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Testing the Efficiency of the Won/Dollar Foreign Exchange Market: The Case of Technical Trading Rules*

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This study investigates the efficiency of the won/dollar foreign exchange market by analyzing daily won/dollar exchange excess returns and employing five commonly used technical trading rules representative of algorithmic trading strategies. The results, based on averaging the returns of 436 sub-trading rules to mitigate data mining concerns, reveal that the statistical significance of excess returns diminishes steadily throughout the 1990s, 2000s, and 2010s. Combined bootstrap methods and tests on technical trading rules demonstrate that excess returns from these technical strategies are not statistically distinguishable from those generated by null models such as RWD, AR(1), and CAPM in recent years, implying increased support for the adaptive market hypothesis or the efficient market hypothesis. The in-sample buy-sell returns from the five technical trading rules, which are generated by rolling 500-sample windows 6781 times, exhibit similar patterns. Notably, the one-period-ahead out-of-sample forecast results based on identical rolling regression windows indicate that CAPM, which attributes significant portions of excess returns to systematic risk, achieves superior performance in comparison to both the five technical trading rules and other null models evaluated.

JEL Classification: C1, E3, G1
Keywords: Technical Trading Rules, Efficient Market Hypothesis, Bootstrap Test, CAPM

I. Introduction

On July 31, the Bank of Japan raised its policy rate to 0.25%, and on August 2, it was reported that the U.S. unemployment rate rose to 4.3% in July, leading to

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significant disruption in global equity markets.[1] One primary explanation for the steep decline in global stock prices, despite little evidence of fundamental macroeconomic deterioration, is the role of algorithmic trading among institutional investors. According to leading research institutions, algorithmic trading constitutes 70-80% of all trading in the US. Algorithmic trading is the process by which computer programs are utilized to automatically execute buy and sell transactions for liquid assets, such as stocks, bonds, derivatives, and foreign exchange. Among the prevalent techniques in algorithmic trading are technical trading rules (TTR), which entail the use of past price or trading volume data to chart asset price trajectories, with a primary objective of accurately identifying optimal buy and sell timings.

The efficient market hypothesis applies the rational expectations hypothesis to the stock or foreign exchange market. Under the efficient market hypothesis, the optimal prediction for tomorrow's asset price is simply today's asset price, as it incorporates all information available at that moment. Therefore, the unexplained component in asset price movements is not a systematic error that cannot be mitigated through portfolio diversification, but a random error. The efficient market hypothesis is categorized into three forms: weak, semi-strong, and strong. According to the weak form, it is not feasible to forecast future asset prices using technical analysis, since historical price movements do not have predictive power for future price changes.

Empirical research from the 1960s and early 1970s, led by proponents of the efficient market hypothesis (e.g., Fama and Blume, 1966), concluded that technical trading rules did not successfully predict stock prices, even though such strategies had been widely employed on Wall Street. However, from the 1980s onwards, critics of the efficient market hypothesis began to challenge it based on both theoretical grounds and empirical findings. One influential study by Brock, Lakonishok, and LeBaron (1992) demonstrated that technical trading rules were effective in predicting U.S. stock prices.

Regarding the foreign exchange market, Meese and Rogoff (1983) found that neither exchange rate determination models nor time series models for advanced economies could outperform random walk models in out-of-sample forecasting, and there has been no subsequent empirical evidence that decisively disproves the random walk behavior of exchange rates in advanced economies. Based on triennial BIS statistics, average daily turnover in the foreign exchange market reached $7.5 trillion globally and $67.7 billion in Korea in 2022. These amounts represent increases of 14.1% and 22.55% over 2019, respectively, indicating that investors could achieve substantial profits if they manage to predict exchange rate movements.

For Korea, a small open economy, the volume of foreign exchange market transactions has continued to grow, driven by a persistent current account surplus

[1] In Korea, the KOSPI and KOSDAQ experienced declines of 8.8% and 11.3%, respectively, on Monday, August 5, compared to Friday, August 2, as a result of the unwinding of yen carry trades.

and expansion in both outbound and foreign direct and indirect investment. Furthermore, starting in July 2024, the operating hours of the foreign exchange market will be extended from the existing 9:00 a.m. to 3:30 p.m. window to 2:00 a.m. the following day, thereby encompassing the London Financial Market session. The market is also anticipated to become more vibrant as authorized foreign financial institutions based outside Korea gain access to participate in the domestic market. However, as transaction volumes expand and the proportion of algorithmic trading among major institutional investors rises, volatility in the won/dollar exchange rate is expected to increase regardless of changes in macroeconomic fundamentals.

Within the context of the stock market, debates persist between proponents of the efficient market hypothesis and those supporting the inefficient market hypothesis. While numerous studies have assessed the domestic stock market utilizing technical trading rules, there is a noticeable scarcity of domestic research focused exclusively on the won/dollar foreign exchange market. Accordingly, this study seeks to evaluate the efficiency of the won/dollar foreign exchange market by applying technical trading rules, which represent a key strategy in algorithmic trading, using daily won/dollar exchange rate and interest rate data from 1995 to the present, as available from domestic sources.

Initially, I assess whether the five most widely recognized technical trading rules—momentum, filter, moving average (MA), trading range breakout (TRB), and channel breakout (CB)—are capable of generating profits through buying or selling won/dollar. To address concerns regarding data mining, I calculate the mean trading returns derived from employing 16, 84, 144, 96, and 96 sub-techniques of momentum, filter, MA, TRB, and CB rules, respectively. These sub-techniques are based on different short- and long-term moving average values, resistance and support thresholds, and investment horizons. The overall analysis period is segmented into three sub-periods to account for the occurrence of the currency crisis, the global financial crisis, and structural shifts in internal and external economic conditions. Additionally, I investigate the efficiency of the won/dollar foreign exchange market by evaluating the applicability of random walk with drift (RWD), AR(1), and the capital asset pricing model (CAPM), alongside testing the forecasting performance of technical trading rules through bootstrap methodology utilizing these models. To supplement in-sample bootstrap simulation findings, I also conduct rolling regressions and contrast the results with out-of-sample forecasting estimates.

The empirical analysis of trading returns in the won/dollar foreign exchange market using technical trading rules reveals that buy returns, sell returns, and buy-sell returns display statistical significance according to the specific trading rule employed. Nevertheless, when forecast performance is evaluated by averaging returns across a wide variety of rule specifications to minimize data mining concerns, the statistical significance of excess returns consistently declines across the 1990s, 2000s, and 2010s. Moreover, the bootstrap analysis conducted with the RWD, AR(1), and

CAPM models provides further support for the conclusion that market efficiency in the won/dollar foreign exchange market has improved in recent years. Collectively, evidence from rolling regression analysis and out-of-sample forecasting indicates that the excess returns in the won/dollar foreign exchange market are more effectively accounted for and predicted by the CAPM relative to technical trading rules and other benchmark models.

