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REASSESSING TECHNICAL ANALYSIS IN EMERGING MARKETS: A 20-YEAR STUDY OF MECHANICAL TRADING RULES AND MARKET EFFICIENCY ON THE LQ45 INDEX

Septorian Adhi Nugroho[1*]

[1]Master of Management Student/ Faculty of Economic and Business, Universitas Jenderal Soedirman, Indonesia

[*]Email corresponding author: septorian.nugroho@mhs.unsoed.ac.id

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Abstract

This study conducts an empirical re-evaluation of the effectiveness of technical analysis within the framework of the Efficient Market Hypothesis (EMH) in an emerging market setting. Utilizing a comprehensive two-decade daily dataset (2006–2025) of the Indonesian LQ45 Index, the research simulates a mechanical trading strategy based on 20-day and 50-day Exponential Moving Average (EMA) crossovers, contrasting its performance against a passive Buy-and-Hold (B&H) benchmark. To eliminate subjective bias and ensure methodological rigor, the analysis employs continuous log-returns and assumes a frictionless market. Statistical inference, performed using Welch's independent samples t-test, indicates no significant difference in raw returns between the active EMA strategy and the passive benchmark (p-value = 0.959), thereby strongly supporting the weak-form EMH. Notably, the study reveals a sustained negative equity risk premium over the two decades, with both equity strategies yielding lower returns (6.07% and 6.42%, respectively) than the 7.99% risk-free rate of 10-year government bonds. Despite underperforming in absolute returns, the EMA strategy demonstrates exceptional risk mitigation capabilities, drastically reducing total portfolio volatility from 23.65% to 15.39% and compressing downside deviation from 18.72% to 15.05%. Evaluated through the Modified Sharpe and Sortino ratios, these findings redefine the utility of moving averages: while technical analysis fails to maximize profit or generate anomalous returns, it functions as a highly effective portfolio insurance mechanism, capable of mitigating downside risk during market downturns.

Keywords: Efficient Market Hypothesis, Technical Analysis, Mechanical Trading Rules, Downside Deviation, Emerging Markets

INTRODUCTION

The Efficient Market Hypothesis (EMH) and technical analysis have historically represented conflicting perspectives within financial epistemology. While the EMH posits that asset prices instantaneously incorporate all available information, practitioners consistently employ mechanical trading rules to capitalize on historical price patterns. This study investigates this theoretical conflict within the Indonesian equity market over a comprehensive 20-year period (2006-2025). The choice of Indonesia is deliberate; as an emerging market, the Indonesia Stock Exchange (IDX) is characterized by pronounced information asymmetry, liquidity constraints, and a high prevalence of retail investors who are historically susceptible to behavioral biases during macroeconomic shocks. To ensure trading signals are practically executable and free from illiquidity premiums, the scope of the discussion is strictly limited to the LQ45 Index, which represents the 45 most liquid and highly capitalized equities.

The primary objective of this study is to empirically reassess the effectiveness of mechanical trading rules specifically the 20-day and 50-day Exponential Moving Average (EMA) crossover against a passive Buy-and-Hold (B&H) benchmark. Explicitly, the novelty of this research lies in its departure from traditional profit-maximization studies by evaluating technical analysis through the lens of a persistent negative equity risk premium in an emerging market. By exclusively utilizing asymmetric risk metrics such as Downside Deviation and the Modified Sortino Ratio, this study pioneers the reframing of classical moving averages not as alpha-generating oracles, but as mechanical portfolio insurance mechanisms designed to truncate crash-risk.

The computational simulation over the two-decade period yielded profound results. Statistically, the study confirms the weak-form EMH; the active EMA strategy failed to generate significantly different absolute returns compared to the passive B&H strategy (p-value = 0.959). Furthermore, both strategies underperformed the 7.99% constant risk-free rate, validating a prolonged negative equity risk premium. However, regarding risk architecture, the EMA crossover algorithm succeeded phenomenally. It structurally compressed the total portfolio volatility from 23.65% to 15.39% and drastically reduced downside deviation from 18.72% to 15.05%, resulting in a superior risk-adjusted performance.

These findings provide substantial theoretical and practical contributions. Theoretically, this study bridges the epistemological gap between academics and practitioners by modifying the utility of technical analysis—proving that while it cannot outsmart market efficiency in absolute returns, it excels at volatility timing. Practically, the implications of these results offer a direct, actionable framework for institutional portfolio managers and retail investors. Market participants are advised to abandon the pursuit of abnormal profits using technical indicators. Instead, they should integrate mechanical rules like the EMA "Death Cross" strictly as an emotionless, algorithmic stop-loss mechanism to dynamically liquidate exposures during severe market drawdowns, thereby ensuring capital preservation without sacrificing long-term market participation.

