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The predictability of technical analysis in foreign exchange market using forward return: evidence from developed and emerging currencies

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ABSTRACT

Technical analysis in the foreign exchange (Forex) market has yielded mixed results, particularly regarding its effectiveness over different holding periods in swing trading. This study addresses this gap by evaluating 497 technical trading rules across 10 currencies over 22 years (January 2000 to December 2022). Focusing on swing trading windows of 1-7 days, the research introduces the concept of an 'optimal holding period,' examining how price movements align with trading signals at varying time lags post-signal. The results demonstrate that technical trading rules significantly predict price movements in both developed and emerging market currencies, with emerging markets showing higher levels of predictability. Notably, simple moving average (SMA) indicators perform most effectively for emerging market currencies, while oscillator-based strategies prove more successful for developed markets. These findings have practical implications for Forex traders employing short-term strategies, providing actionable insights for optimizing trade timing. Additionally, the study opens new avenues for future research on the role of technical analysis in enhancing trading performance in global currency markets.

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1. Introduction

The predictability of currency returns is a critical topic due to its potential implications for market efficiency and its practical value for investors. Historically, most asset pricing research has focused on understanding the equity market, where empirical studies have identified various anomalies that prompt investors to apply technical analysis techniques to outperform the market. Technical analysis, often called 'Chartist analysis,' involves generating trading recommendations based on time series properties of financial assets (Hsu et al., 2016). These recommendations can be either qualitative, relying on visual patterns, or quantitative, driven by mathematical models. Numerous studies have examined the predictability and profitability of technical trading rules across financial markets to identify successful trading strategies and test market efficiency. While technical analysis has been thoroughly explored in equity markets, its application to the foreign exchange (FX) market has received comparatively less attention (Park & Irwin, 2007).

The FX market is the world's largest and most liquid financial market, with an average daily trading volume of $7.5 trillion in 2022, a significant increase from around $2 trillion in 2004 (Bank For International Settlements, 2022). Unlike the relatively more stable stock market, the FX market is characterized by high volatility, nonlinearity, and irregular price movements, making it one of the most complex financial environments (Ahmed et al., 2020). These unique features provide FX traders with a wide range of trading opportunities, particularly for short-term strategies, where technical analysis has proven popular. Surveys show that 30–40% of FX traders globally believe exchange rates are primarily driven by technical

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analysis, particularly over short-term horizons of up to six months (Menkhoff & Taylor, 2007). The strong reliance on technical analysis in FX trading reflects a deep-rooted behavior among professional traders, who often find it more effective in navigating the market's intricacies.

Recent research on the application of technical analysis in FX markets has addressed its profitability (Zarrabi et al., 2017), directional currency movement prediction (Yıldırım et al., 2021), market efficiency during financial crises (Yamani, 2021a, 2021b), and the integration of technical analysis with Bayesian statistics (Hassanniakalager et al., 2021). Other studies, like Deng et al. (2021), have investigated specific trading techniques such as the Ichimoku Kinkohyo strategy. However, despite these contributions, results have often been inconsistent due to differences in parameter settings, such as the timing of trading signal generation, and concerns over data mining biases. The inconsistencies across studies highlight the need for a more systematic approach to understanding how technical analysis can be effectively applied in the FX market, particularly in terms of rule parameterization and holding periods.

This study seeks to address this gap by exploring the profitability and parameterization of technical trading rules in FX markets. It investigates the predictability of multiple currencies, spanning developed and emerging markets, to identify optimal rule configurations that real-life traders can apply. A central focus of this research is on the 'optimal holding period,' which is key to maximizing the effectiveness of technical trading rules (TTRs). Specifically, the study addresses three main questions: (i) How effective are specific TTRs in predicting FX price movements during swing trading, and how do parameter settings and holding periods influence their performance? (ii) Does the predictability of technical analysis differ across currencies in developed and emerging markets? (iii) What are the key challenges for technical analysis researchers, and how can they be addressed?

Using a novel methodology, this research evaluates the effectiveness of 497 technical trading rules over a sample of 10 currencies from January 2000 to December 2022. The study focuses on short-term trading, examining how price movements align with trading signals at different day lags after the signals are generated. By introducing the concept of an 'optimal holding period,' the research provides valuable insights into the timing of trades. The results show that technical trading rules predict price movements in developed and emerging market currencies, with higher predictability observed in emerging markets. Among the technical trading rules tested, simple moving average (SMA) indicators performed best with emerging market currencies, while oscillators such as the relative strength index (RSI) were more effective for developed market currencies.

The significance of this research lies in its potential to provide actionable insights for academic researchers and practitioners in the FX market. By focusing on swing trading with a 1–7 day holding period, the study fills a gap in the literature and offers practical recommendations for optimizing TTRs. For traders, these findings suggest specific parameter settings and time lags that can be used to enhance short-term trading strategies. For researchers, the study provides a deeper understanding of how technical trading models can be optimized and adapted to different market conditions, helping to address the inconsistencies often found in previous studies. Additionally, this work contributes to the broader field of asset pricing theory, where technical analysis is often overlooked despite its widespread use among market participants. By exploring FX markets' behavioral and technical aspects, this study offers new perspectives on how technical analysis can inform real-world trading decisions and market efficiency.

The structure of the paper is as follows: Section 1 introduces the research topic. Section 2 provides an overview of the FX market, including the principles and categories of technical analysis. Section 3 reviews the empirical literature on the predictability and profitability of technical trading rules. Section 4 outlines the data and methodology employed in the research. Section 5 presents the main findings, and Section 6 concludes with recommendations for future research avenues.

2. The FX market and technical analysis

The foreign exchange market is a non-centralized financial market where all currencies are bought and sold simultaneously. It is the largest and most liquid financial market globally, with a daily trading volume exceeding $ 7 trillion (Bank For International Settlements, 2022). The gigantic volume of trade in the FX market, the increased competition between market participants, and the sophistication of technology have made the market more complex (Hassanniakalager et al., 2021). The FX market operates continuously from Monday morning in New Zealand to Friday evening in the USA (Chan et al., 2019). Typically, the default ISO currency pair features the USD as the base currency and the other as the quote, except for pairs like EUR/USD, GBP/USD, NZD/USD, and AUD/USD, where the USD is the quote currency (Ozturk et al., 2016). The major segments of the FX market include spot transactions, forward market, FX swaps, and FX options (Bank For International Settlements, 2022; Zarrabi et al., 2017).

Technical analysis refers to the application of historical market data that helps to forecast the direction or trend of financial asset prices (Hassanniakalager et al., 2021). It dates back to the early work of Charles Dow, the Wall Street Journal editor, using past price behavior to make trading decisions in financial markets (Neely, 1997). Known as 'Chartist analysis,' it involves techniques that provide recommendations for financial assets based on their time series properties (Hsu et al., 2016). Although the technical analysis theories vary from one to another, the main viewpoint is the recurrent nature of patterns or trends in the prices of securities. Chartists optimistically believe that learning these patterns enables them to predict securities' future prices. Technical analysis has attracted contrasting views about its effectiveness in predicting market movements (Coakley et al., 2016). Empirical findings from several early and widely cited studies assessing technical analysis in the stock market, such as Fama and Blume (1966), Vanhorne and Parker (1968), and Jensen and Benington (1970), reported negative returns.