This study is structured as follows. Section II provides a review of prior research investigating the predictability of foreign exchange market returns using technical trading rules, highlighting both the commonalities and distinctions between the present and previous studies. Section III details the five technical trading rules employed in this study. Section IV reports summary statistics on the won/dollar and dollar index returns, utilizing short-term interest rates. Section V evaluates the statistical significance of buy and sell returns generated by the five technical trading rules across various timeframes. Section VI assesses the predictive ability of these technical trading rules through RWD, AR(1), and CAPM bootstrap tests, thereby analyzing the efficiency of the won/dollar exchange market. Section VII conducts rolling regressions and compares the performance of out-of-sample forecasts. Section Ⅷ discusses the economic implications of the findings for the won/dollar FX market. Finally, Section Ⅸ provides the overall summary and conclusion of the study.

II. Literature Review

Early research by Dooley and Shafer (1976, 1984), Logue and Sweeney (1977), and Cornell and Dietrich (1978) showed that technical trading rules were effective in forecasting currency returns in the foreign exchange market, in contrast to their limited usefulness for stock returns. Notably, the empirical findings of Sweeney (1986) and Levich and Thomas (1993) played a significant role in challenging the early academic skepticism regarding the predictability of currency returns. Allen and Taylor (1990), along with Taylor and Allen (1992), conducted surveys indicating that technical trading rules were commonly adopted by market practitioners. LeBaron (1999) contended that the returns from technical trading in the foreign exchange market were influenced by intervention from the FRB, whereas Neely (2002) rejected this explanation. Osler and Chang (1995) analyzed the effectiveness of technical patterns, and Neely, Weller, and Ulrich (2009) investigated the underlying causes of the observed return volatility. Specifically, Neely et al. (2009) asserted that the outcomes of technical trading rules were better explained by the adaptive markets hypothesis rather than data snooping or disclosure bias. Ivanova, Neely, Weller, and Famiglietti (2021) further contended that the CAPM, along with its extensions, was unable to account for most of the excess returns generated by technical trading rules in currency markets, providing indirect evidence in favor of adaptive market models that emphasize non-risk-related factors. Additionally, Menkhoff and Taylor (2007) and Neely and Weller (2012) reviewed the literature on technical trading. More recent studies have expanded the data sets and methodologies employed. For instance, Hsu, Taylor, and Wang (2016) found that technical trading rules exhibited significant predictive power and generated excess returns in 30 developed and emerging market currencies, attributing this performance to market inefficiencies or behavioral biases. Hutchinson, Kyziropoulos, Brien, Reilly, and Sharma (2022) employed a sample comprising G11 and 24 global currencies, finding that the effectiveness of technical trading rules decreased substantially over time, and that any abnormal returns could be entirely attributed to time series momentum.[2]

Despite the abundance of international research on technical trading rules, limited attention has been given to their application in Korea, particularly within the won/dollar foreign exchange market as opposed to the equities market. Lee, Pan, and Liu (2001) analyzed daily won/dollar exchange rates from 1988 to 1995 and demonstrated that the MA and CB approaches produced statistically significant returns in in-sample tests, though these returns were absent in out-of-sample evaluations. Ryoo (2001), examining daily data for one year and ten months following the adoption of a floating exchange rate regime, reported substantial returns using both MA and filter rules. However, Ahn (2008), utilizing data from 1998 to 2007, found no statistically significant excess returns from the filter rule. He maintained that the won/dollar foreign exchange market operated as an efficient market where technical trading strategies failed to be profitable, thereby contrasting Ryoo (2001).

Incorporating not only the filter, MA, and CB rules prevalent in prior research, this study also applies momentum and TRB rules as well as multiple sub-strategies within each category. Unlike previous domestic studies, which neglected interest rates, this analysis includes them and evaluates the return predictability from 1995 to the most recent period for which such data are available. The study uniquely uses the dollar index return as the market portfolio, differentiating itself from international research. Additionally, I assess market efficiency and model adequacy through RWD, AR(1), and CAPM bootstrap simulations. This analysis spans a substantially longer timeframe compared to earlier studies, encompassing events such as the currency crisis, the global financial crisis, and the COVID-19 pandemic. Accordingly, rolling regressions are employed to explore how these periods of crisis influence the excess returns derived from technical trading strategies. The study also seeks to compare the divergence between out-of-sample and in-sample performances of technical trading rules and null models using parallel rolling regressions, an aspect infrequently discussed in previous literature.

[2] Time series momentum is defined as a strategy that involves purchasing assets that have recently performed well and selling those that have underperformed (Moskowitz, Ooi, and Pedersen, 2012).

III. Technical Trading Rules

Building on established research (e.g., Ivanova et al., 2021; Hutchinson et al., 2022), which employed momentum, filters, MA, TRB, and CB as technical trading rules in the foreign exchange market, the present study adopts these frameworks to rigorously evaluate the efficiency of the won/dollar foreign exchange market.

1. Momentum Rule

In one of the empirical studies challenging the weak efficient market hypothesis, Jegadeesh and Titman (1993) found that stocks exhibiting significant price increases due to investor underreaction continued to rise, indicating a momentum effect during the uptrend. Therefore, the momentum rule prescribes taking a long position when the cumulative foreign exchange return over a k day window is positive, and a short position when the return is negative. Since $k \in \{20, 50, 150, 200\}$ is employed as the cumulative return period and $h \in \{1, 5, 10, 25\}$ serves as the holding period, there are 16 distinct sub-rules for the momentum rule.

2. Filter Rule

The filter rule prescribes purchasing foreign exchange if the closing price of the daily spot rate exceeds the lowest price over the previous k days by a filter size b, and selling if the closing price falls below the highest price by a filter size b. I_{t-1} is defined as follows.

$$I_{t-1} = \begin{cases} +1, \ if \ ln\left(\frac{S_t}{S_{t-1,k}^{min}}\right) \geq b \\ -1, \ if \ ln\left(\frac{S_{t-1,k}^{max}}{S_t}\right) \geq b \\ 0, \ otherwise \end{cases} \tag{1}$$

where I_{t-1} takes a value of 1 for long positions and -1 for short positions and S_t denotes the won/dollar exchange rate at time t. $S_{t-1,k}^{min} = \min(S_{t-1}, S_{t-2}, \cdots, S_{t-k})$ and $S_{t-1,k}^{max} = \max(S_{t-1}, S_{t-2}, \cdots, S_{t-k})$ specify the minimum and maximum values of S, respectively, over the latest period considered. I analyze a total of 84 sub-rules based on filter sizes $b \in \{0.001, 0.005, 0.010\}$, formation periods $k \in \{1, 2, 5, 10, 20, 25, 50\}$, and holding periods $h \in \{1, 5, 10, 25\}$.