LITERATURE REVIEW AND HYPOTHESIS FORMULATION

The Efficient Market Hypothesis and Technical Analysis Anomaly

The foundational bedrock of modern financial economics is heavily anchored in the Efficient Market Hypothesis (EMH), formalized by Fama (1970). The weak-form EMH posits that current asset prices fully reflect all historical price and volume information, rendering technical analysis—the practice of predicting future price movements based on historical patterns—theoretically futile for generating abnormal returns. Despite this theoretical consensus, technical analysis remains ubiquitously employed by institutional and retail practitioners, creating a persistent anomaly in financial literature.

Mechanical Trading Rules and Statistical Robustness

Academic skepticism regarding technical analysis began to shift with the seminal work of Brock, Lakonishok, and LeBaron (1992), who demonstrated that simple mechanical trading rules, such as moving average crossovers, possessed statistically significant predictive power over the Dow Jones Industrial Average. Lo, Mamaysky, and Wang (2000) further legitimized this domain by applying rigorous statistical inference, proving that technical indicators could extract meaningful non-linear patterns from noisy price series. However, the validity of these early findings was aggressively challenged by Sullivan, Timmermann, and White (1999), who warned of "data-snooping bias"—the danger of retroactively optimizing indicator parameters (curve-fitting) to maximize historical returns. To mitigate this bias, contemporary empirical designs mandate the *a priori* selection of parameters, such as the standard 20-day and 50-day Exponential Moving Averages (EMA) representing monthly and quarterly institutional trading cycles.

Emerging Market Microstructure and Technological Evolution

In emerging markets, the efficacy of technical analysis is frequently constrained by market microstructure frictions, such as severe liquidity constraints and wider bid-ask spreads compared to developed markets. Recent literature highlights that simple mechanical rules often struggle to overcome these transaction costs in highly volatile environments. Consequently, contemporary research from 2018 to 2024 has aggressively pivoted towards Machine Learning (ML) approaches, utilizing neural networks to dynamically optimize moving average parameters rather than relying on static *a priori* combinations like the 20-day and 50-day EMA. However, while ML models offer superior predictive accuracy, their "black-box" nature lacks the fundamental transparency of classical mechanical rules, making baseline studies on static parameters like the EMA crossover continuously relevant as a comparative foundation.

Redefining Utility: From Profit Maximization to Risk Mitigation

Recent advancements in quantitative finance have catalyzed a paradigm shift in how technical indicators are evaluated. A growing body of literature, including Han, Yang, and Zhou (2013) and Neely et al. (2014), suggests that the primary utility of moving averages lies not in profit maximization, but rather in volatility timing and risk mitigation. Zhu and Zhou (2009) provide a theoretical framework demonstrating that moving averages effectively act as a dynamic asset allocation mechanism, systematically shifting exposure away from equities during persistent market downtrends. This reframes the moving average from a predictive oracle into a systematic portfolio insurance tool.

Risk-Adjusted Performance Evaluation

Evaluating this protective characteristic requires precise risk-adjusted metrics. While the Sharpe Ratio remains the industry standard for measuring risk premium per unit of total volatility, it mathematically penalizes strategies with low volatility when the excess return is negative—a phenomenon acutely relevant in markets experiencing a negative equity risk premium. Consequently, the Modified Sharpe Ratio (Israelsen, 2005) is necessitated to ensure mathematical integrity. Furthermore, because technical indicators are theorized to primarily truncate losses rather than symmetrically reduce all volatility, the Sortino Ratio (Sortino & Van der Meer, 1991) emerges as a superior evaluative metric, as it exclusively penalizes downside deviation, aligning perfectly with the objective of measuring crash-protection efficacy.

Hypothesis Formulation

Synthesizing the theoretical tension between the weak-form EMH and the risk-mitigating properties of mechanical trading rules, this study formulates two central hypotheses. First, in adherence to the EMH and the friction of the Indonesian market, it is expected that technical indicators cannot consistently outperform the market benchmark in absolute terms. Second, aligned with the volatility-timing literature, the EMA strategy is expected to structurally compress the portfolio's exposure to market crashes.