Understanding technical analysis requires exploring its relation to the efficient market hypothesis (EMH), principles, and categories. Weak-form efficiency, a form of EMH, states that using technical trading rules (TTRs) by exploiting historical data may not fetch profitable returns (Zarrabi et al., 2017). On the contrary, as a part of the ongoing debate, existing technical analysis research produced favorable evidence, yielding positive returns. Researchers outlined three fundamental principles of technical analysis (Neely, 1997; Ozturk et al., 2016; Teodor & Bogdan, 2015). First, market action, represented by price movement and volume, discounts all relevant information, negating the need to forecast fundamental drivers. Second, financial asset prices move in trends, with technical analysis aiming to identify these trends early and make profits by selling (buying) when the price increases (decreasing). Third, asset price history repeats itself, with prices moving in recognizable and persistent patterns (Menkhoff & Taylor, 2007).

Technical analysis can be divided into qualitative and quantitative approaches (Coakley et al., 2016; Menkhoff & Taylor, 2007; Ozturk et al., 2016). The qualitative approach, or Chartism, involves visually inspecting time-series data charts to identify long-term trends and patterns by connecting peaks and troughs geometrically. The quantitative approach, involving technical trading rules (TTR), focuses on short-term fluctuations and uses mathematical formulas and algorithms to analyze price data (Neely, 1997). Oscillator rules, a commonly utilized TTR, include the Relative Strength Index (RSI), which measures the speed of price movement to indicate overbought or oversold conditions. Likewise, Moving Average trading rules identify trends and filter out short-term fluctuations. Other advanced tools, such as Fibonacci retracement and Elliot waves, are extensively employed in technical analysis (Jarusek et al., 2022). Combining qualitative and quantitative techniques is common in technical analysis. However, the qualitative approach involves more subjective analysis due to behavioral and judgmental biases.

3. Empirical review

Technical analysis in the FX market has gained significance because of its higher predictability and profitability (Hassanniakalager et al., 2021; Lebaron, 1999; Menkhoff & Taylor, 2007; Quintanilla García et al., 2012; Teodor & Bogdan, 2015; Zarrabi et al., 2017). Prior studies highlight that decision-makers and FX professionals widely use technical analysis to forecast currency fluctuations. Technical trading rules can be classified into several categories, potentially thousands of variations based on different rules and parameterizations (Hsu et al., 2016; Kuang et al., 2014). Despite their popularity, there is a notable lack of literature focusing on many trading rules in emerging FX markets (Kuang et al., 2014). The scope of recent works related to technical analysis in the FX market were confined to assessing currencies during global financial crisis (Yamani, 2021a), integrating technical analysis with Bayesian statistics (Hassanniakalager et al., 2021), predicting the directional movement of currencies using a deep learning technique (Yıldırım et al., 2021) and examining limited number of trading rules (Dockery & Todorov, 2023).

Earlier studies testing technical analysis in FX and futures markets have generally reported abnormal profits (Park & Irwin, 2007). For instance, Cornell and Dietrich (1978) observed the profitability of technical analysis using filter rules and moving averages in the FX market. Park and Irwin (2007) reviewed earlier studies and summarized significant profitable trading signals, such as the filter rule (0.5%, 1%, 2%, and 3%), which generated substantial net annual returns during the sample period. Sweeney (1986) confirms the existing findings on the usefulness of filter rules on multiple dollar exchange rates, considering both transaction costs and risk. Park and Irwin (2007) emphasized the importance of studying the average performance of all trading rules rather than focusing on individual ones. Consistently, Lento (2008) proposed the Combined Signal Approach (CSA), which tests multiple technical indicators together, arguing that this method increases profitability compared to testing indicators individually (Lento, 2007).

Existing literature on technical analysis has extensively discussed the efficient market hypothesis (EMH) when examining its profitability in the FX market (Coakley et al., 2016; Hsu et al., 2016; Katusiime et al., 2015; Kuang et al., 2014; Lento, 2008; M'ng, 2018; Neely, 1997; Park & Irwin, 2007; Tharavanij et al., 2017; Yamani, 2021a, 2021b; Yao & Tan, 2000)). EMH posits that currency prices reflect all available information, rendering technical trading signals based on historical data ineffective in generating returns (Fama, 1965). The three forms of EMH include weak-form, semi-strong, and strong-form—which differ in the extent of information reflected in asset prices (Park & Irwin, 2007). Most notably, the weak form efficiency contends that the prices of securities reflect available information on historical prices. Consistently, recent studies have observed that the effect of technical trading rules has declined over time in the FX market (Hassanniakalager et al., 2021).

On the contrary, Qi and Wu (2006) argue that the FX market has become more efficient over time, suggesting that technical analysis does not violate the weak form of market efficiency (Gerritsen, 2016). Similarly, Neely (1997) argued that the profitability of technical analysis does not necessarily contradict EMH, citing other issues such as data snooping, risk measurement, and accurate pricing. Other researchers propose the adaptive market hypothesis (AMH), which states that market efficiency varies with conditions (Hsu et al., 2016; Katusiime et al., 2015). The adaptive market hypothesis states that the factors that push prices toward their efficient levels are weak and do not function instantaneously. Consistent with this argument, Zarrabi et al. (2017) found that the profitability of technical trading rules lacks consistency even though many are profitable for a shorter period. In sharp contrast to these arguments, studies like Quintanilla García et al. (2012), Lebaron (1999), suggest that FX markets are inefficient.

Research over the past decade has extensively examined the profitability of FX trading. Technical analysis gained prominence when economic fundamentals failed to explain currency price movements (Menkhoff & Taylor, 2007). Vajda (2014) found that strategies based on technical indicators yield profits, though caution is advised. Coakley et al. (2016) and Hsu et al. (2016) concluded that technical analysis has predictive power in emerging and developed markets. Jamali and Yamani (2019) and Narayan et al. (2015) reported significant profits while testing momentum-based strategies in emerging markets. Yamani (2021a) observed improved profitability for FX rates during the 2007–2008 financial crisis using moving average, momentum, and RSI trading rules. Most recently, Dockery and Todorov (2023) have uncovered the profitability of five trading rules: filter rules, trading range breakout, moving average, and Bollinger bands over 14 currency pairs. Yamani (2021b) utilized forward unbiasedness and technical trading rules to understand if the markets deviated from efficiency during the global financial crisis and showed positive abnormal returns for technical rules. Along the line, Yıldırım et al. (2021) found that technical indicators possess a predictive ability of directional movement of currencies when combined with a deep learning technique called 'long short-term memory' (LSTM).

However, Menkhoff and Taylor (2007) argued that theoretical evidence for the profitability of technical analysis is inconclusive and complex. They suggested that while technical analysis might be occasionally profitable, it is not consistently so, which would otherwise indicate a wholly inefficient FX market. Supporting this argument, Hassanniakalager et al. (2021) found positive abnormal returns using 7,846 technical rules for EUR/USD, GBP/USD, and USD/JPY; however, the excess returns were minimal. Potì et al. (2020) observed excess predictability in forward contracts for six exchange rates early in their sample period but less predictability in spot rates. Zarrabi et al. (2017) reported short-term rewards for over 7,600 trading rules covering six currencies, yet they observed that the profitability of those many rules is inconsistent across time. Kuang et al. (2014) and Neely (1997) sought reasons behind experienced traders using technical trading rules if they do not generate profits consistently. Lui and Mole (1998) suggested that professional traders rely more on technical analysis in the short term. Conversely, Schulmeister (2008) argued that the positive results from trading rules may result from the widespread use of these models as information sources. Katusiime et al. (2015) found that excess returns from predictive technical trading rules decline when transaction costs are considered. Kuang et al. (2014) noted that technical trading rules often fail to explain returns in emerging markets and may be prone to data mining biases.