3. MA (moving average) Rule

The MA rule generates a buy signal when the short-term moving average of the spot rate exceeds the long-term moving average by a predetermined band b, and a sell signal when it falls below by that band b. $MA_{t,k}$ and I_{t-1} are represented as follows.

$$MA_{t,k} = \frac{1}{k}\sum_{i=0}^{k-1} S_{t-i} \tag{2}$$

$$I_{t-1} = \begin{cases} +1, & if\ MA_{t,ks} > (1+b)MA_{t,kl} \\ -1, & if\ MA_{t,ks} < (1-b)MA_{t,kl} \\ 0, & otherwise \end{cases} \tag{3}$$

In this context, $MA_{t,k}$ denotes the moving average of the spot rate over the specified period (k), while ks and kl refer to the number of days used for calculating the short and long moving averages, respectively. For the moving averages, $ks \in \{1, 2, 5\}$ and $kl \in \{20, 50, 150, 200\}$, and the filter size and holding period parameters are $b \in \{0.000, 0.005, 0.010\}$ and $h \in \{1, 5, 10, 25\}$. As a result, the MA rule encompasses 144 distinct sub-rules.

4. TRB (trading range breakout) Rule

A trading range is identified by examining the highest and lowest exchange rates within the past k periods. In technical analysis, investors typically sell or buy foreign exchange when the exchange rate approaches these extremes, resulting in pressure that creates resistance or support levels, which in turn prevents the exchange rate from breaching previous highs or lows. Nevertheless, when the exchange rate surpasses these resistance or support thresholds, it tends to move sharply upward or downward. Consequently, such breakouts are interpreted by investors as signals to sell or buy. The TRB rule issues a buy signal when the exchange rate exceeds the maximum of the past period by more than a specified band k, and a sell signal when it falls more than a specific band k below the minimum. I_{t-1} is denoted as follows.

$$I_{t-1} = \begin{cases} +1, & if\ S_t > (1+b)S_{t-1,k}^{max} \\ -1, & if\ S_t < (1-b)S_{t-1,k}^{min} \\ 0, & otherwise \end{cases} \tag{4}$$

The considered number of formation periods is k $\in$ {5, 10, 15, 20, 25, 50, 100, 200}, while the filter size and holding period are defined as b $\in$ {0.001, 0.005, 0.010} and h $\in$ {1, 5, 10, 25}, respectively. As a result, the TRB rule encompasses a total of 96 sub-rules.

5. CB (channel breakout) Rule

A foreign exchange is defined to be trading within a channel when the highest rate $S_{t-1,k}^{max}$ during the previous k days remains within a certain fixed proportion (f) of the lowest rate $S_{t-1,k}^{min}$. Per the CB rule, if such a channel exists, a buy signal is generated when the spot rate exceeds the channel by a predetermined band (b), while a sell signal occurs if the spot rate falls below the channel by band (b). I_{t-1} is expressed as follows.

$$\text{If} \quad \frac{\left(S_{t-1,k}^{max}-S_{t-1,k}^{min}\right)}{S_{t-1,k}^{min}} \leq f$$

$$I_{t-1} = \begin{matrix} +1, \ if\ S_t > (1+b)S_{t-1,k}^{max} \\ -1, \ if\ S_t < (1-b)S_{t-1,k}^{min} \\ 0, \ otherwise \end{matrix} \tag{5}$$

Consistent with the TRB rule, $k \in \{5, 10, 15, 20, 25, 50, 100, 200\}$ is utilized for the number of formation periods, with $b \in \{0.000, 0.005, 0.010\}$ and $h \in \{1, 5, 10, 25\}$ representing the filter size and holding period, respectively. Due to the CB rule's requirement that $b<f$, a value of 0.1 is set for f. Consequently, a total of 96 sub rules are in the CB rule framework.

IV. Summary Statistics

This study employs the daily won/dollar exchange rate (closing price) from January 3, 1995 to June 28, 2024, covering the period during which daily call rate data are available, resulting in a sample size of 7282 observations. The domestic interest rate is represented by the call rate (overnight-all trades), and the U.S. interest rate is proxied by the federal funds rate.[3]

Daily excess return is calculated from the spot exchange rate and the risk-free asset return as follows:

$$r_t = 100 \times (lnS_t - lnS_{t-1}) + (i_{t-1}^{*} - i_{t-1})/365 \tag{6}$$

[3] No substantial variation in the results is observed when replacing call rates and the federal funds rate with CDs (91-day) and U.S. Treasury bills (3-month) throughout the analysis period. Earlier research similarly reports no significant difference in findings when interest rates are excluded as opposed to when they are included.

where S_t denotes the won/dollar exchange rate at time t, and i_{t-1} and i^*_{t-1} represent the returns of the risk-free asset on the won and the dollar at time t-1, respectively. When a specified trading rule generates a buy signal at time t-1, the investor borrows the won at the domestic interest rate, converts it to dollars at the exchange rate prevailing at time t-1, and earns 1-day U.S. interest income. The excess return is $I_{t-1}r_t$, where I is assigned a value of +1 for a long position and -1 for a short position.

When estimating the CAPM, prior studies frequently use U.S. stock returns as the market portfolio, whereas this study utilizes the dollar index. The Federal Reserve constructs the dollar index to measure the overall effect of dollar exchange rate fluctuations on U.S. trade. As of February 4, 2019, the dollar index was reorganized into a broad dollar index and two subsidiary indices—the advanced foreign economies (AFE) dollar index and the emerging market economies (EME) dollar index. The broad dollar index employed in this study's empirical analysis comprises exchange rates of 26 countries whose bilateral trade with the United States exceeds 0.5% of total U.S. bilateral trade. The revised dollar index encompasses trade in services as well as goods, and the Fed has provided daily data since January 3, 2006, while the pre-revised dollar index is available through December 31, 2019. Accordingly, I use the pre-revised dollar index from 1995 to 2005 and the revised dollar index from 2006 onward, adjusting the pre-revised index so that its value on January 3, 2006, matches the revised index. The federal funds rate is implemented as