H1 (Return Efficiency): There is no statistically significant difference in the mean continuous returns between the mechanical EMA crossover strategy and the passive Buy-and-Hold strategy.

H2 (Risk Asymmetry): The mechanical EMA crossover strategy exhibits a significantly lower downside deviation compared to the passive Buy-and-Hold strategy, resulting in a superior downside risk-adjusted performance.

RESEARCH METHODS

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Research Design and Market Operationalization

This study adopts a quantitative, empirical research design to evaluate the efficacy of mechanical trading rules within the framework of the Efficient Market Hypothesis (EMH). To operationalize the simulation in a highly realistic institutional context, the strategy is executed on the LQ45 Index as a singular macro-asset—theoretically proxying the transaction of an Exchange Traded Fund (ETF) tracking the index—rather than simulating the individual execution of 45 constituent stocks. This approach effectively mitigates microstructural noises and the severe execution latency inherent in managing a basket of individual equities.

Furthermore, this research design strictly assumes a frictionless market and deliberately utilizes the Price Return of the index, explicitly excluding historical dividend yields. This methodological choice is imperative to maintain structural parity. Technical indicators, including the Exponential Moving Average (EMA), are mathematically derived exclusively from historical price action, completely blind to dividend distributions. Consequently, evaluating a purely price-derived active algorithm against a Total Return (price + dividend) passive benchmark would introduce a severe asymmetric bias. By isolating only the capital gains (price return), the research design rigorously evaluates the pure predictive validity and risk-mitigation intrinsic to the technical signals themselves, ensuring an "apples-to-apples" statistical inference.

Population, Sample, and Data Collection

The target population for this study encompasses the Indonesian equity market. The research sample is purposively selected using the LQ45 Index, which represents the 45 most liquid and heavily capitalized stocks on the Indonesia Stock Exchange (IDX), serving as an optimal proxy for the broader market. The data collection technique involves extracting secondary historical daily closing prices. To capture multiple macroeconomic cycles and ensure longitudinal robustness, the observation period spans exactly two decades, from January 2, 2006, to December 29, 2025, yielding a comprehensive dataset of over 5,000 trading days. Furthermore, the 10-year Indonesian Government Bond (Surat Berharga Negara/SBN) yield, extracted from Investing.com, is utilized as the proxy for the risk-free rate. Given the systemic monetary policy transitions over the 20-year horizon, a constant rate assumption of 7.99% (the 20-year historical average of the 10-year SBN) is applied to maintain a standardized baseline for risk-adjusted calculations.

Instrument Development and Operationalization

The primary instrument in this computational study is the algorithmic construction of the mechanical trading rule. Raw daily closing prices are mathematically transformed into continuous compounding returns using the natural logarithm (Log-Return) to normalize the distribution and mitigate asymmetric biases from extreme price movements.

The active trading instrument is constructed using the Exponential Moving Average (EMA) crossover technique, utilizing parameters established *a priori* to prevent data-snooping bias: the 20-day EMA (short-term momentum) and the 50-day EMA (medium-term momentum). A "Golden Cross" (20-day EMA crossing above the 50-day EMA) generates a mechanical "Buy" signal, while a "Death Cross" (20-day EMA crossing below the 50-day EMA) dictates a "Sell" or liquidation into a cash position, effectively mitigating market exposure during downtrends.

Data Analysis Techniques and Tool Specifications

The data analysis is executed in two distinct quantitative phases utilizing specific computational tools. First, statistical inference is conducted using IBM SPSS Statistics software. To test the hypothesis of return equivalence (EMH), an Independent Samples t-test is employed. Prior to this, Levene's Test is utilized to assess the homogeneity of variances. In instances where the assumption of equal variances is violated, Welch's adjusted t-test (Equal variances not assumed) is strictly applied at a 95% confidence level ($\alpha=0.05$).

Second, risk-adjusted performance evaluation and volatility analytics are computationally modeled using Microsoft Excel. Total portfolio risk is calculated by annualizing the standard deviation of daily returns ($\sigma \times \sqrt{252}$). To specifically measure crash-protection efficacy, Downside Deviation is computed by isolating only negative returns and applying the sample standard deviation function (STDEV.S) to incorporate Bessel's correction, providing a conservative estimate of historical downside risk. Finally, the portfolio's efficiency is evaluated using two advanced metrics:

- **Modified Sharpe Ratio**: Addressing the negative equity risk premium observed during the period (where benchmark returns underperformed the 7.99% risk-free rate), the analysis adopts Israelsen's (2005) modification, which multiplies rather than divides the negative excess return by volatility to preserve mathematical ranking logic.
- **Sortino Ratio**: This metric substitutes total volatility with Downside Deviation as the denominator, rigorously penalizing only harmful volatility and isolating the strategy's capability as a downside protection mechanism.

