain the following equation:

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$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix} = \begin{bmatrix} 1 & x_0^T & & O_{1 \times T} \\ 1 & & x_1^T & & \\ \vdots & & \ddots & \\ 1 & O_{1 \times T} & & x_{T-1}^T \end{bmatrix} \times \begin{bmatrix} \alpha_0 \\ A_1^T \\ \vdots \\ A_T^T \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_T \end{bmatrix}$$
(3)

Deontay
$$\begin{bmatrix} x_1\\x_2\\\vdots\\x_T \end{bmatrix}$$
; $\beta = \begin{bmatrix} u_0\\A_1^T\\\vdots\\A_t^T \end{bmatrix}$; $U = \begin{bmatrix} u_1\\u_2\\\vdots\\u_T \end{bmatrix}$; $M = \begin{bmatrix} 1 & x_0 & \cdots & O_{1\times T} \\ 1 & x_1^T & \cdots & \\ 1 & O_{1\times T} & \cdots & x_{T-1}^T \end{bmatrix}$

where $O_{1 \times T}$ is a 1 \times *T* null matrix. Equation (3) can be simplified accordingly:

$$y = M \times \beta + u \tag{4}$$

In a similar manner, Equation (2) can be re-written as:

Denote :
$$Z = \begin{bmatrix} -A_0^T \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$
; $W = \begin{bmatrix} 0_{q \times 1} & -I_q & & 0_{q \times q} \\ 0_{q \times 1} & I_q & -I_q & \vdots \\ \vdots & & \ddots & \\ 0_{q \times 1} & 0_{q \times q} & & \dots & -I_q \end{bmatrix}$; $V = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_T \end{bmatrix}$

The following equation is obtained:

$$Z = W \times \beta + V \tag{5}$$

Equations (4) and (5) form the equation system of the TV-AR model in the matrix form. It can also be deducted as below:

$$\begin{bmatrix} \gamma \\ Z \end{bmatrix} = \begin{bmatrix} M \\ W \end{bmatrix} \beta + \begin{bmatrix} u \\ v \end{bmatrix}$$

The result below is obtained using ordinary least squares (OLS) regression:

$$\hat{\beta} = \left(\begin{bmatrix} M \\ W \end{bmatrix}^T \begin{bmatrix} M \\ W \end{bmatrix} \right)^{-1} \begin{bmatrix} M \\ W \end{bmatrix}^T \begin{bmatrix} \gamma \\ Z \end{bmatrix}$$

Market efficiency is quantified using the following formula, which was used in the work of Noda (2016), a special case of Ito et al. (2014):

$$ME_t = \left| \frac{\sum_{j=1}^{p} \hat{\alpha}_{j,t}}{1 - \left(\sum_{j=1}^{p} \hat{\alpha}_{j,t}\right)} \right|$$

His formula measures the deviation from the zero coefficients of the corresponding time-varying moving average (TV-MA) model to our TV-AR $_{-} \circ r \wedge _{-}$

model. Hence, the large deviations of ME_t from zero is considered evidence of market inefficiency.

Lastly, the authors also employ the bootstrap procedure to construct the confidence band for ME_t . The details of the bootstrapping steps are elaborated in the work of Noda (2016). The bootstrap is conducted under the null hypothesis of zero autocorrelations with 2000 iterations.

4.1.2. non-Linear Models: the Mcleod-Li Test:

Stock returns typically exhibit nonlinear dependency, which is disregarded by linear tests. We implement the McLeod–Li test (McLeod and Li, 1983) to accurately represent this nonlinear dependency. The test statistics are denoted by:

$$Q_{(m)} = \frac{n(n+2)}{n-k} \sum_{k=1}^{m} r_a^2(k)$$

Where $r_a^2(k) = \frac{\sum_{t=k-1}^n e_t^2 e_{t-k}^2}{\sum_{t=1}^n e_t^2}$ $(k = 0, 1, ..., n-1), r_\alpha^2$ denotes autocorrelation of e_t^2 . If the e_t series is IID, then the $Q_{(m)}$ is asymptotically distributed as x_m^2 : The null hypothesis of the test represents no return autocorrelation against the presence of the nonlinear ARCH/GARCH effects in data.

5. Empirical results:

In this section, performing empirical analysis in two steps the first step contains three linear tests (the wild Bootstrapping of AVR test, the Automatic Portmanteau test and the TV-AR model), and the nonlinear test of MacLeod-Li and the generalized spectral analysis. Hereafter the second stage as a further and robust test contains two tests the state space test (Markov Switching Model), and a measure of long-term memory of time series, The Hurst exponent.