[Table 1] Summary Statistics of Excess Returns

Period	'95.01.04 - '24.06.28		'95.01.04 - '00.12.29		'01.01.02 - '10.12.30		'11.01.03 - '24.06.28	
Variable	Won/$	Dollar Index	Won/$	Dollar Index	Won/$	Dollar Index	Won/$	Dollar Index
Mean	0.003 (0.010)	0.002 (0.004)	0.019 (0.034)	0.009 (0.007)	-0.009 (0.016)	-0.010 (0.007)	0.004 (0.009)	0.008 (0.006)
Std.	0.822	0.320	1.296	0.264	0.777	0.346	0.532	0.322
Skewness	-1.140	-0.028	-1.137	-0.366	-0.834	-0.180	-0.124	0.218
Kurtosis	107.693	7.835	73.532	8.650	55.930	8.548	6.182	6.439
Maximum	13.413	1.891	13.413	1.473	10.210	1.884	3.159	1.891
Minimum	-20.392	-2.567	-20.392	-2.234	-13.254	-2.567	-4.383	-2.091
Q(10)	31.36 [0.00]**	14.36 [0.16]	28.31 [0.00]**	14.00 [0.17]	5.17 [0.88]	10.88 [0.37]	16.75 [0.08]$^{+}$	12.47 [0.26]

Notes: 1) The excess return r_t is computed as $100 \times (\ln S_t - \ln S_{t-1}) + (i^*_{t-1} - i_{t-1})/365$. Here, S denotes the won/dollar exchange rate (or the dollar index), while i and i^* represent the call rate (or the weighted average policy rate for the euro area+8 countries) and the federal funds rate, respectively.

2) Q (10) denotes the modified Ljung-Box test statistic used for 10*th* order serial correlation.

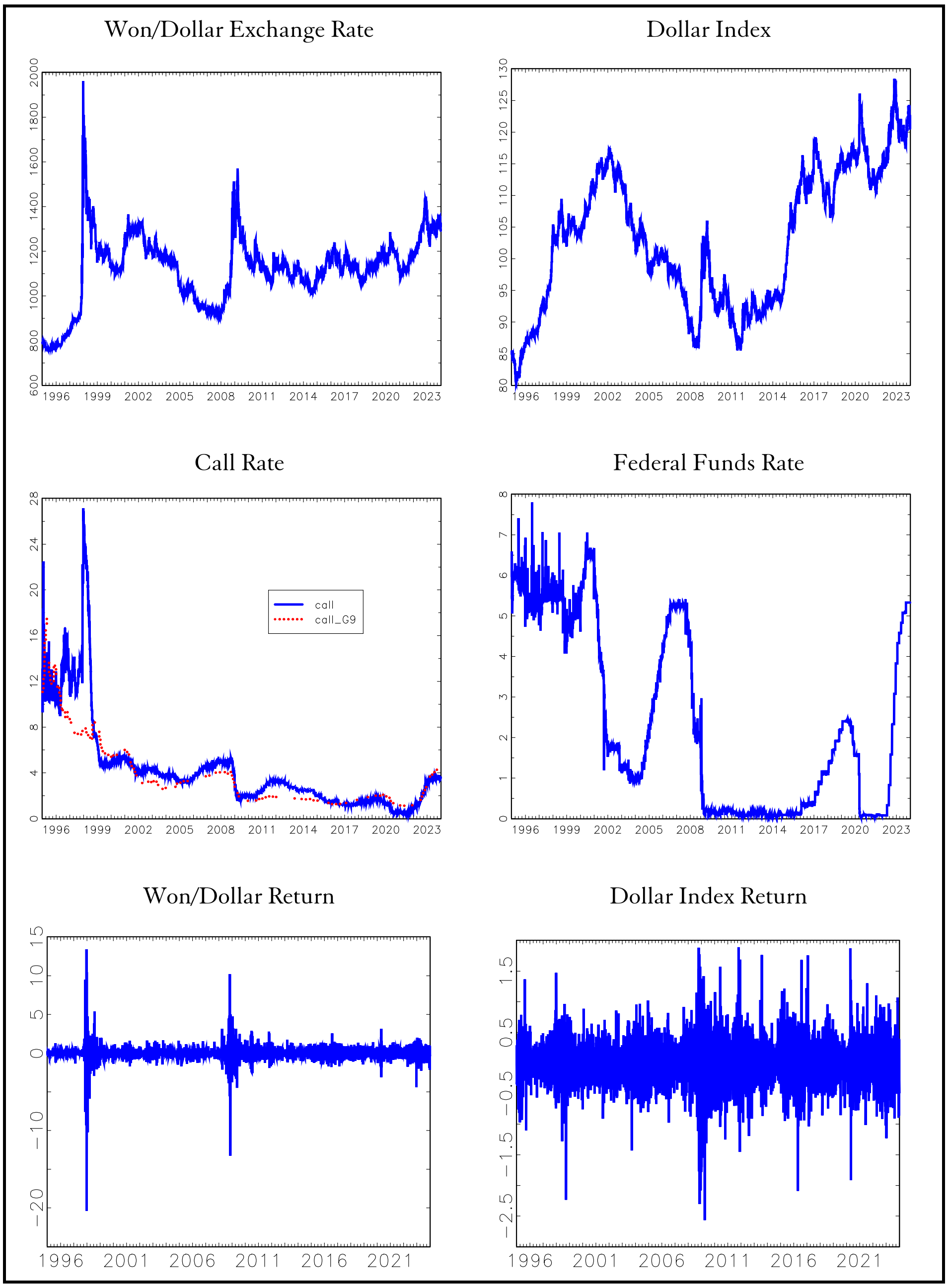
3) Figures shown in [ ] denote p-values; $^{+}$ and ** mark statistical significance at the 10% and 1% thresholds, respectively.

the U.S. interest rate, and the global interest rate is constructed as a weighted average of the interest rates of major trading partners. The global weighted average interest rate is determined by applying the 2017-dollar index currency weights from the Federal Reserve website to each country's base rate. To address data availability constraints, the euro area and 8 countries accounting for a weight of 2% or more among the 26 regions or countries are included: the euro area (18.6%), China (16.2%), Canada (13.6%), Mexico (13.3%), Japan (6.4%), the United Kingdom (5.1%), South Korea (3.4%), India (2.7%), and Switzerland (2.7%). The return on the dollar index is calculated using Equation (6), identical to the method applied for the won/dollar return.