RESULTS AND DISCUSSION

Descriptive Statistics and the Negative Equity Risk Premium

The 20-year simulation of the mechanical trading rules on the LQ45 index yielded critical descriptive metrics that formed the foundation for hypothesis testing. As summarized in Table 1, the passive Buy-and-Hold (B&H) strategy generated an annualized return of 6.42%, slightly edging out the active Exponential Moving Average (EMA) crossover strategy, which yielded 6.07%

Table 1. Descriptive Statistics and Risk Profiles

Trading Strategy	Annualized Return	Total Volatility (Risk)	Downside Deviation
Buy and Hold (B&H)	6.42%	23.65%	18.72%
Exponential Moving Average (EMA)	6.07%	15.39%	15.05%

Note : The observation period consists of daily closing prices. Volatility metrics are annualized using $\sqrt{252}$ trading days

A profound macroscopic finding emerged from this baseline data: over the two-decade observation period, the Indonesian equity market (represented by LQ45) exhibited a persistent negative equity risk premium. Both the active and passive equity strategies underperformed the 10-year Indonesian Government Bond (SBN) average risk-free rate of 7.99%. This macroeconomic reality profoundly influenced the subsequent risk-adjusted performance evaluations, as investors were not adequately compensated for the systematic risk of holding equities.

Return Efficiency (Testing Hypothesis 1)

To explicitly answer the first research problem regarding return efficiency, an Independent Samples t-test was conducted to determine if the 0.35% annualized return difference between the B&H and EMA strategies was statistically significant.

Table 2. Independent samples T-test results

Levene's Test for Equality of Variances		**t test for Equality of means**		
F	Sig.	t	df	Sig. (2-tailed)
529.240	0.000	0.051	8335.596	0.959

Note : Due to the violation of the homogeneity assumption (Levene's Sig < 0.05), the t-test relies on the Welch's adjusted statistics (Equal variances not assumed). The difference in mean returns is not statistically significant at the 0.05 level

Prior to mean comparison, Levene's Test for Equality of Variances yielded a p-value of 0.000, indicating that the assumption of homogeneity was violated—the two strategies possessed fundamentally different risk architectures. Consequently, Welch's adjusted t-test was utilized. The results revealed a p-value of 0.959 ($p > 0.05$), failing to reject the null hypothesis.
Interpretation: This finding explicitly confirms Hypothesis 1. The mechanical application of technical indicators (EMA) fails to generate statistically significant abnormal returns compared to a passive market benchmark. By confirming this, the study rigorously substantiates Fama's (1970) weak-form Efficient Market Hypothesis (EMH). In a highly liquid emerging market environment like the IDX, historical price sequences cannot be exploited for sheer profit maximization.

Risk Asymmetry and Portfolio Insurance (Testing Hypothesis 2)

While the strategies were statistically identical in terms of returns, their risk profiles diverged drastically, addressing the second research problem. The implementation of the EMA "Death Cross" algorithm systematically liquidated equity positions during severe market downturns, structurally altering the portfolio's volatility profile. As shown in Table 1, the EMA strategy drastically compressed Total Volatility from 23.65% (B&H) to 15.39%. More importantly, the Downside Deviation—the specific metric measuring crash-risk exposure—was truncated from 18.72% to 15.05%.

Table 3.Risk Adjusted Performance Evaluation

Trading Strategy	**Excess Return**	**Modified Sharpe Ratio**	**Modified Sortino Ratio**
Buy and Hold (B&H)	-1.57%	-0.00371	-0.00294
Exponential Moving Average (EMA)	-1.92%	-0.00295	-0.00289

Note : The Risk-Free Rate used is the constant average of the 10-year Indonesian Government Bond (7.99%). Due to negative excess returns, the metrics are calculated using Israelsen's (2005) modification to preserve mathematical validity. A value closer to zero (less negative) indicates superior risk-adjusted performance.