Furthermore, data-snooping bias is critical when testing technical analysis trading indicators. The lack of pre-specified parameters for each trading indicator compels researchers to search through numerous technical trading rules, raising the possibility that profitable signals may arise by chance (Park & Irwin, 2007). This bias can undermine the validity of individual rule testing. Hsu et al. (2016) confirmed that data-snooping bias occurs when individual tests are conducted using the same dataset without testing all models collectively for significance. To address data-snooping bias, Kuang et al. (2014) and Hsu et al. (2016) proposed using Stepwise SPA (Single-Period Approximation) tests. Another method involves splitting the sample into two halves and testing profitable trading rules in the second half, known as the optimization of trading rules (Park & Irwin, 2007). This approach addresses traders' practices of selecting the most profitable rules. Methodologies employed by Kuang et al. (2014) and Hsu et al. (2016) reveal that parameter optimization and out-of-sample testing closely simulate real-world scenarios and help address data-snooping bias. Qi and Wu (2006) suggested that simpler and more widely accepted procedures are still needed for adequate data-snooping controls despite the widespread acknowledgment of data-snooping issues.

Summarizing the empirical studies discussed, recent and early research generally agrees on the profitability and predictability of technical analysis indicators in the FX market compared to the stock market. Among studies that find technical analysis profitable in the FX market, there are mixed results regarding the best rules as no standardized rule parameterization has been established for successful trading, with rule parameters implicitly including the number of days (forward lags) a signal should last. Challenges for the technical analysis in the FX market also include making decisions on optimal parameters, implicit holding periods, and inconsistency across time and markets. Additionally, both current and earlier studies express concerns about data-snooping bias. Some studies find technical analysis's profitability illusory even after accounting for data-snooping issues, while others have adopted various methods to address this bias, finding technical analysis profitable both before and after considering these biases.

4. Methodology and data

4.1. Data

We study 10 foreign exchange currencies, including six from developed and four from emerging markets. The developed market currencies are the Australian dollar (AUD/USD), Canadian dollar (CAD/USD), Euro (EUR/USD), New Zealand dollar (NZD/USD), Swedish krona (USD/SEK), and Sterling pound (GBP/USD). The emerging market currencies are the Israeli Shekel (USD/ILS), Russian Ruble (USD/RUB), Brazilian Real (USD/BRL), and Turkish Lira (USD/TRY). The sample period for emerging market daily data spans from 1 January 2000, to 31 December 2022. The data was collected using the Bloomberg terminal. The currency return is calculated using the formula introduced by Hsu et al. (2016):

$$R_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{1}$$

where St represents the spot foreign exchange rate on timeframe *(t)*, and S_{t-1} represents the spot foreign exchange rate on the previous time frame *(t-1)*. A value of (S_t/S_{t-1}) greater than 1 indicates currency appreciation (long-buying) against the quote currency, while a value less than 1 indicates currency depreciation (short selling) against the quote currency. The returns are calculated without adjustment for transaction costs or interest rates.

4.2. Technical analysis rules

4.2.1. The Oscillator Rules

The Oscillator Rules, also known as Overbought or Oversold indicators, measure the speed of price movement to identify potential corrections or reversals. One popular oscillator rule is the Relative Strength Index (RSI). The RSI is calculated using the following equation:

$$RSI_t(h) = 100\left[\frac{U_t(h)}{U_t(h) + D_t(h)}\right] \tag{2}$$

where $U_t(h)$ represents the accumulated-up movements over the previous *(h)* period timeframe, and $D_t(h)$ represents the accumulated-down movements (absolute value) over the previous *(h)* period timeframe.

$U_t(h)$ and $D_t(h)$ are calculated as provided in Equations 3 and 4, respectively:

$$U_t(h) = \sum_{j=1}^{h} \iota\left(S_{t-j} - S_{t-j-1} > 0\right)\left(S_{t-j} - S_{t-j-1}\right) \tag{3}$$

$$D_t(h) = \sum_{j=1}^{h} \iota\left(S_{t-j} - S_{t-j-1} < 0\right)\left|S_{t-j} - S_{t-j-1}\right| \tag{4}$$

where ι(.) is an indicator variable that can be either zero if the statement between the parentheses is false or one of it is true. The RSI is then normalized between 0 and 100 to measure the speed or strength of the up-movement relative to the down-movement. A value of RSI equal to or above 70 indicates overbought conditions, suggesting a potential reversal down, while a value of RSI equal to or below 30 indicates oversold conditions, suggesting a potential upward correction. The RSI parameters are tested using different lookback periods *(h),* as Hsu et al. (2016) suggested.

4.2.2. Moving average rules

Moving Average (MA) indicators are trend detectors that smooth the time-series data to distinguish trends from noise or fluctuations. This study considers two types of Moving Average Rules: Simple Moving Averages (SMA) and Exponential Moving Averages (EMA). For the SMA rules, two approaches are employed: SMA crossing with spot rate (SMA-Spot-Cross) and SMA crossing with different SMA (SMA-SMA-Cross). SMA- SMA-Cross. In addition to SMA and EMA, we also adopt other exotic and innovative MA versions, namely the Horizontal Average of Moving Average (HAMA) (M'ng, 2018) and 'Kaufman' Adaptive Moving Average (KAMA) as suggested by Kaufman (1995).

4.2.3. Testing the predictability of trading rules

This section tests the predictability of technical analysis indicators by comparing the mean return of each indicator for buy and sell signals, as suggested by Bessembinder and Chan (1995). Instead of using bootstrapping p-values, this study will utilize One-Way ANOVA statistics to identify significant indicators at a 95% confidence level. Steele and Esmahi (2015) employed one-way ANOVA to investigate the impact of technical analysis indicators on trading outcomes, highlighting their predictive power. Similarly, Krishnan and Menon (2009) examined the effects of currency pairs, time frames, and technical indicators on Forex trading profit, likely using ANOVA. One-way ANOVA allows for formal hypothesis testing of variations in indicator parameters across different market returns. While bootstrap simulation is effective for estimating confidence intervals, it does not directly facilitate hypothesis testing as ANOVA does.

We test 497 indicators individually across 10 currencies, totaling 4,970 indicators. These include SMA crossing (60 SMA × 7 forward return lags), RSI (9 RSI × 7 forward return lags), HAMA (1 HAMA × 7 forward return lags), and KAMA (1 KAMA × 7 forward return lags).

Our research methodology extends beyond evaluating indicators on the same or the next day after a trading rule signal. It also examines the duration of signal effectiveness by testing various forward return lags. This approach seeks to optimize trading rules by identifying the best holding periods for each currency.

The empirical results section will present the significant and best-performing indicators, with full results provided in appendices due to the extensive volume of test outputs. Additionally, graphical examples will visually explain each technical analysis indicator, using random data from one of the sample currencies to illustrate the indicator graphically.

The results are organized into three sections: the most predictable currencies, the most predictable technical analysis indicators, and the most predictable markets within the sample of currencies and technical rules. This structure, influenced by studies such as Hsu et al. (2016), aims to provide clear insights into the performance of different indicators and their effectiveness in specific markets.

5. Results and analysis

5.1. Descriptive results

This section presents the descriptive results of the study, including the mean returns and standard deviations for different forward return periods (2-7 days) for each currency over the entire period. These returns are considered holding period returns, reflecting the forward effect of each trading signal. Positive returns indicate a buy or long position, while negative returns represent a sell or short position. The standard deviation of each currency return measures daily volatility over up to one week. The statistics reported include mean returns (Average return over a period), standard deviation (Measure of return volatility), skewness (Asymmetry of return distribution), kurtosis (Peakedness of return distribution), Jarque-Bera statistic (Test for normality of returns), and unit root test results (Stationarity test for time series). Tables 1–3 offer a comprehensive overview of the data properties before proceeding to further econometric modeling.