5.1. Econometrics Analysis:

5.1.1. Linear Models:

5.1.1.1. The Wild Bootstrapping Approach of Automatic Variance Ratio Test (WAVR):

Figure 3 illustrates the progression of random bootstrapping within AVR test statistics. The results indicate that the efficiency degree is unstable, fluctuating between efficiency and inefficiency, with a trend toward the improvement of market efficiency. Panel (A) shows this pattern well; the AVR test data fluctuated but stayed above the lower limit from 2020 to 2022, indicating market inefficiency. This period defined the culmination of the index variations' development. No intrinsic variation could explain such performance.

For the Americas, panel (B) displays the same pattern as panel (A). However, the AVR test data in the EMEA and APAC regions fluctuated while remaining above the upper limit for the duration of the period, indicating that the market is not efficient. For values that exceed 1, a momentum effect is observed in the market. Indexes may experience inefficiencies as a result of reduced economic development, size, liquidity, depth, breadth, requirements, and market accessibility, all of which can be significantly influenced by global economic disruptions. This inefficiency leads to a heightened degree of performance variability in the long term.

Panel (C) is more variable than panel (B), but episodic inefficiency can make this effect greater than one (momentum) or less than one (mean reversion). Economic development, market size, and investors, particularly foreign ones, reinforce these effects. The test results support AMH and indicate that, despite recent disruptions, the groundwork established by these reforms may facilitate a more rapid recovery. Given the reinstatement of investor confidence, it is imperative to observe the modifications and progress of these markets amid persistent economic challenges.

Figure 3: Shows The Wild Bootstrapping Approach of Automatic Variance Ratio Test (WAVR) for Developed, Emerging, and Frontier Markets. Panel (A.1): Developed Markets (Americas)



Panel (A.2): Developed Markets (EMEA)


















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5.1.1.2. the Automatic Portmanteau Test (AP):

Figure 4 displays the results of the Automatic Portmanteau test (AP), which is run as a robust check of the WAVR test to ensure that no positive and negative correlation offset happened. The results are consistent with the WAVR test. The efficiency degree is unstable, varying between efficiency and inefficiency, with a trend toward improving market efficiency. As a result, the test results are in favor of the AMH.



Figure 4: Shows the Automatic Portmanteau Test (AP) for Developed, Emerging, and





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5.1.1.3. The Time-Varying Autoregressive Model Approach (TV-AR):

The degree of market efficiency (MEt) obtained from this approach is presented in Figure 5, with the solid black line showing the time-varying degree of market efficiency (Met), Dashed black lines represent the 95% confidence bands, Blue dotted line is the efficiency threshold, with guidance by highlight the green regions indicate *Efficient* market states (Efficiency < 0.05), on the other hand the red regions indicate *Inefficient* market states (Efficiency \geq 0.05).

The results of the TV-AR demonstrate a strong alignment with the findings from the other set of autocorrelation tests. This acts as confirmation for the series of autocorrelation tests, showcasing the strength of the findings and the alignment of the conclusions with an alternative method.

The main variation between efficiency and inefficiency for different regions, in all developed markets, and the Americas in emerging markets is episodic efficiency followed by high spikes of inefficiency; these spikes are corrected every time to make an efficient episode. These corrections can be caused by Changes in Economic Policy or Regulation, market structure, liquidity level, and market size. On the other hand, the emerging markets (EMEA, APAC) and frontier markets can see the opposite. Efficiency is characterized by short episodes with higher spikes and lower corrections, while inefficiencies can persist for longer periods. This effect may present opportunities for abnormal returns but also indicates potential long-term inefficiencies in the market.

Figure 5: Shows The Time-Varying Autoregressive Model Approach (TV-AR) for Developed, Emerging, and Frontier Markets.



Panel (A.1): Developed Markets (Americas)



Panel (A.2): Developed Markets (EMEA)























The time-varying degree of Market efficiency test. Notes: The bold black line indicates the time-varying degree of market efficiency and the Dashed black lines represent the 95% confidence bands, Blue dotted line is the efficiency threshold, with guidance by highlight the green regions indicate Efficient market states (Efficiency < 0.05), on the other hand the red regions indicate Inefficient market states (Efficiency ≥ 0.05).