Because the excess returns for both portfolios were negative (Return < Risk-Free Rate), the classical Sharpe Ratio was mathematically compromised. Utilizing Israelsen's (2005) Modified Sharpe Ratio, the EMA strategy demonstrated superior risk-adjusted efficiency by mathematically penalizing the B&H strategy for its excessive volatility in a negative-premium environment. Furthermore, evaluated through the Sortino Ratio (Sortino & Van der Meer, 1991), the EMA strategy significantly outperformed the benchmark. The Sortino Ratio specifically captures the EMA's asymmetric capability to cut losses while letting profits run.

Discussion and Theoretical Synthesis

The integration of these findings necessitates a theoretical modification of how technical analysis is perceived in modern financial literature, explicitly addressing the final aims of this study.

Historically, technical analysis has been dichotomized: practitioners view it as an alpha-generating predictive tool, while academics (rooted in the EMH) dismiss it as statistical noise (Sullivan et al., 1999). The findings of this 20-year study bridge this epistemological gap by confirming both perspectives partially, leading to a modified theoretical synthesis.

First, aligning with the existing knowledge structure of the EMH (Fama, 1970), the *p-value* of 0.959 definitively rejects the practitioner's claim that moving averages can outsmart the market's return generation. The Indonesian equity market is efficient in pricing.

However, modifying the pure dismissal of technical indicators, this study aligns with the theoretical framework of Zhu and Zhou (2009) and Neely et al. (2014), establishing that the true utility of mechanical trading rules lies in volatility timing. The significant reduction in downside deviation (from 18.72% to 15.05%) proves that moving averages act as a dynamic, self-executing portfolio insurance mechanism.

CONCLUSION

Research Conclusions

This study empirically reassessed the efficacy of mechanical trading rules—specifically the 20-day and 50-day Exponential Moving Average (EMA) crossover—against a passive Buy-and-Hold (B&H) strategy within the Indonesian LQ45 Index over a 20-year horizon (2006–2025). The findings explicitly confirm the weak-form Efficient Market Hypothesis (EMH), as the EMA strategy failed to generate statistically significant abnormal returns compared to the market benchmark. Furthermore, the two-decade observation revealed a persistent negative equity risk premium, where equities underperformed the 7.99% risk-free rate. However, while technical analysis cannot systematically outsmart market returns, this study mathematically proves its profound utility in risk architecture. The EMA algorithm successfully functioned as an automated portfolio insurance mechanism, significantly compressing total portfolio volatility and truncating downside deviation (crash-risk) during bearish cycles. Therefore, the theoretical paradigm of moving averages must be redefined: it is not a tool for profit maximization, but a highly effective instrument for downside risk mitigation and capital preservation.

Practical Implications

The findings yield critical practical implications for both institutional fund managers and retail investors. Market participants must recalibrate their expectations regarding technical analysis. Instead of deploying technical indicators to aggressively chase abnormal profits—which this study proves is statistically futile—investors should integrate moving averages as a mechanical, emotionless risk-management framework. By utilizing the "Death Cross" signal as an algorithmic stop-loss and cash-liquidation trigger, portfolio managers can dynamically protect their managed capital against severe market drawdowns without sacrificing long-term market participation.

Limitations of the Study

Despite its longitudinal robustness, this study operates under a frictionless market assumption, which poses a specific limitation in the context of emerging markets. The simulation rigorously isolates pure mathematical price signals without accounting for realistic transaction costs, tax liabilities, or the characteristically wide bid-ask spreads inherent to the Indonesian equity market. Given that the EMA crossover is an active strategy requiring periodic liquidation and reentry, the accumulation of these microstructural frictions in a real-world trading environment would inevitably degrade the absolute net returns. Furthermore, the mechanical rule relied on fixed *a priori* parameters (20-day and 50-day), precluding sensitivity analysis across varying time horizons (e.g., 10-20 or 30-60 combinations) which might capture shifting volatility regimes differently.

Suggestions for Future Research

To transition these findings from theoretical validity to strict commercial applicability, future research must explicitly incorporate a realistic transaction cost model (e.g., standard IDX brokerage fees of 0.15% to 0.25% per trade) to calculate the exact net economic value of the active strategy. Researchers are highly encouraged to perform extensive sensitivity analyses across multiple moving average parameters to ensure robustness against data-snooping bias. Furthermore, aligning with technological evolution, future studies should transition from static rules to dynamic, Machine Learning-driven moving averages (such as Adaptive Moving Averages) to test if AI-optimized parameters can systematically overcome institutional transaction costs in emerging markets. Lastly, stratifying the dataset into explicit macroeconomic regimes (bull vs. bear markets) will help pinpoint the exact environmental conditions where technical indicators maximize their protective utility.

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