5.2. Empirical findings

We focus on two technical indicators: simple moving averages (SMA) and relative strength index (RSI). The analysis explores the performance and significance of these indicators for both emerging markets and developed currencies.

Table 1. Descriptive statistics of currency returns (2000–2022).

Currency	Mean (2 days)	Std. dev. (2 Days)	Mean (3 days)	Std. dev. (3 days)	Mean (4 days)	Std. dev. (4 days)	Mean (5 days)	Std. dev. (5 days)	Mean (6 days)	Std. dev. (6 days)	Mean (7 days)	Std. dev. (7 days)
USDILS	−0.0001	0.0110	−0.0003	0.0150	−0.0004	0.0182	−0.0006	0.0208	−0.0008	0.0233	−0.001	0.0252
EURUSD	−0.0002	0.0101	−0.0005	0.0135	−0.0007	0.0162	−0.0010	0.0185	−0.0012	0.0206	−0.0014	0.0226
GBPUSD	−0.0002	0.0091	−0.0004	0.0123	−0.0006	0.0148	−0.0008	0.0169	−0.0010	0.0189	−0.0013	0.0207
USDRUB	0.0002	0.0160	0.0000	0.0220	−0.0001	0.0262	−0.0003	0.0301	−0.0004	0.0336	−0.0006	0.0367
AUDUSD	−0.0003	0.0107	−0.0005	0.0151	−0.0007	0.0187	−0.0009	0.0216	−0.0011	0.0242	−0.0014	0.0266
USDCAD	−0.0001	0.0089	−0.0002	0.0126	−0.0004	0.0154	−0.0005	0.0179	−0.0007	0.0201	−0.0009	0.0221
NZDUSD	−0.0002	0.0095	−0.0004	0.0132	−0.0006	0.0161	−0.0008	0.0187	−0.0010	0.021	−0.0012	0.0231
USDSEK	−0.0003	0.0108	−0.0006	0.0152	−0.0009	0.0188	−0.0011	0.0217	−0.0013	0.0243	−0.0016	0.0267
USDBRL	0.0003	0.0129	0.0000	0.0183	−0.0002	0.0221	−0.0004	0.0254	−0.0006	0.0283	−0.0008	0.031
USDTRY	0.0004	0.0148	0.0001	0.0210	−0.0001	0.0255	−0.0003	0.0291	−0.0006	0.0325	−0.0008	0.0356

Note: The mean returns for most currency pairs are close to zero, indicating that the returns are negligible on average over the given periods. Standard deviations are relatively higher for more volatile currencies like USDRUB and USDTRY, suggesting higher risk and volatility.

Table 2. Skewness, Kurtosis, and Jarque-Bera Statistic.

Currency	Skewness	Kurtosis	Jarque-Bera statistic	p-value
USDILS	−0.108	2.937	7.334	0.025
EURUSD	0.103	2.872	5.747	0.054
GBPUSD	−0.098	3.014	8.410	0.015
USDRUB	0.256	3.217	11.563	0.003
AUDUSD	−0.088	2.954	6.922	0.031
USDCAD	0.062	2.876	5.458	0.065
NZDUSD	−0.123	3.046	9.181	0.010
USDSEK	0.136	2.937	7.761	0.021
USDBRL	0.342	3.319	13.687	0.001
USDTRY	0.467	3.731	17.387	0.000

Note: **Skewness**: Measures the asymmetry of the return distribution. Values close to zero indicate a symmetrical distribution. For example, USDILS and GBPUSD have skewness values near zero, indicating relatively symmetrical distributions. **Kurtosis:** Measures the 'tailenders' of the return distribution. A kurtosis value close to 3 indicates a normal distribution. Most currency pairs have kurtosis values around 3, indicating slight deviations from normality. **Jarque-Bera Statistic**: Tests whether the sample data has the skewness and kurtosis matching a normal distribution. High values and low p-values (<0.05) suggest non-normality. For instance, USDBRL and USDTRY show significant deviations from normality.

Table 3. Unit root test (ADF Test).

Currency pair	ADF statistic	p-value	Stationarity (at 5% level)
USDILS	−5.321	0.000	Yes
EURUSD	−4.810	0.000	Yes
GBPUSD	−4.635	0.000	Yes
USDRUB	−3.611	0.001	Yes
AUDUSD	−4.202	0.000	Yes
USDCAD	−5.112	0.000	Yes
NZDUSD	−4.365	0.000	Yes
USDSEK	−4.925	0.000	Yes
USDBRL	−3.367	0.004	Yes
USDTRY	−3.247	0.009	Yes

Note: The Augmented Dickey-Fuller (ADF) test checks for the presence of a unit root, indicating whether a time series is stationary. The test results show that all currency pairs are stationary at the 5% significance level. The negative ADF statistics and p-values below 0.05 confirm that the null hypothesis of a unit root is rejected for all pairs, indicating that the returns do not follow a random walk and revert to a mean over time. This stationarity is crucial for econometric modeling as it justifies using time series techniques.

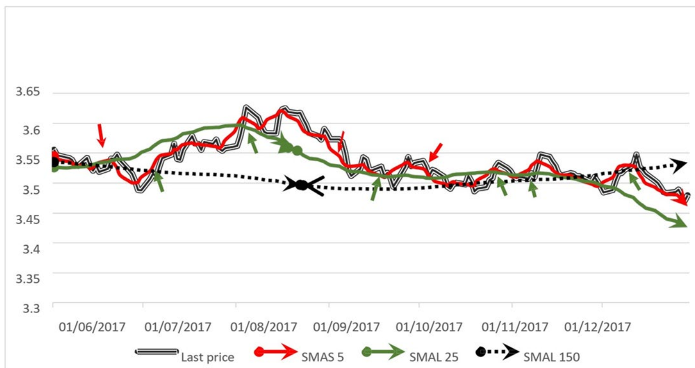

Figure 1. Daily chart of USDILS adding several simple moving averages (SMA).

5.2.1. Simple moving averages (SMA)

First, the research visually examines a sample period of closing prices for the Israeli Shekel against the US Dollar (USD/ILS), along with three different SMAs: a short SMA of order 5, a long SMA of order 25, and a long SMA of order 150. SMAs are known for smoothing price fluctuations and identifying trends.

By analyzing these SMA indicators, it is observed that combining multiple moving averages can generate buy or sell signals. Specifically, a sell signal occurs when the short moving average crosses and remains below the long moving average, while a buy signal occurs when the short moving average crosses and remains above the long moving average. Figure 1 visually demonstrates the simple moving average crossover mechanism by incorporating two long-period SMAs (SMAL 25 and SMAL 150), represented by green and black lines, respectively, and a shorter-period SMA (SMAS 5), represented by a red line, in the time series data of a specific currency pair. It becomes visually evident that whenever a longer SMA intersects with a shorter SMA, the subsequent directional movement (trend) is influenced accordingly, moving upward or downward until the next crossover occurs.

The study then identifies each currency's most significant and best-performing SMA indicators. Table 4 presents the significant SMA indicators for the best-performing currency pairs in emerging markets. Notably, all moving average indicators, except for the short SMA indicators for the Turkish Lira (USD/TRY), are significant at a confidence level of $p<.05$ for most holding periods (2 to 7 days).

In contrast, the analysis of developed currencies in Table 5 reveals no significant and correctly signed SMA indicators for the next day's holding position after the signal is generated.

The study further examines the optimal holding periods for the identified SMA indicators by converting them into daily basis returns, as shown in Table 6. The returns marked with an asterisk (*) represent the highest return for each currency associated with a significant SMA indicator.