5.1.2. non-Linear Models:

4.1.2.1. the Mcleod-Li Test:

The MacLeod-Li test, a powerful tool in our research, effectively detects nonlinear dependency in time series returns. The test results, as shown in Figure 6, reveal that the degree of market efficiency has undergone several alternating periods of efficiency and inefficiency. Notably, the linear tests have overlooked some of these periods of inefficiency. The p-value above 5% significance line indicates market efficiency, while market inefficiency is indicated by a p-value below that line. Consequently, the markets have alternated between periods of efficiency and inefficiency. This test offers a unique perspective on nonlinear dependency, a perspective that linear tests may overlook (Cont, 2001). Market psychology and transaction costs, two significant factors causing non-linearity, are well-documented. Several studies have identified these nonlinear dependencies (Almudhaf et al., 2020; Ghazani et Ebrahimi, 2019; Lim et Brooks, 2011; Ghazani et Araghi, 2014; Shahid et al., 2019). Therefore, the inclusion of a nonlinear test may yield more accurate results, given the stock exchange's nonlinear effects. This underscores that only developed markets experience periods of efficiency and inefficiency. These changes are evident in a nonlinear test, indicating that different markets may react and adjust to these conditions over time, which can stabilize in the long run. Finally, the test results align with previous tests, thereby supporting the adaptive market hypothesis (AMH).

Figure 6: Shows the Mcleod-Li Test for Developed, Emerging, and Frontier Markets.





























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18 Year

16

14



The p-values of the MacLeod-Li test. Notes: The bold blue line indicates The p-values of the MacLeod-Li test and the black lines represent the 5% significance level, the Green shaded areas: Efficient periods (p-value ≥ 0.05), and the Red shaded areas: Inefficient periods (p-value < 0.05).

5.2. Further and Robust Analysis: Markov-switching model:

The Markov Switching analysis conducted in 26 countries, which are classified as developed, emergent, and frontier markets, reveals distinct patterns that shift considerably based on the market type. The model provides evidence of market behavior that varies over time by effectively identifying transitions between high- and low-volatility states.

Low-volatility regimes are maintained for an extended period in developed markets, which is indicative of institutional robustness and enhanced market efficiency. Emerging markets demonstrate a higher frequency of transitioning, which suggests that they are moderately efficient and are more susceptible to external and policy-driven disruptions. The structural fragility and limited informational efficiency of frontier markets are underscored by their highest volatility and least regime persistence.

Table 2 show the results of Markov switching analysis, with two volatility regimes: The Model identified two distinct regimes: an efficient market regime with low volatility ($\sigma^2 = 3.575e-05e$) for Canda (S&P_TSX Index) and an inefficient market regime with high volatility ($\sigma^2 = 7.777e-05$) for China (SSEC

Index). And Regime Persistence: The model suggests a high probability of remaining in the efficient market regime (p[0->0] = 0.9860) for Canda (S&P_TSX Index), and a low probability of transitioning from the inefficient market to the efficient market (p[1->0] = 0.2508) for Bahrain (BAX Index).

More importantly, the regimes that have been identified are situated on a continuum between efficient and inefficient market states. The Adaptive Market Hypothesis (AMH) posits that the efficiency of a market is contingent upon the environment, the behavior of investors, and the structures of institutions. This pattern is consistent with these notions.

Overall, the results highlight how useful Markov Switching models are for understanding complex market changes and offer a strong way to study how market efficiency changes in different economic systems.

Figure 7: Shows the Markov-switching model for Developed, Emerging, and Frontier Markets.



Panel (A.1): Developed Markets (Americas)



Panel (A.2): Developed Markets (EMEA)



