Table 1 presents the summary statistics for the returns of the won/dollar and the dollar index. The analysis period ('95.01.04-'24.06.28) encompasses the currency crisis, global financial crisis, and COVID-19 crisis, and previous empirical studies have demonstrated that the effectiveness of technical trading rules has diminished over time. Consequently, I divide the sample into three subperiods: '95.01.04-'00.12.29, '01.01.02-'10.12.30, and '11.01.03-'24.06.28, as well as examine the full period. The average returns for both the won/dollar and the dollar index across the entire sample period ('95.01.04-'24.06.28) are 0.003% and 0.002%, respectively, both of which are approximately zero. This pattern persists when examining each subperiod, with mean returns not statistically different from 0%. The standard deviation of the won/dollar return considerably exceeds that of the dollar index return but has decreased markedly in recent years, in contrast to the dollar index. The skewness of the won/dollar return remains negative during all periods but has become less pronounced in recent years, mirroring the behavior of kurtosis. The minimum absolute value for the won/dollar return is larger than its maximum, a result of the pronounced high interest rate environment during the currency crisis; similar to other statistics, its absolute value declines over time. In contrast, the skewness, kurtosis, maximum, and minimum statistics for the dollar index return remain largely unchanged across the sample periods. Q(10) reports the modified Ljung-Box test statistic for 10*th* order serial correlation. These results indicate that serial correlation in the won/dollar return is substantial in the periods surrounding the currency crisis ('95.01.04-'00.12.29), while serial correlation in the dollar index return stays low for all periods.[4]

[4] The descriptive statistics for the won/dollar rate of change and the dollar index rate of change are not significantly different from those of the two returns.

[Figure 1] Exchange Rate and Interest Rate Trends



Notes: 1) The excess return r_t is measured as $100 \times (\ln S_t - \ln S_{t-1}) + (i^*_{t-1} - i_{t-1})/365$. Here, S refers to the won/dollar exchange rate (or dollar index), i and i^* correspond to the call rate (or the weighted average policy rate for the euro area+8 countries) and the federal funds rate, respectively.

2) call_G9 denotes the weighted average policy rate for the euro area+8 countries.

Figure 1 illustrates the movements of the won/dollar exchange rate and the dollar index. Generally, the won/dollar exchange rate has tracked the movements of the dollar index, except for sharp increases during the currency crisis and the global financial crisis. The call rate (call) and the weighted average interest rate of the euro area+8 countries (call_G9) also largely followed similar trends, except for divergent movement during the currency crisis and temporary rises before the global financial crisis and the inflationary period. Nevertheless, both have generally declined. The federal funds rate dropped steeply after the IT bubble burst, the subprime mortgage crisis, and the COVID-19 pandemic, only to rise again during the subsequent inflationary episode. Owing to the sharp increase in the won/dollar exchange rate during the currency crisis, the won/dollar return displays higher standard deviation and pronounced serial correlation relative to the dollar index return for the crisis and post-crisis period, as reflected in Table 1. After 2010, however, the volatility of the won/dollar return has subsided.

V. Empirical Findings

1. Highest Returns by Rule and Period

To address the data snooping issue as discussed earlier, this study not only investigates five technical trading rules: momentum, filter, MA, TRB, and CB, but also evaluates 16, 84, 144, 96, and 96 sub-rules, respectively, for each rule. Table 2 presents the forecasting results for the sub-rule achieving the highest buy-sell return among the 16, 84, 144, 96, and 96 sub-rules for each rule, over both the full sample period and its sub-periods. In Table 2, ks and kl denote the number of days applied for short-term and long-term moving averages in the MA rule, as well as analogous periods for the other rules. b and h indicate the filter size and the holding period, respectively. Buy>0 (Sell>0) refers to the probability that buy (sell) returns exceed zero. Buy, Sell, and Buy-Sell denote the returns from buying, selling, and the difference between them, respectively. Values in ( ) correspond to t-values.

[Table 2] Best Buy-Sell Returns by Technical Trading Rule

Period	Rule	Momentum	Filter	MA	TRB	CB
	ks	1	1	5	1	1
	kl	200	5	20	200	100
	b	0.000	0.010	0.010	0.005	0.010
	h	25	25	25	25	25
’95.01.04-’24.06.28 (entire period)	N(Buy)	3226	1876	1074	114	22
	N(Sell)	3829	1698	982	58	4167
	Buy>0	0.529	0.478	0.499	0.614	0.545
	Sell>0	0.448	0.449	0.415	0.466	0.497
	Buy	0.448 (3.964)**	0.466 (3.675)**	1.092 (7.419)**	5.356 (13.063)**	3.172 (3.406)**
	Sell	-0.215 (-3.537)**	-0.303 (-3.231)**	-0.683 (-5.222)**	-0.237 (-0.578)	0.100 (0.172)
	Buy-Sell	0.663 (6.496)**	0.770 (5.443)**	1.775 (9.517)**	5.593 (8.119)**	3.072 (3.387)**
	ks	1	1	5	1	1
	kl	20	1	20	200	100
	b	0.000	0.010	0.010	0.005	0.005
	h	25	25	25	25	25
’95.01.04-’00.12.29 (period before and after the currency crisis)	N(Buy)	652	128	211	32	22
	N(Sell)	776	103	176	7	702
	Buy>0	0.525	0.461	0.460	0.875	0.818
	Sell>0	0.432	0.447	0.295	0.429	0.494
	Buy	1.885 (4.291)**	3.877 (5.358)**	4.124 (7.092)**	17.669 (12.644)**	12.479 (7.641)**
	Sell	-0.789 (-3.821)**	-0.413 (-1.131)	-2.373 (-4.932)**	0.180 (-0.143)	0.165 (-1.108)
	Buy-Sell	2.644 (7.025)**	4.290 (4.604)**	6.496 (8.983)**	17.488 (5.555)**	12.314 (7.823)**
	ks	1	1	5	1	1
	kl	200	5	20	200	200
	b	0.000	0.010	0.010	0.005	0.005
	h	25	25	25	25	5
’01.01.02-’10.12.30 (period in the 2000s)	N(Buy)	610	600	325	26	3
	N(Sell)	1647	614	402	32	971
	Buy>0	0.428	0.443	0.449	0.577	1.000
	Sell>0	0.421	0.373	0.413	0.500	0.420
	Buy	0.285 (2.880)**	0.251 (2.602)**	0.659 (3.799)**	2.384 (3.406)**	3.222 (3.179)**
	Sell	-0.415 (-1.502)	-0.572 (-2.189)*	-0.496 (-1.487)	-0.387 (-0.233)	-0.122 (-1.098)
	Buy-Sell	0.700 (3.800)**	0.823 (3.785)**	1.156 (4.081)**	2.771 (2.701)**	3.344 (3.249)**
	ks	1	1	2	1	1
	kl	20	50	50	15	50
	b	0.000	0.010	0.005	0.010	0.010
	h	25	25	25	5	10

Period	Rule	Momentum	Filter	MA	TRB	CB
'11.01.03-'24.06.28 (post-2010 period)	N(Buy)	1680	2305	1400	29	19
	N(Sell)	1596	940	1191	24	2169
	Buy>0	0.552	0.544	0.546	0.586	0.526
	Sell>0	0.486	0.470	0.472	0.542	0.500
	Buy	0.175 (0.969)**	0.209 (1.277)	0.209 (1.090)	0.311 (1.342)**	0.532 (1.297)
	Sell	0.023 (-1.003)	-0.096 (-2.317)*	-0.058 (-2.088)*	-0.142 (-0.690)	0.074 (0.611)
	Buy-Sell	0.151 (1.707)+	0.305 (3.116)**	0.267 (2.678)**	0.454 (1.419)	0.459 (1.222)

Notes: 1) For the momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, there are 16, 84, 144, 96, and 96 sub-rules, respectively. This depends on ks (short-term MA or current time), kl (long-term MA or the considered formation period), b (filter size), and h (holding period).