For short-term trading (up to one week), a combination of short-moving averages (e.g. SMA(9, 20)) yields the highest returns for certain currency pairs. For instance, USD/ILS shows the highest return of 0.011% for the short position and 0.018% for the long position when using SMA(9, 20) daily. The optimal holding periods vary across currencies, from daily to weekly.

Table 4. Simple moving average cross (SMA) for emerging market currencies.

Currency	Position	Simple moving average	Two days holding	Three days holding	Four days holding	Five days holding	Six days holding	Seven days holding
USD/ILS	Short position	Best performance MA indicators	SMA(9,20)	SMA(7,20)	SMA(7,20)	SMA(7,20)	SMA(7,20)	SMA(7,20)
		Highest return	*0.012%	0.024%	0.034%	0.045%	0.054%	0.061%
		P-value	0.03	0.004	0.001	0.000	0.000	0.000
		Number of significant MAs	3	13	44	55	53	54
	long position	Best performance MA indicators	SMA(9,20)	SMA(7,20)	SMA(7,20)	SMA(7,20)	SMA(7,20)	SMA(7,20)
		Highest return	*0.017%	0.032%	0.048%	0.064%	0.077%	0.089%
		P-value	0.03	0.004	0.001	0.000	0.000	0.000
		Number of significant MA	3	13	44	50	53	54
USD/TRY	Short position	Best performance MA indicators	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)
		Highest return	0.081%	0.162%	0.224%	*0.326%	0.404%	0.487%
		p-value	0.035	0.004	0.000	0.000	0.000	0.000
		Number of significant MA	3	11	22	29	31	34
	long position	Best performance MA indicators	–	–	–	–	–	–
		Highest return	–	–	–	–	–	–
		p-value						
		Number of significant MA	0	0	0	0	0	0
USD/BRL	Short position	Best performance MA indicators	SMA(9,50)	SMA(9,50)	SMA(10,50)	SMA(10,20)	SMA(10,20)	SMA(10,20)
		Highest return	0.053%	0.102%	0.147%	0.201%	0.258%	*0.320%
		p-value	0.012	0.001	0.00	0.00	0.00	0.00
		Number of significant MA	5	22	36	48	53	59
	long position	Best performance MA indicators	SMA(9,50)	SMA(9,50)	SMA(10,150)	SMA(10,20)	SMA(10,20)	SMA(10,20)
		Highest return	0.021%	0.039%	0.053%	0.077%	0.103%	*0.133%
		p-value	0.012	0.001	0.00	0.00	0.00	0.00
		Number of significant MA	5	22	36	44	50	55
USD/RUB	Short position	Best performance MA indicators	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)
		Highest return	0.057%	0.115%	0.175%	*0.235%	0.292%	0.343%
		p-value	0.00	0.00	0.00	0.00	0.00	0.00
		Number of significant MA	19	39	44	52	57	58
	long position	Best performance MA indicators	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)	SMA(10,25)
		Highest return	0.023%	0.049%	0.075%	*0.101%	0.123%	0.141%
		p-value	0.00	0.00	0.00	0.00	0.00	0.00
		Number of significant MA	17	24	26	29	32	36

In summary, SMA indicators demonstrate predictive power for both developed and emerging market currencies. Short-term trading using SMA indicators shows variations in the optimal holding periods for different currencies. While the moving average rules tend to be more significant for most short-term days in emerging market currencies, they are less significant for developed currencies. Additionally, long SMA indicators for emerging market currencies tend to have shorter lookback periods than developed currencies, indicating the need for a longer period to determine the long-term trends in developed currencies, showing the degree of market efficiency for different markets.

5.2.2. Relative strength index (RSI)

The study explores the relative strength index (RSI) as another technical analysis indicator. Like the SMA analysis, the examination visually inspects a sample period currency, focusing on USD/ILS spot prices combined with RSI(25). The chart reveals that price movements follow upward trends when the RSI exceeds the lower limit (30) and downward trends when the price exceeds the upper limit (70). Figure 2. illustrates how the Relative Strength Index (RSI) visually signals whether the price is overbought or oversold by depicting the upper and lower limits on a specific RSI parameter (15).

Table 7 presents the significant and correctly signed RSI indicators for developed market currencies. Notably, USD/ILS shows a significant RSI indicator RSI(50) for holding periods ranging from 3 to 7 days. On the other hand, the remaining emerging market currencies do not exhibit significant RSI indicators for short trading holding periods. In contrast, developed currencies (Table 6) show more significant RSI indicators with variations across holding periods.

To determine the optimal holding periods, the study converts the RSI indicators into daily basis returns, as shown in Table 8. The highest return per currency for each significant RSI indicator is marked with an asterisk (*).

Like the SMA analysis, the RSI indicators show a diversity of optimal holding periods for short-term trading. Some currencies, such as USD/ILS, EUR/USD, NZD/USD, and USD/SEK, exhibit the highest returns when traded on a 3-day basis. Other currencies, such as USD/BRL, GBP/USD, and USD/CAD, show optimal

Table 5. Simple moving average cross (SMA) for developed market currencies.

Currency	Position	Simple Moving Average	Two days holding	Three days holding	Four days holding	Five days holding	Six days holding	Seven days holding
EUR/US D	Short position	Best performance MA indicators	–	SMA(6,150)	SMA(5,150)	SMA(5,150)	SMA(5,150)	SMA(5,150)
		Highest return	–	*0.031%	0.045%	0.051%	0.063%	0.054%
		P-value	–	0.01	0.00	0.00	0.00	0.00
		Number of significant MA	0	16	18	28	35	38
	long position	Best performance MA indicators	–	SMA(6,150)	SMA(6,150)	SMA(5,150)	SMA(5,150)	SMA(5,150)
		Highest return	–	*0.034%	0.0452%	0.066%	0.065%	0.073%
		P-value	–	0.01	0.00	0.00	0.00	0.00
		Number of significant MA	0	15	13	25	34	33
GBP/USD	Short position	Best performance MA indicators	–	–	–	–	SMA(5,200)	SMA(6,200)
		Highest return	–	–	–	–	*0.013%	0.0167%
		P-value	–	–	–	–	0.04	0.02
		Number of significant MA	0	0	0	0	4	10
	long position	Best performance MA indicators	–	–	–	–	SMA(6,200)	SMA(6,200)
		Highest return	–	–	–	–	*0.062%	0.046%
		P-value	–	–	–	–	0.032	0.01
		Number of significant MA	0	0	0	0	2	6
AUD/US D	Short position	Best performance MA indicators	–	–	SMA(6,20)	SMA(4,20)	SMA(4,20)	SMA(2,20)
		Highest return	–	–	*0.062%	0.046%	*0.062%	0.046%
		P-value	–	–	0.03	0.01	0.01	0.02
		Number of significant MA	0	0	2	6	10	11
	long position	Best performance MA indicators	–	–	SMA(6,20)	SMA(4,20)	SMA(4,20)	SMA(2,20)
		Highest return	–	–	*0.040%	0.050%	0.057%	0.058%
		P-value	–	–	0.03	0.01	0.01	0.02
		Number of significant MA	0	0	1	6	9	11
NZD/US D	Short position	Best performance MA indicators	–	–	–	SMA(7,150)	SMA(6,150)	SMA(6,150)
		Highest return	–	–	–	0.062%	*0.081%	0.095%
		P-value	–	–	–	0.05	0.00	0.02
		Number of significant MA	0	0	0	6	9	14
	long position	Best performance MA indicators	–	–	–	SMA(7,150)	SMA(6,150)	SMA(6,150)
		Highest return	–	–	–	0.041%	0.053%	*6.123%
		p-value	–	–	–	0.02	0.03	0.06
		Number of significant MA	0	0	0	3	9	11
USD/SEK	Short position	Best performance MA indicators	–	SMA(9,150)	SMA(9,150)	SMA(9,150)	SMA(9,150)	SMA(9,150)
		Highest return	–	*0.039%	0.058%	0.077%	0.097%	0.117%
		p-value	–	0.03	0.01	0.00	0.00	0.00
		Number of significant MA	0	4	4	13	18	23
		Best performance MA indicators	–	SMA(9,150)	SMA(9,150)	SMA(9,150)	SMA(9,150)	SMA(9,150)
		Highest return	–	*0.032%	0.042%	0.054%	0.076%	0.079%
	long position	*p-value*	–	0.034	0.03	0.00	0.00	0.00
		Number of significant MA	0	5	10	18	23	29
USD/CA D	Short position	Best performance MA indicators	–	–	–	–	–	–
		Highest return	–	–	–	–	–	–
		p-value	–	–	–	–	–	–
		Number of significant MA	0	0	0	0	0	0
	long position	Best performance MA indicators	–	–	–	–	–	SMA(3,25)
		Highest return	–	–	–	–	–	*1.323%
		p-value	–	–	–	–	–	0.03
		Number of significant MA	0	0	0	0	0	4