| Developed | Markets (Am | <u>ericas)</u> | | | | |
|------------------|-------------------|----------------|---------|------------|--------------|--|
| | Market | S&P500 | | S&P_TSX | | |
| | Regressor | Estimate | P-value | Estimate | P-value | |
| Regime-1 | Intercept | 0.0011 | 0.000 | 0.0006 | 0.000 | |
| | Var ₁ | 3.705e-05 | 0.000 | 3.575e-05 | 0.000 | |
| Regime-2 | Intercept | -0.0008 | 0.128 | -0.0020 | 0.019 | |
| | Var ₂ | 0.0003 | 0.000 | 0.0004 | 0.000 | |
| Transition | Matrix | P11 | P21 | P11 | P21 | |
| | Parameters | 0.9804 | 0.0435 | 0.9860 | 0.0799 | |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 | |
| | AIC | -23250.927 | | -24422.541 | | |
| | Log likelihood | 11631.463 | | 12217.271 | | |
| Developed | Markets (EM | EA) | | | | |
| Developed | Market | FTSE | FTSE100 | | DAX | |
| | Regressor | Estimate | P-value | Estimate | P-value | |
| Regime-1 | Intercept | 0.0005 | 0.000 | 0.0009 | 0.000 | |
| 8 | Var ₁ | 4.374e-05 | 0.000 | 6.874e-05 | 0.000 | |
| Regime-2 | Intercept | -0.0010 | 0.105 | -0.0014 | 0.044 | |
| U | Var ₂ | 0.0003 | 0.000 | 0.0004 | 0.000 | |
| Transition | Matrix | P11 | P21 | P11 | P21 | |
| | Parameters | 0.9802 | 0.0668 | 0.9798 | 0.0615 | |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 | |
| | AIC | -23532.396 | | -22038.714 | | |
| | Log | 11772.198 | | 11025.357 | | |
| | likelihood | | | | | |
| | Market | AE | Х | CA | С | |
| | Regressor | Estimate | P-value | Estimate | P-value | |
| Regime-1 | Intercept | 0.0009 | 0.000 | 0.0009 | 0.000 | |
| | Var_1 | 4.914e-05 | 0.000 | 5.263e-05 | 0.000 | |
| Regime-2 | Intercept | -0.0011 | 0.048 | -0.0012 | 0.034 | |
| | Var ₂ | 0.0003 | 0.000 | 0.0003 | 0.000 | |
| Transition | Matrix | P11 | P21 | P11 | P21 | |
| | Parameters | 0.9772 | 0.0536 | 0.9748 | 0.0602 | |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 | |
| | AIC | -23135.375 | | -22841.716 | | |
| | Log | 11573.688 | | 11426.858 | | |
| | likelihood | | | | | |
| Developed | Markets (APA | <u>AC)</u> | 225 | | N. 200 | |
| | Market | Nikkei | 225 | S&P/AS | <u>X_300</u> | |
| | Regressor | Estimate | P-value | Estimate | P-value | |
| Regime-1 | Intercept | 0.0010 | 0.000 | 0.0006 | 0.000 | |
| D | Var ₁ | 9.33e-05 | 0.000 | 4.287e-05 | 0.000 | |
| Regime-2 | Intercept | -0.0020 | 0.034 | -0.0015 | 0.013 | |
| | Var ₂ | 0.0005 | 0.000 | 0.0003 | 0.000 | |
| Transition | Matrix | P11 | P21 | P11 | P21 | |
| | | _ oV • _ | | | | |

Table (2) Markov Switching Model Statistical Analysis Developed Markets (Americas)

| | Parameters | 0.9816 | 0.0773 | 0.9852 | 0.0569 |
|-------------------|------------------|-------------|---------|------------|---------|
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| | AIC | -20867.709 | | -24575.635 | |
| | Log | 10439.855 | | 12293.818 | |
| | likelihood | | | | |
| Source(s): l | Research data | | | | |
| Emerging 1 | Markets (Ame | ricas) | | | |
| | Market | Boves | spa | COLC | AP |
| | Regressor | Estimate | P-value | Estimate | P-value |
| Regime-1 | Intercept | 0.0003 | 0.164 | 0.0003 | 0.045 |
| | Var_1 | 0.0002 | 0.000 | 4.939e-05 | 0.000 |
| Regime-2 | Intercept | -0.0028 | 0.508 | -0.0013 | 0.125 |
| | Var ₂ | 0.0019 | 0.000 | 0.0004 | 0.000 |
| Transition | Matrix | P11 | P21 | P11 | P21 |
| | Parameters | 0.9960 | 0.1098 | 0.9684 | 0.1301 |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| | AIC | -19919.745 | | -22152.618 | |
| | Log | 9965.873 | | 11082.309 | |
| | likelihood | | | | |
| | Market | S&P_BM | V_IPC | <u>.</u> | |
| | Regressor | Estimate | P-value | | |
| Regime-1 | Intercept | 0.0002 | 0.251 | | |
| | Var ₁ | 5.745e-05 | 0.000 | | |
| Regime-2 | Intercept | 2.56e-05 | 0.971 | | |
| | Var ₂ | 0.0003 | 0.000 | | |
| Transition | Matrix | P11 | P21 | | |
| | Parameters | 0.9860 | 0.0656 | | |
| | P-value | 0.000 | 0.001 | | |
| | AIC | -23177.215 | | | |
| | Log | 11594.607 | | | |
| | likelihood | | | | |
| Emerging I | Markets (EME | 2 <u>A)</u> | | - | |
| | Market | EGX(100 | _EWI) | Premier N | Aarket |
| | Regressor | Estimate | P-value | Estimate | P-value |
| Regime-1 | Intercept | 0.0024 | 0.000 | 0.0004 | 0.000 |
| | Var_1 | 0.0001 | 0.000 | 2.039e-05 | 0.000 |
| Regime-2 | Intercept | -0.0056 | 0.000 | -0.0024 | 0.021 |
| | Var ₂ | 0.0007 | 0.000 | 0.0005 | 0.000 |
| Transition | Matrix | P11 | P21 | P11 | P21 |
| | Parameters | 0.9552 | 0.1523 | 0.9684 | 0.1923 |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| | AIC | -19272.027 | | -25324.053 | |
| | Log | 9642.014 | | 12668.026 | |
| | likelihood | | | | |
| | Market | QE_Ge | neral | Tadav | vul |
| | Regressor | Estimate | P-value | Estimate | P-value |