2) Buy and Sell indicate the average return from buy and sell positions, respectively, over the holding period (h). Buy-Sell refers to the difference between these returns; Table 2 reports the sub-rules that yield the largest such difference.

3) Buy>0 (Sell>0) refers to the proportion of buy (sell) returns that are greater than zero.

4) Figures shown in ( ) denote t-values; +, *, and ** mark statistical significance at the 10%, 5%, and 1% levels, respectively.

For the momentum rule over the full sample period ('95.01.04-'24.06.28), the maximum buy-sell return of 0.663% occurs when $ks=1$, $kl=200$, $b=0$, and $h=25$ across the 16 sub-rules. The number of buy and sell signals is 3226 and 3829, respectively, while the probabilities that buy and sell returns are greater than zero are 52.9% and 44.8%. The buy and sell returns are 0.448% and -0.215%, respectively, with both achieving statistical significance at the 1% level, as indicated by the t-values shown in parentheses. The calculation of t-values for buy, sell, and buy-sell returns follows the method of Brock et al. (1992).

$$\frac{\mu_b-\mu}{(\sigma^2/T+\sigma^2/T_b)^{1/2}},\quad \frac{\mu_s-\mu}{(\sigma^2/T+\sigma^2/T_s)^{1/2}},\quad \frac{\mu_b-\mu_s}{(\sigma^2/T_b+\sigma^2/T_s)^{1/2}} \tag{7}$$

where μ and T represent the mean of the total returns and the sample size, respectively. $\mu_b(\mu_s)$ and $T_b(T_s)$ indicate the average buy (sell) return and the counts of buys (sells), respectively. σ^2 reflects the variance over the entire period.

For the filter rule, the buy-sell return reaches its maximum value of 0.770% under the conditions $ks=1$, $kl=5$, $b=0.01$, and $h=25$ among 84 sub-rules. For the MA rule, the highest observed buy-sell return is 1.775% when $ks=5$, $kl=20$, $b=0.01$, and $h=25$ across 144 sub-rules. For both the filter and MA rules, the probability that the buy return exceeds zero is less than 50%. The TRB rule exhibits the highest buy-sell return at 5.593%, achieved when $ks=1$, $kl=200$, $b=0.005$, and $h=25$ among the 96 sub-rules. As we progress from momentum, filter, and MA to TRB, there is a decrease in the number of buy and sell signals, accompanied by an increase in buy-sell returns.[5] For the CB rule, the highest buy-sell return recorded is 3.072%, occurring when $ks=1$, $kl=100$, $b=0.01$, and $h=25$ across 96 sub-rules. While parameters ks, kl, and b differ according to the specific rule, the holding period (h) remains constant at 25 days. The rationale is that the returns reported in Table 2 refer to the entire holding period, rather than the average daily return. Therefore, to obtain the average daily return, one must divide the reported value by h, which is 25. Reporting overall returns in Table 2 is aimed at demonstrating that some technical trading rules yield positive returns even after including transaction costs. Neely and Weller (2013) assigned transaction costs of 0.05%, 0.04%, and 0.03% for the 1970s, 1980s, and 1990s, respectively, in developed markets. Table 2 demonstrates that technical trading rules can achieve significant excess returns even after accounting for these transaction costs, depending on the rule applied. Menkhoff and Taylor (2007) and Hsu, Taylor, and Wang (2016) contended that the inclusion of transaction costs does not necessarily eliminate the potential for significant returns via technical trading rules.[6]

Given that Korea has experienced several transformations over the last 30 years, including financial market liberalization and economic crises, Table 2 presents the highest-performing sub-rules for each of the five rules by segmenting the overall analysis into three distinct periods. During the pre- and post-currency crisis period ('95.01.04-'00.12.29), it is evident that specific rules are able to generate higher buy-sell returns relative to the full sample period. Nonetheless, the sub-rules producing the highest returns are not always identical to those optimal over the entire period, as

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[5] Serban (2010) contended that exchange rates demonstrate behavior similar to that of stock prices, specifically exhibiting momentum and mean reversion patterns. Serban (2010) further indicated that a pure mean reversion strategy generates lower average returns, whereas approaches integrating both mean reversion and momentum outperform conventional trading strategies, including carry trades and moving average rules, in out-of-sample forecasting for exchange rates across five countries.

[6] As previously noted, existing Korean studies did not account for interest rates, yet the summary statistics of the won/dollar exchange rate are not significantly different from those of the won/dollar return. Similarly, the estimation outcomes from technical trading rules exhibit minimal variation. Kalemli-Özcan and Varela (2025) employed the expected exchange rate S^e_{t+h}, instead of the actual exchange rate S_{t+h}, in equation (6) to define the UIP premium and decomposed it into an interest rate differential (IR differential) and an exchange rate adjustment (ER adjustment). By utilizing survey data on expected exchange rates, Kalemli-Özcan and Varela (2025) demonstrated that the UIP premium and ER adjustment are strongly correlated for advanced economies, whereas for emerging markets, the UIP premium and IR differential exhibit a high correlation. For emerging markets, similar findings are obtained when actual exchange rates are used. However, since this study employs daily returns, the daily excess returns exhibit a correlation coefficient close to 1 with the ER adjustment based on actual exchange rates, but the correlation with the IR differential is substantially lower. Kalemli-Özcan and Varela (2025) classified Korea as an emerging market. Nevertheless, the empirical findings of this study reveal that the relationship between exchange rates and interest rates during the period '95.01.04-'10.12.30 aligns with emerging market characteristics, whereas the relationship from '11.01.03-'24.06.28 resembles that of an advanced economy. As evidenced by the forward premium puzzle, an increase in Korean interest rates is associated with a decline in the won/dollar exchange rate, rather than an increase.

demonstrated with the filter and CB rules. In the 2000s ('01.01.02-'10.12.30), the analysis indicates not only a reduction in the magnitude of buy-sell returns compared to the preceding period, but also reveals that the optimal sub-periods for the momentum, filter, MA, and CB rules have shifted. This pattern suggests that out-of-sample predictions may have poorer predictive performance than in-sample estimates. In the period following 2010 ('11.01.03-'24.06.28), predictive accuracy declines even further. The deterioration in forecasting performance is attributed to increased efficiency in the foreign exchange market as investors respond to publicly available forecast results or as market conditions evolve.