Table 6. Comparable adjusted returns for SMA.

	Position	Two days holding	Three days holding	Four days holding	Five days holding	Six days holding	Seven days holding
USD/ILS	short	*0.011%	0.021%	0.033%	0.042%	0.051%	0.063%
	long	*0.018%	0.032%	0.047%	0.068%	0.074%	0.07%
USD/TRY	short	0.082%	0.169%	0.226%	*0.328%	0.415%	0.478%
	long	–	–	–	–	–	–
USD/BRL	short	0.054%	0.117%	0.149%	0.202%	0.267%	*0.310%
	long	0.071%	0.049%	0.055%	0.078%	0.107%	*0.134%
USD/RUB	short	0.067%	0.14%	0.17%	*0.231%	0.21%	0.35%
	long	0.025%	0.069%	0.085%	*0.111%	0.124%	0.145%
EUR/USD	short	–	0.045%	0.051%	0.063%	0.054%	0.045%
	long	–	0.0452%	0.066%	0.065%	0.073%	0.0452%
GBP/USD	short	–	–	–	–	*0.013%	0.0167%
	long	–	–	–	–	*0.062%	0.046%
AUD/USD	short	–	–	*0.062%	0.046%	*0.062%	0.046%
	long	–	–	*0.014%	0.01%	0.01%	0.01%
NZD/USD	short	–	–	–	0.02%	*0.016%	0.02%
	long	–	–	–	0.01%	*0.011%	0.01%
USD/SEK	short	–	*0.019%	0.02%	0.02%	0.02%	0.02%
	long	–	*0.015%	0.01%	0.01%	0.01%	0.01%
USD/CAD	short	–	–	–	–	–	–
	long	–	–	–	–	–	*0.227%

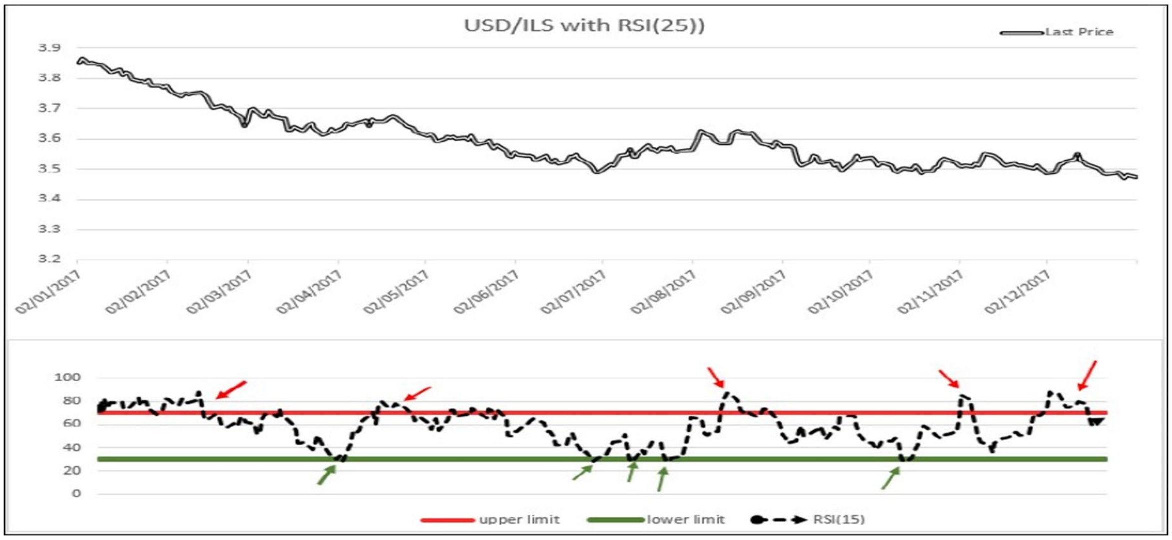

Figure 2. USD/ILS and RSI (25).

Table 7. Relative Strength Index (RSI) is the best performance indicator for developed market currencies.

Currency	Position	Relative Strength Index	Two days	Three days	Four days	Five days	Six days	Seven days
EUR/US D	Short position	Best performance RSI indicators	–	RSI(20)	RSI(20)	RSI(20)	RSI(20)	**RSI(20)**
		Highest return	–	*0.072	0.096	0.113%	0.144%	**0.152**
		P-value	–	0.014	0.011	0.006	0.004	**0.005**
		Number of significant RSIs	0	1	1	3	3	**2**
	long position n	Best performance RSI indicators	–	–	RSI(50)	RSI(50)	RSI(50)	**RSI(50)**
		Highest return	–	–	0.413	*0.598	0.695%	**0.754**
		P-value	–	–	0.006	0.000	0.000	**0.000**
		Number of significant RSIs	0	0	1	1	1	**1**
GBP/US D	Short position n	Best performance RSI indicators	–	–	–	–	–	**RSI(50**
		Highest return	–	–	–	–	–	***0.359**
		p-value	–	–	–	–	–	**0.053**
		Number of significant RSIs	0	0	0	0	0	**1**
	long position	Best performance RSI indicators	–	–	–	–	–	**RSI(50)**
		Highest return	–	–	–	–	–	***0.284**
		p-value	–	–	–	–	–	**0.052**
		Number of significant RSIs	0	0	0	0	0	**1**
AUD/US D	Short position	Best performance RSI indicators	–	–	RSI(5 0)	RSI(50)	RSI(50)	**RSI(50)**
		Highest return	–	–	0.064	*0.122	0.132%	**0.096**
		p-value	–	–	0.05	0.02	0.00	**0.002**
		Number of significant RSIs	0	0	1	1	1	**1**
	long position	Best performance RSI indicators	–	–	RSI(50)	RSI(50)	RSI(50)	**RSI(50)**
		Highest return	–	–	0.31	0.44%	*0.652	**0.721**
		p-value	–	–	0.05	0.02	0.00	**0.002**
		Number of significant RSIs	0	0	1	1	1	**1**
NZD/US D	Short position	Best performance RSI indicators	–	RSI(15)	RSI(15)	RSI(20)	RSI(20)	**RSI(20)**
		Highest return	–	*0.123	0.154	0.172%	0.235%	**0.231**
		p-value	–	0.00	0.00	0.00	0.00	**0.001**
		Number of significant RSIs	0	1	2	2	2	**2**
	long position	Best performance RSI indicators	–	–	–	–	–	**-**
		Highest return	–	–	–	–	–	**-**
		p-value	–	–	–	–	–	**-**
		Number of significant RSIs	0	0	0	0	0	**0**
USD/SE K	Short position	Best performance RSI indicators	–	RSI(50)	RSI(50)	–	RSI(50)	**RSI(50)**
		Highest return	–	*0.283	0.003	–	–	**-**
		p-value	–	0.02	0.02	–	0.01	**0.047**
		Number of significant RSIs	0	2	1	0	1	**1**
	long position	Best performance RSI indicators	–	RSI(10)	RSI(20)	RSI(20)	RSI(20)	**RSI(20)**
		Highest return	–	*0.077	0.121	0.115%	0.129%	**0.114**
		p-value	–	0.01	0.01	0.00	0.00	**0.00**
		Number of significant RSIs	0	1	2	2	1	**1**
USD/CA D	Short position	Best performance RSI indicators	–	–	–	RSI(10)	RSI(10)	**RSI(10)**
		Highest return	–	–	–	*1.672	1.736%	**1.665**
		p-value	–	–	–	0.01	0.01	**0.004**
		Number of significant RSIs	0	0	0	1	1	**2**
	long position	Best performance RSI indicators	–	–	–	–	–	**RSI(10)**
		Highest return	–	–	–	–	–	***1.321**
		p-value	–	–	–	–	–	**0.03**
		Number of significant RSIs	**0**	**0**	**0**	**0**	**0**	**1**