| Regime-1 | Intercept | 0.0005 | 0.000 | 0.0007 | 0.000 |
|--|---|--|--|--|---|
| 8 | Var ₁ | 3.56e-05 | 0.000 | 3.678e-05 | 0.000 |
| Regime-2 | Intercept | -0.0013 | 0.052 | -0.0016 | 0.018 |
| 8 | Var ₂ | 0.0003 | 0.000 | 0.0003 | 0.000 |
| Transition | Matrix | P11 | P21 | P11 | P21 |
| | Parameters | 0.9609 | 0.1444 | 0.9750 | 0.0807 |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| | AIC | -23739.251 | | -23460.603 | |
| | Log | 11875.625 | | 11736.302 | |
| | likelihood | | | | |
| | Market | DFM Ge | eneral | | |
| | Regressor | Estimate | P-value | - | |
| Regime-1 | Intercent | 0.0006 | 0.000 | | |
| Regime-1 | Var | 6.649e-05 | 0.000 | | |
| Regime_? | Intercent | -0.0013 | 0.000 | | |
| Regime-2 | Vara | 0.0013 | 0.290 | | |
| Transition | Val2 Motrix | D11 | D21 | | |
| manshion | Parameters | 0.9851 | 0.0877 | | |
| | P_value | 0.9851 | 0.0077 | | |
| | | -22178 769 | 0.000 | | |
| | Log | 11095 385 | | | |
| | likelihood | 110/5.505 | | | |
| Emerging | Markats (APA | \mathbf{C} | | • | |
| | | | | | |
| Entry | Market | <u>SSE</u> | С | NSE | I |
| <u>Linerging</u> | Market Regressor | <u>SSE</u> Estimate | C P-value | NSE Estimate | P-value |
| Regime-1 | Market Regressor Intercept | SSE Estimate 0.0003 | C P-value 0.094 | NSE Estimate 0.0008 | EI P-value 0.000 |
| Regime-1 | Markets Regressor Intercept Var ₁ | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 | C P-value 0.094 0.000 | NSE Estimate 0.0008 6.029e-05 | DI P-value 0.000 0.000 |
| Regime-1 Regime-2 | Market Market Regressor Intercept Var ₁ Intercept | <u>SSE</u> Estimate 0.0003 7.777e-05 -0.0011 | <u>P-value</u> 0.094 0.000 0.294 | NSE Estimate 0.0008 6.029e-05 -0.0013 | EI P-value 0.000 0.000 0.114 |
| Regime-1 Regime-2 | Market Regressor Intercept Var ₁ Intercept Var ₂ | <u>SSE</u> Estimate 0.0003 7.777e-05 -0.0011 0.0006 | C P-value 0.094 0.000 0.294 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 | <u>P-value</u> 0.000 0.000 0.114 0.000 |
| Regime-1 Regime-2 Transition | Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix | <u>SSE</u> Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 | C P-value 0.094 0.000 0.294 0.000 P21 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 | P-value 0.000 0.000 0.114 0.000 P21 |
| Regime-1 Regime-2 Transition | Markets (1114 <u>Regressor</u> Intercept Var ₁ Intercept Var ₂ Matrix Parameters | <u>SSE</u> Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 | EI P-value 0.000 0.000 0.114 0.000 P21 0.0717 |
| Regime-1 Regime-2 Transition | Markets (1114 Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value | <u>SSE</u> Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition | Markets (MAA Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition | Markets (1114 Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 | P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition | Markets (1114 Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood | SSE Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 | P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition | Markets (1114 Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market | SSE Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 KS1 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition | Markets (MAA Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 <u>KS1</u> Estimate | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 | Markets (MAA Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 <u>KS1</u> <u>Estimate</u> 0.0005 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 | Markets (1114 Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 <u>KS1</u> <u>Estimate</u> 0.0005 5.432e-05 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 Regime-2 | Markets (MAA Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ Intercept Var ₂ | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 <u>KS1</u> <u>Estimate</u> 0.0005 5.432e-05 -0.0011 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 0.107 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 Regime-2 | Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ Intercept Var ₂ | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 <u>KS1</u> <u>Estimate</u> 0.0005 5.432e-05 -0.0011 0.0003 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 0.107 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 Regime-2 Transition | Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix | <u>SSE0</u> Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 <u>KS1</u> Estimate 0.0005 5.432e-05 -0.0011 0.0003 P11 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 0.107 0.000 P21 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 Regime-2 Transition | Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters | SSE Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 KS1 Estimate 0.0005 5.432e-05 -0.0011 0.0003 P11 0.9828 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 0.107 0.000 P21 0.000 P21 0.000 0.107 0.000 P21 0.0645 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 Regime-2 Transition | Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value | SSE Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 KS1 Estimate 0.0005 5.432e-05 -0.0011 0.0003 P11 0.9828 0.000 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 0.107 0.000 P21 0.000 P21 0.000 P21 0.000 0.107 0.000 P21 0.000 0.107 0.000 P21 0.000 0.000 0.000 0.294 0.000 0.294 0.000 0.294 0.000 0.294 0.000 0.294 0.000 P21 0.0856 0.000 0.000 0.294 0.000 0.294 0.000 0.294 0.000 P21 0.0856 0.000 0.000 0.000 0.294 0.000 0.000 0.294 0.0000 0.0000 0.0000 0.00000 0.00000 0.00000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 Regime-2 Transition | Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC | <u>SSE</u> <u>Estimate</u> 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 <u>KS1</u> <u>Estimate</u> 0.0005 5.432e-05 -0.0011 0.0003 P11 0.9828 0.000 -22514.088 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 0.107 0.000 P21 0.000 P21 0.000 0.107 0.000 P21 0.000 0.107 0.000 P21 0.0645 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |
| Regime-1 Regime-2 Transition Regime-1 Regime-2 Transition | Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log likelihood Market Regressor Intercept Var ₁ Intercept Var ₂ Matrix Parameters P-value AIC Log Intercept Var ₁ Natrix Parameters P-value AIC Log Matrix Parameters P-value AIC Log Matrix Parameters | SSE Estimate 0.0003 7.777e-05 -0.0011 0.0006 P11 0.9830 0.000 -21041.925 10526.962 KS1 Estimate 0.0005 5.432e-05 -0.0011 0.9828 0.000 -22514.088 11263.044 | C P-value 0.094 0.000 0.294 0.000 P21 0.0856 0.000 1 P-value 0.002 0.000 0.107 0.000 P21 0.000 P21 0.002 0.000 0.107 0.000 P21 0.0645 0.000 | NSE Estimate 0.0008 6.029e-05 -0.0013 0.0004 P11 0.9852 0.000 -22494.961 11253.480 | P-value 0.000 0.000 0.114 0.000 P21 0.0717 0.000 |