2. Average Returns by Rule

As outlined above, substantial disparities exist in returns among sub-rules, and the sub-rule yielding the highest return in each period does not remain consistent across segments. To mitigate concerns regarding data snooping, I examine the performance of all five rules by calculating the average return across their respective sub-rules. Table 3 reports the average return for each rule, both for the aggregate period and each sub-period. Distinct from Table 2, Table 3 provides the mean of daily returns normalized by the holding period (h).

Examining the entire sample period as presented in Table 2, the TRB rule yields the highest buy-sell return of 0.133%, while it registers the smallest total number of transactions, whereas the momentum rule records the lowest buy-sell return of 0.025%. When the periods are analyzed separately, the average buy-sell return for the majority of rules during the pre- and post-currency crisis period ('95.01.04-'00.12.29) is roughly three times greater than the average for the full sample period. In contrast, during the 2000s ('01.01.02-'10.12.30), the average buy-sell returns for all rules decline compared to the preceding period. Furthermore, while the TRB rule achieved the highest buy-sell return (0.436%) among the five rules in the earlier period, the CB rule attains the highest buy-sell return (0.176%) in the 2000s. In the post-2010s period ('11.01.03-'24.06.28), in contrast to prior periods, all rules deliver negative buy-sell returns, with the TRB rule recording the lowest buy-sell return at -0.037%. This shift exemplifies the winner-loser reversal described by De Bondt and Thaler (1985), where the TRB rule, formerly the best performer among the five rules in the earlier sample, becomes the worst performer after 2010. This observation further demonstrates that out-of-sample forecasts can exhibit substantially weaker predictive power compared to in-sample estimates.

[Table 3] Average Returns by Technical Trading Rule

Period	Rule	Momentum	Filter	MA	TRB	CB
'95.01.04-'24.06.28 (entire period)	N(Buy)	3381	3955	2840	321	342
	N(Sell)	3784	1943	2929	289	4375
	Buy>0	0.503	0.488	0.500	0.527	0.548
	Sell>0	0.458	0.461	0.457	0.467	0.478
	Buy	0.016	0.018	0.021	0.109	0.076
		(2.134)*	(1.754)$^{+}$	(2.615)**	(3.934)**	(2.507)*
	Sell	-0.009	-0.017	-0.013	-0.024	-0.006
		(-1.977)*	(-2.055)*	(-2.302)**	(-1.042)	(-1.311)
	Buy-Sell	0.025	0.035	0.035	0.133	0.082
		(3.560)**	(3.193)**	(4.094)**	(3.307)**	(2.894)**
'95.01.04-'00.12.29 (period preceding and following the currency crisis)	N(Buy)	677	719	603	71	77
	N(Sell)	681	326	462	49	696
	Buy>0	0.520	0.492	0.518	0.637	0.639
	Sell>0	0.435	0.415	0.409	0.476	0.430
	Buy	0.069	0.077	0.083	0.388	0.182
		(2.011)*	(1.807)$^{+}$	(2.462)*	(4.549)**	(2.017)*
	Sell	-0.025	-0.048	-0.043	-0.048	-0.025
		(-1.973)*	(-1.866)$^{+}$	(-2.400)*	(-0.827)	(-1.700)$^{+}$
	Buy-Sell	0.093	0.125	0.126	0.436	0.206
		(3.450)**	(2.978)**	(4.004)**	(3.347)**	(2.544)*
'01.01.02-'10.12.30 (2000s period)	N(Buy)	838	1272	694	99	98
	N(Sell)	1529	745	1216	116	1543
	Buy>0	0.460	0.465	0.467	0.474	0.529
	Sell>0	0.443	0.429	0.450	0.417	0.436
	Buy	0.004	0.010	0.014	0.047	0.156
		(1.038)	(1.286)	(1.546)	(0.606)	(1.672)$^{+}$
	Sell	-0.016	-0.032	-0.018	-0.054	-0.020
		(-0.658)	(-1.454)	(-0.666)	(-0.951)	(-1.003)
	Buy-Sell	0.020	0.042	0.032	0.101	0.176
		(1.469)	(2.297)*	(1.894)$^{+}$	(1.169)	(1.909)$^{+}$
'11.01.03-'24.06.28 (post-2010 period)	N(Buy)	1739	1921	1423	145	164
	N(Sell)	1467	860	1151	121	2086
	Buy>0	0.518	0.500	0.509	0.497	0.509
	Sell>0	0.490	0.503	0.487	0.514	0.516
	Buy	0.003	0.002	0.000	-0.019	-0.008
		(-0.282)	(-0.288)	(-0.600)	(-0.377)	(-0.052)
	Sell	0.008	0.006	0.005	0.018	0.011
		(0.352)	(0.299)	(0.007)	(0.328)	(1.066)
	Buy-Sell	-0.055	-0.004	-0.005	-0.037	-0.019
		(-0.549)	(-0.474)	(-0.494)	(-0.483)	(-0.278)

Notes: 1) For momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, 16, 84, 144, 96, and 96 sub-rules are applied, respectively, depending on ks (short-term moving average or current time), kl (long-term moving average or relevant formation period), b (filter size), and h (holding period). Table 3 presents the mean results of all sub-rules for each rule.

2) Buy, Sell, and Buy-Sell indicate the overall average returns of buy, sell, and buy-sell strategies per day, not per holding period (h), respectively.

3) Buy>0 (Sell>0) represents the proportion of buy (sell) returns that exceed 0.

4) Figures shown in ( ) denote t-values; $^{+}$, *, and ** mark statistical significance at the 10%, 5%, and 1% levels, respectively.

VI. Bootstrap Simulation Test

Implementing a comprehensive evaluation of all technical trading strategies using conventional statistical tools is complicated and requires careful treatment of intricate dependencies among trading techniques. To address this challenge, I employ the bootstrap method introduced by Brock et al. (1992) to jointly test the statistical significance of the technical trading strategies discussed above. For example, such a bootstrap-based test may determine whether 'abnormal' excess returns yielded by technical trading rules arise from an autoregressive process or are attributable to a common risk factor. This framework enables the examination of a broader set of null hypotheses beyond the AR or CAPM frameworks. The bootstrap method also offers insights into how the model specification might need adjustment if these statistical tests reject the null model, especially in the context of explaining excess returns in the won/dollar foreign exchange market. The t-ratios noted earlier are based on assumptions of normality, stationarity, and time independence. However, it is widely recognized that exchange rates among major industrialized economies are characterized not only by linear unpredictability but also by unconditionally leptokurtic and conditionally heteroskedastic distributions. These distinctive features are more effectively captured using simulated distributions under null models of excess returns. Additionally, by analyzing the standard deviation of returns across buy and sell periods, the bootstrap method helps illuminate whether the observed predictability in excess returns stems from market inefficiencies or reflects time-varying equilibrium returns.