Table 8. Comparable adjusted returns for RSI.

	Position	Two days holding	Three days holding	Four days holding	Five days holding	Six days holding	Seven days holding
USD/ILS	short	–	*0.098%	0.08%	0.06%	0.06%	0.06%
	long	–	*0.045%	0.035%	0.033%	0.022%	0.012%
USD/BRL	short	–	–	–	–	–	–
	long	–	–	–	–	–	*0.014%
USD/RUB	short	–	–	*0.003%	–	–	–
	long	–	–	–	–	–	–
EUR/USD	short	–	*0.045%	0.032%	0.033%	0.038%	0.037%
	long	–	–	0.14%	*0.1439%	0.14%	0.13%
GBP/USD	short	–	–	–	–	–	*0.064%
	long	–	–	–	–	–	*0.045%
AUD/USD	short	–	–	0.04%	*0.045%	0.022%	0.022%
	long	–	–	0.14%	0.15%	*0.132%	0.13%
NZD/USD	short	–	*0.066%	0.052%	0.024%	0.052%	0.056%
	long	–	–	–	–	–	–
USD/SEK	short	–	*0.144%	0.00%	–	−0.12%	−0.082%
	long	–	*0.032%	0.033%	0.035%	0.043%	0.023%
USD/CAD	short	–	–	–	*0.412%	0.33%	0.29%
	long	–	–	–	–	–	*0.223%

Table 9. Kaufman adaptive moving average (KAMA) and horizontal average of moving average (HAMA) significant and best performance indicators.

Currency	Indicator	Number of significant indicators/FWD	position	Highest return	On FWD return	*p*-value
USD/ILS	KAMA(10,1)	1	Long	0.017%	Two days	0.042
		1	short	0.011%	Two days	0.046
USD/BRL	HAMA(X,1)	1	short	0.005%	Six days	0.045
USD/RUB	HAMA(X,1)	4	short	0.011%	Four days	0.051

returns when traded weekly. The optimal holding periods may not be symmetric, with different holding periods for buy and sell signals.

In summary, RSI indicators demonstrate less significance for emerging market currencies than developed ones. RSI signals are emitted less frequently than moving average signals, as RSI indicators are discrete signals while moving averages provide continuous signals. The study notes that RSI indicators are less reliable than other technical indicators due to the lower number of significant RSI signals.

5.2.3. Exotic moving averages: KAMA and HAMA

We introduce two exotic moving averages: Kaufman Adaptive Moving Average (KAMA) and Horizontal Average of Moving Average (HAMA). Appendix C provides all the significant calculations for KAMA and HAMA.

Table 9 reveals that among the sample currencies, only USD/ILS shows significant results for KAMA, indicating buy and sell signals. Based on KAMA, the daily returns for USD/ILS are 0.017% for buying and 0.011% for selling.

Additionally, the study visually examines HAMA (Figure 3) and finds that averaging different-sized moving averages does not necessarily result in smoother trends compared to longer moving averages. HAMA is observed to be more trend-following than long SMAs.

In conclusion, KAMA shows significance only for USD/ILS, while HAMA exhibits some significance for certain currencies such as USD/BRL and USD/RUB.

5.3. Discussion

The results of this research indicate that technical analysis demonstrates abnormal positive returns for both emerging and developed market currencies, highlighting a degree of predictive power. This supports the conclusions of earlier studies, such as those by Zarrabi et al. (2017) and Dockery and Todorov (2023). For example, Dockery and Todorov (2023) recently examined the profitability of four technical trading rules—filter rules, trading range breakout, moving averages, and Bollinger Bands—across 14

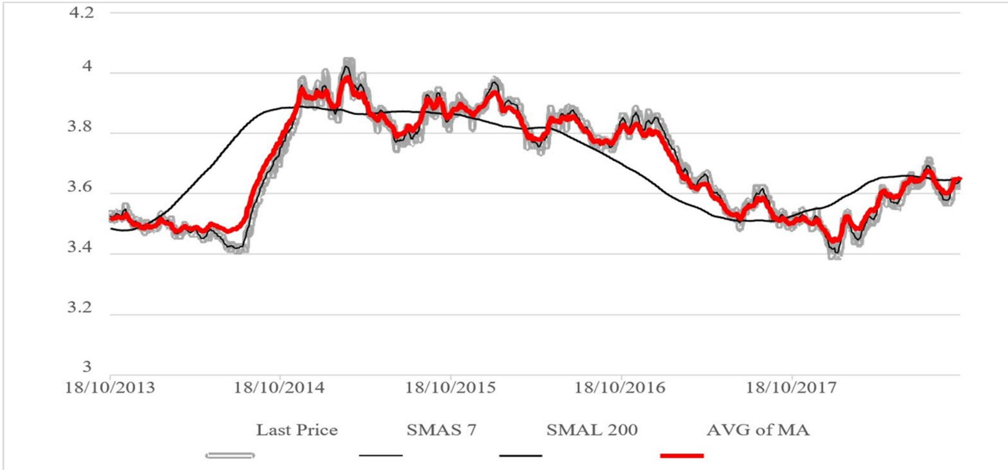

Figure 3. USD/ILS and HAMA.

currency pairs under varying market conditions. Meanwhile, Zarrabi et al. (2017) found that although many technical trading rules yield short-term profits, they tend to lack long-term consistency. Moreover, the majority of currencies analyzed in this study showed at least one significant trading rule recommendation (buy or sell) that corresponded with the direction of the return, consistent with the findings of Gerritsen (2016).

This paper employs a methodology using a seven-day forward lag (holding period), revealing that currencies exhibit distinct behaviors after generating a trading signal. For instance, the EUR/USD may only show favorable movement when applying a moving average indicator on the third lag (two days after the position is held). This phenomenon can be attributed to 'nonsynchronous trading,' a concept examined by Bessembinder and Chan (1995), who analyzed returns on buy and sell days by incorporating a one-day lag between the signal and the trading outcome. It was found that currencies often exhibit optimization after nonsynchronous trading, particularly in short-term strategies. This underscores the importance of determining the ideal holding period for each currency and technical indicator. Gerritsen (2016) referred to this challenge as 'timing skills,' noting that positive (negative) returns often follow a buy (sell) signal for a specific week.