| Frontier M | larkets (EMEA) | | | | |
|-----------------|----------------------------|---------------|-----------|---------------|------------|
| | Market | BAZ | X | AMM | AN |
| | Regressor | Estimate | P-value | Estimate | P-value |
| Regime-1 | Intercept | 0.0001 | 0.076 | -0.0002 | 0.056 |
| | Var ₁ | 8.127e-06 | 0.000 | 8.146e-06 | 0.000 |
| Regime-2 | Intercept | 7.316e-05 | 0.824 | 6.634e-05 | 0.723 |
| | Var ₂ | 7.557e-05 | 0.000 | 5.054e-05 | 0.000 |
| Transition | Matrix | P11 | P21 | P11 | P21 |
| | Parameters | 0.9234 | 0.2508 | 0.9158 | 0.0914 |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| | AIC | -28037.689 | | -25876.870 | |
| | Log | 14024.844 | | 12944.435 | |
| | likelihood | | | | |
| | Market | MAS | SI | MSX | 30 |
| | Regressor | Estimate | P-value | Estimate | P-value |
| Regime-1 | Intercept | 4.388e-05 | 0.629 | -1.246e-05 | 0.871 |
| | Var ₁ | 1.926e-05 | 0.000 | 1.438e-05 | 0.000 |
| Regime-2 | Intercept | -1.364e-05 | 0.983 | -0.0005 | 0.462 |
| | Var ₂ | 0.0002 | 0.000 | 0.0002 | 0.000 |
| Transition | Matrix | P11 | P21 | P11 | P21 |
| | Parameters | 0.9595 | 0.2212 | 0.9683 | 0.2077 |
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| | AIC | -26080.995 | | -27012.590 | |
| | Log | 13046.498 | | 13512.295 | |
| | likelihood | | | | |
| | Market | TUNIN | DEX | | |
| | Regressor | Estimate | P-value | | |
| Regime-1 | Intercept | 0.0003 | 0.000 | | |
| D · 0 | Var ₁ | 1.022e-05 | 0.000 | | |
| Regime-2 | Intercept | -0.0008 | 0.187 | | |
| — | Var ₂ | 0.0001 | 0.000 | | |
| Transition | Matrix | PII | P21 | | |
| | Parameters | 0.9714 | 0.1999 | | |
| | P-value | 0.000 | 0.000 | | |
| | AIC | -28493.548 | | | |
| | Log | 14252.774 | | | |
| F (1) 1 | likelihood | | | | |
| Frontier M | larkets (APAC) | IZ O | r | 101 | т |
| | Market | <u> </u> | l D 1- | | l D. 1. |
| ר י ת | Kegressor | Esumate | r-value | | r-value |
| Kegime-I | Intercept | 0.0014 | 0.000 | 0.0014 | 0.000 |
| Decia 2 | var ₁ | 3.042e-05 | 0.000 | 5.408e-05 | 0.000 |
| Kegime-2 | Intercept | -0.0012 | 0.012 | -0.0025 | 0.000 |
| Transition | var ₂ Motrix | 0.0002 D11 | 0.000 | 0.0003 D11 | 0.000 |
| i ransition | Iviatrix | ГП | P21 | ГП | r21 |

| | Parameters | 0.9547 | 0.0974 | 0.9635 | 0.0887 |
|--------|--------------------|------------|--------|------------|--------|
| | P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| | AIC | -23310.109 | | -22017.808 | |
| | Log | 11661.055 | | 11014.904 | |
| | likelihood | | | | |
| Source | (s): Research data | | | | |

6. Conclusions and Suggestions for Future Research:

6.1. Conclusions:

In this research, AMH investigated its practical implications in crosscountry analysis for different types of markets. Developed, emerging, and frontier financial markets classified based on different economic and market conditions from 2010 to 2024. First, the Martingale Difference Hypothesis (MDH) for autocorrelation linear and nonlinear tests with moving windows used to examine the evolution degree of market efficiency. Secondly, a robust test applied to evidence of market behavior that varies over time by effectively identifying transitions between high- and low-volatility states that are timevarying and if they are related to market inefficiency, as the AMH implies thirdly, inspect the relation between the market efficiency, market inefficiency, and some market conditions, to prove that any strategy can be observed by adaptivity market hypothesis. As a suitable framework to understand financial markets behavior, the empirical findings exhibit that the degree of efficiency is time-varying.

The research indicates that the predictability of stock returns is subject to fluctuations over time. Moreover, the efficacy of each market demonstrates a unique pattern of behavior over time. thereafter Markets have a cyclical pattern of efficiency and inefficiency. The increase in computing power helps with these changes, and the speed at which agents can access information may explain this situation. This leads to a comparison with studies conducted in the Americas for both developed and emerging markets. Despite using different analytical frameworks, the results are consistent with the adaptive market hypothesis. (Kim J. H., 2011; Dzung & Quang, 2019; Fahmy, 2021; ENOW, 2022; Villarreal-Samaniego, 2023; Cruz-Hernández, 2024; Marco Aurélio dos Santos, 2024), in opposite the emerging and frontier markets, showed the effect of inefficiency during the periods, with longer and shorter episodes depending on the size of markets, economic reforms and the ability to regional and international investors to participate in longer terms, this can make some corrections effect then observe

efficient periods, but in some markets the inefficiency can dominate for a longer time, this result can be suitable for the literature studies discussed before, in Europe (Sherlock, 2018; Aleknevičienė, 2021), in Asians (Todea A. U., 2009; Rehman, 2018; Khunnawannaphong, 2024; Ozkan, 2020; Bhatia, 2024; Hirayama, 2020), finally in Africa and Middle east Markets (Ndubuisi, 2018; Aytekin, 2023; Pınar Evrim Mandacı, 2019; Mostafa Lekhal, 2020)

The Egyptian market, currently identified as less efficient, needs a shift toward data-driven strategies. The absence of comprehensive studies has allowed for the rise of subjective decision-making and analysis approaches. The situation presents an urgent need for these approaches to expand and for the market to improve its efficiency. The reality of the Egyptian market is complex, but with the ongoing technological advancements, there is a sense of reassurance for the future. The financial industry is well-positioned to benefit from these advancements with new intelligent analytical tools that can help explore quantitative data and understand more about qualitative data. This technological leap is set to aid the market in developing an objective (systematic) approach driven by data, build more informative strategies for institutional and individual agents, and make the market more stable in the long term.