The findings also align with those of Hsu et al. (2016), who identified EUR/USD, USD/SEK, and NZD/USD as the most predictable developed market currencies. Similarly, Dockery and Todorov (2023) observed positive returns for several developed currencies, including EUR/USD and USD/NZD. For the worst-performing currencies, our study echoes previous findings by Cornell and Dietrich (1978), who reported that the 25-day moving average yielded the poorest returns for GBP/USD and USD/CAD but the highest returns for the German Mark (the precursor to the Euro). Cornell and Dietrich (1978) further noted that the Euro performed exceptionally well, while the British Pound and Canadian Dollar had the fewest significant simple moving averages (SMAs) and returns—findings consistent with those of Dockery and Todorov (2023). These results were obtained after applying the Relative Strength Index (RSI) indicator, as recommended by Dockery and Todorov (2023), to further validate its utility as a technical indicator in future research, alongside the more traditional simple moving average and two less conventional moving average indicators. Notably, the Israeli Shekel (USD/ILS) performed remarkably well as an emerging market currency, along with USD/BRL and USD/RUB.

Our research suggests that emerging market currencies are generally more predictable, especially when using moving average indicators, which support the profitability of emerging markets over developed ones, as argued by Jamali and Yamani (2019) and Hsu et al. (2016). Jamali and Yamani (2019) assert that emerging market currencies tend to have lower turnover, less competition among traders, and clearer trend identification. However, our study reveals that the RSI indicator tends to be more effective for developed market currencies. Nonetheless, moving average indicators consistently provide the highest-performing strategies, corroborating the findings of Hsu et al. (2016). Qi and Wu (2006) identified short-term moving averages as the best-performing rules, while Neely (1997) argued that oscillator rules, such as RSI, are more effective in non-trending markets. Our research suggests that developed markets are less trend-driven compared to emerging markets. Unlike Neely (1997), however, this study indicates that technical analysis can be effective across multiple time frames, from daily to weekly, based on daily trading signals.

5.4. Robustness test

To ensure the robustness of our findings and to account for potential data snooping bias, we conducted additional analyses using more robust techniques, such as fractal integration. The fractal dimension is a numerical measure that provides insight into the complexity of the return series. The Fractal Dimension (D) measures how a fractal pattern scales with size. It's calculated using different methods depending on the fractal type and context. One common method is the box-counting method. It typically ranges between 1 and 2 for financial time series. A fractal dimension closer to 2 indicates more complexity and noise, suggesting that the market exhibits high randomness and less predictable trends. Conversely, a dimension closer to 1 implies a less complex series with stronger trends or patterns, which may indicate higher predictability. For currency returns, a fractal dimension lower than 1.5 generally points to the presence of a trending market (persistence), while a dimension higher than 1.5 indicates a more anti-persistent or mean-reverting behavior. This insight helps traders and analysts to develop strategies suited to market conditions. The table below presents the fractal dimensions of the currency pairs.

Table 10 presents the fractal dimensions of the currency pairs.

The fractal dimension results indicate that most currency pairs exhibit high complexity, suggesting that the return series are fractal and self-similar over different time scales. This complexity can be leveraged to enhance trading strategies and improve predictive accuracy. The fractal dynamics in the return series confirm the predictive power of technical trading rules across different currency pairs. These robust techniques enhance our understanding of market behavior and support the practical application of our research in trading strategies. The fractal dimensions of various currency pairs highlight differences in market complexity and predictability. Currency pairs like USD/ILS (1.41), USD/RUB (1.40), NZD/USD (1.36), USD/BRL (1.42), and USD/TRY (1.39) all exhibit higher complexity. These pairs show significant randomness and noise compared to the other currency pairs, indicating that their markets are more unpredictable and challenging to forecast. Trading strategies for these pairs should be highly adaptable, incorporating trend-following and mean-reversion approaches to handle the inherent unpredictability and mixed trends.

In contrast, currency pairs such as EUR/USD (1.25), AUD/USD (1.24), USD/CAD (1.22), GBP/USD (1.20), and USD/SEK (1.21) display moderate complexity. These pairs exhibit more structured market behaviors with identifiable trends but still contain elements of randomness. For these pairs, trend-following strategies can be effective, though traders should remain vigilant for potential reversals and market shifts.

6. Conclusion and suggested future research

This research investigates the predictive power of 497 technical trading rules across various holding periods on 10 developed and emerging currencies, offering fresh insights into the optimal use of technical analysis in currency markets. The findings confirm that technical indicators exhibit significant predictive power in developed and emerging market currencies. Notably, emerging markets demonstrate higher

Table 10. Fractal dimensions for the currency pairs.

Currency pair	Fractal dimension	Interpretation
USD/ILS	1.41	High complexity
EUR/USD	1.25	Moderate complexity
GBP/USD	1.20	Moderate complexity
USD/RUB	1.40	High complexity
AUD/USD	1.24	Moderate complexity
USD/CAD	1.22	Moderate complexity
NZD/USD	1.36	High complexity
USD/SEK	1.21	Moderate complexity
USD/BRL	1.42	High complexity
USD/TRY	1.39	High complexity

predictability, consistent with previous studies that highlight the differences in market efficiency between emerging and developed economies.

A key contribution of this study is the identification of optimal holding periods and parameter configurations for these trading rules. The results indicate that trading signals remain effective for up to seven days, likely due to factors such as nonsynchronous trading and the timing skills of market participants. This insight is particularly useful for traders looking to fine-tune their short-term strategies, especially within intraweek trading windows. The study underscores the practical importance of understanding how different holding periods impact the success of technical signals, allowing for better optimization in currency trading strategies.

One limitation of this research is its exclusion of profitability analysis for the trading rules studied. While we established the predictive effectiveness of these rules, future research should integrate considerations such as transaction costs, interest rate differentials, and market liquidity to evaluate the actual profitability of these strategies. Incorporating these factors would provide a more complete picture of how trading rules perform under real-world conditions.

The practical implications of this study are wide-ranging. Traders can directly apply the identified optimal settings to maximize their returns, tailoring strategies based on the specific market and holding period. Meanwhile, policymakers may use these insights to craft regulations that enhance market efficiency, particularly in emerging markets with higher predictability. This could involve initiatives that promote transparency and reduce information asymmetry, fostering a more stable trading environment. Future research should also expand the application of these rules to other asset classes and explore how they perform under varying market conditions, including volatile or crisis periods.

Additionally, this study emphasizes the importance of nonsynchronous trading and timing skills in determining the effectiveness of technical indicators. By accounting for these factors, traders can more effectively navigate the complexities of currency markets, optimizing their strategies to exploit short-term opportunities. Policymakers, too, can draw from these insights to design market interventions aimed at improving fairness and transparency, ensuring that technical trading does not disproportionately favor certain participants over others.

In conclusion, while this research advances the understanding of technical trading rules in currency markets, it also highlights areas for further investigation. Addressing the current study's limitations and broadening the scope of future research will deepen our knowledge of technical analysis in financial markets. This, in turn, will benefit traders and policymakers, helping to enhance market efficiency and stability across global financial systems.

Author's contributions

Authors contributed to developing this manuscript as follows:

Seri Ghanem: Conceptual and design and drafting of the paper.

Murad Harasheh: Conceptual and design, interpretation of the data, drafting of the paper, and revising.

Qays Sbaih: Conceptual and design, analysis, and interpretation of the data; and the drafting of the paper.

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Data availability statement

Data is available upon reasonable request from Qays Sbaih qsbaih@gla.ac.uk; qaissbaih@gmail.com

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