6.2. Suggestions:

- 1. Adopt a Dynamic Investment Approach: Recognize that market efficiency is not static—alternate between passive and active investment strategies based on observed market conditions, as AMH suggests.
- 2. Leverage Passive Strategies During Efficient Periods: Utilize ETFs, index funds, risk parity, or low-volatility ETFs during highly efficient market phases where alpha generation is less likely.
- 3. Utilize Active Strategies in Inefficient Periods: Exploit momentum and mean reversion techniques, event-driven strategies, and sector/country rotation to capture abnormal returns during less efficient times.
- 4. Focus on Emerging and Frontier Markets for Active Allocation: These markets show more frequent shifts between efficiency and inefficiency, presenting greater opportunities for active strategies.
- 5. Monitor Market Conditions Closely (Liquidity, Crisis Events): Align strategies with real-time conditions such as liquidity levels, volatility, and macroeconomic shocks (e.g., pandemics), which influence market behavior and anomaly profitability.

- 6. Integrate AMH into Strategy Design: Use AMH as a theoretical base when constructing or evaluating adaptive trading models, as it accounts for behavioral and structural changes better than EMH.
- 7. Use Regime-Switching Models for Strategy Adjustment: Incorporate tools like Markov switching models to detect when to toggle between active and passive approaches based on efficiency regimes.
- 8. Expand Research to Sector-Level Analysis: Investigate how adaptivity and AMH apply within specific sectors or asset classes, as each may respond differently to global or local events.
- 9. Combine AMH with Machine Learning for Real-Time Adaptation: Employ ML algorithms to dynamically identify efficiency shifts and optimize portfolio allocations accordingly.
- 10. Encourage Policymakers to Consider AMH in Market Regulation: Regulators should recognize that market efficiency is conditional, adjusting policies during times of crisis or instability to ensure fair and functional markets.

6.3. Future Research:

A limitation of this research is that it does not investigate additional market conditions that could impact efficiency and long-term profitability. In addition, this investigation did not examine alternative trading strategies that could offer additional insights into the AMH. Additionally, it initiated a discussion and left it available for further investigation, as future research.

- 1. Future research could investigate the role of adaptivity across distinct levels of market microstructure to better understand the dynamics of asset pricing and its variations over short- and long-term horizons.
- 2. Event-Driven Trading under Adaptive Market Conditions: A Study of Earnings Announcements.
- 3. Are ESG Strategies Adaptively Priced? An AMH Perspective Across Time and Geography.

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هل تتكيف الأسواق المالية بشكل مختلف؟ دراسة مقارنة بين الدول باستخدام فرضية السوق التكيفي

الملخص

- الهدف : تهدف هذه الدراسة إلى فحص الجوانب المختلفة لفرضية السوق التكيفي (AMH)في سياق السوق المالي العالمي، وهو موضوع يحظى باهتمام واسع وأهمية كبيرة. نسعى للإجابة على سؤال: هل يمكن أن تتكيف الأسواق المالية بشكل مختلف؟ وهو سؤال بالغ الأهمية في ظل المشهد المالي الديناميكي الحالي.
- المنهجية/طريقة الدراسة : تقدم هذه الدراسة نهجًا شاملاً من خلال دمج اختبارات خطية ولا خطية متعددة، لضمان قوة ودقة النتائج. تم استخدام فرضية الفرق للمتغيرات العشوائية (MDH)أو اختبارات الارتباط الذاتي لاكتشاف العلاقات الخطية واللاخطية في السلاسل الزمنية، والتي يمكن من خلالها استنتاج مدى صحة فرضية السوق التكيفي. كما تم استخدام مجموعة من الاختبارات التي تعتمد على تقنيات مختلفة لتجاوز عيوب كل طريقة، مما يعكس عمق وصدق النتائج لمنهجية الدراسة.
- تتعمق الدراسة أكثر بإجراء اختبارات متقدمة إضافية لتعزيز فحص فرضية السوق التكيفي، من
 خلال استخدام نموذج ماركوف التبادلي، و هو أداة قوية لتحليل التحولات في الأنظمة التي تؤثر
 في سلوك السوق المالي. يعزز هذا الأسلوب من قوة الدراسة، ويُمكّن من رصد التغيرات في
 هيكل ديناميكيات السوق وتقديم فهم أشمل لفرضية السوق التكيفي.
- النتائج : تُظهر عوائد الأسهم أكثر قابلية للتنبؤ حتى مع مرور الوقت، كما أن كفاءة كل سوق تُظهر نمطًا سلوكيًا فريدًا ومتغيرًا. كما أن الأسواق تمر بدورات من الكفاءة وعدم الكفاءة، ونتائج الاختبارات تدعم فرضية السوق التكيفية.(AMH)

الكلمات المفتاحية:

فرضية كفاءة السوق(EMH) ؛ فرضية السوق التكيفي (AMH)؛ تحليل عبر الدول؛ الأسواق المتقدمة؛ الأسواق الناشئة؛ الأسواق الحدودية؛ فرضية الفرق للمتغيرات العشوائية (MDH)؛ نموذج ماركوف التبادلي.