Four null models are utilized for the joint test of bootstrap and technical trading rules: random walk, AR(1), CAPM, and CAPM & AR(1). It is widely recognized that if uncovered interest parity (UIP) is satisfied, then the excess return in equation (6) will be zero. Additionally, since the work by Meese and Rogoff (1983), no structural or time series model has consistently demonstrated out-of-sample forecasting superiority over the random walk, justifying its role as the default null model. During the period from the introduction of the market average exchange rate system in March 1990 until the adoption of the free floating exchange rate system in December 1996, the range of daily exchange rate fluctuations was constrained, causing the won/dollar exchange rate to inadequately represent daily market conditions and resulting in a serial correlation. The AR(1) model is introduced as the second null model because the modified Ljung-Box test statistic in Table 1 indicates pronounced serial correlation across different sub-periods, despite substantial efforts to control for outliers. Third, if both uncovered interest parity (UIP) and covered interest parity (CIP) are satisfied, $S_{t+1}^{e} = F_{t}^{t+1}$. If $S_{t+1}^{e} \neq F_{t}^{t+1}$, this suggests inefficiency in the foreign exchange market or the presence of a risk premium. Consequently, I include the CAPM—which models excess returns as a function of shared risk factors—as a null model.

1. Test Method

This section employs bootstrap simulation tests to determine whether the won/dollar foreign exchange market can be adequately explained by technical trading rules, or by alternative theoretical or time series models such as the RWD model, AR(1) model, and CAPM. The test approach involves comparing the conditional returns generated by technical trading signals with actual won/dollar exchange rate data to those obtained from simulated datasets under the specified null hypothesis.

The notation for RWD, AR(1), CAPM, and CAPM & AR(1), each serving as null hypothesis models, is defined as follows.[7]

RWD: $$r_t = \alpha_0 + \epsilon_{1,t} \tag{8}$$

AR(1): $$r_t = \alpha_0 + \alpha_1 r_{t-1} + \epsilon_{2,t} \tag{9}$$

CAPM: $$r_t = \alpha_0 + \beta r_{m,t} + \epsilon_{3,t} \tag{10}$$

CAPM & AR(1): $$r_t = \alpha_0 + \beta r_{m,t} + \alpha_1 r_{t-1} + \epsilon_{4,t} \tag{11}$$

In equations (10) and (11), the return on the dollar index is treated as the return on the market portfolio, r_m, and is calculated using equation (6), analogous to the computation for the won/dollar return, r_t.

The estimation results for each model are presented in Table 4. For the full sample period, the estimate of α_0 for RWD is 0.003 and this value is not statistically significant. In the AR(1) model, the estimate of α_1 is 0.162, indicating statistical significance at the 1% level. In the CAPM, the estimate of α_0 is 0.001, which is nearly zero, while the estimate of β is 0.781, exhibiting strong statistical significance. The result $\alpha_0 = 0$ suggests that risks aside from those measured by β do not contribute to determining the won/dollar return. Despite this, previous studies of CAPM indicate that asset price returns are influenced by additional factors beyond the market portfolio. Given the significant AR(1) estimate, I also jointly estimate CAPM & AR(1). Here, the estimate of α_0 is indistinguishable from zero, but the estimates of β and α_1 are highly statistically significant. Moreover, the R^2 value in this model is the highest, at 0.115.

Assessing results by period, the estimate of α_0 remains not significantly different from zero. The estimate of α_1 is greater and more positive during the period before and after the currency crisis ('95.01.04-'00.12.29) compared to subsequent periods,

[7] Refer to Appendix A for detailed explanations of the EGARCH model and the two-phase regime switching models.

after which it gradually decreases and becomes more negative. The estimates of β maintain strong statistical significance across all periods but show a declining trend in magnitude. β is given as $Cov(r, r_m)/Var(r_m)$ and reflects the magnitude of risk associated with the won/dollar foreign currency asset. Since the linear regression estimation indicates that the estimate of β remains statistically significant throughout all periods, I do not proceed to estimate the time-varying or conditional CAPM variants.

The bootstrap simulation procedure involves first estimating equations (8), (9), (10), and (11) using OLS to obtain residuals ($\hat{\epsilon}_{i,t}$, $t=1,\cdots, T$). Next, 1,000 bootstrap simulations are conducted to generate the bootstrap residuals ($\epsilon^*_{t,n}$, $t=1,\cdots, T, n=1, \cdots, 1{,}000$) from these original residuals. Using the bootstrap residuals, the simulated returns ($r^*_{t,n}$) are then calculated. Subsequently, the buy, sell, and buy-sell returns and their respective standard deviations are determined for each set of simulated won/dollar returns by applying technical trading rules.

[Table 4] CAPM & AR(1) Estimates

		RWD	AR(1)	CAPM	CAPM & AR(1)
'95.01.04 - '24.06.28	α_0	0.003(0.010)	0.002(0.010)	0.001(0.009)	0.001(0.009)
	α_1	-	0.162(0.012)**	-	0.149(0.011)**
	β	-	-	0.781(0.029)**	0.765(0.028)**
	R^2	0.000	0.026	0.093	0.115
'95.01.04 - '00.12.29	α_0	0.019(0.034)	0.013(0.032)	0.008(0.033)	0.004(0.031)
	α_1	-	0.323(0.025)**	-	0.302(0.024)**
	β	-	-	1.085(0.125)**	0.916(0.120)**
	R^2	0.000	0.104	0.000	0.139
'01.01.02 - '10.12.30	α_0	-0.009(0.016)	-0.008(0.016)	0.001(0.009)	0.000(0.014)
	α_1	-	0.034(0.020)$^{+}$	-	0.025(0.019)
	β	-	-	0.841(0.042)**	0.840(0.042)**
	R^2	0.000	0.001	0.140	0.141
'11.01.03 - '24.06.28	α_0	0.004(0.009)	0.004(0.009)	-0.001(0.009)	-0.001(0.009)
	α_1	-	-0.060(0.017)**	-	-0.064(0.016)**
	β	-	-	0.638(0.026)**	0.639(0.026)**
	R^2	0.000	0.004	0.149	0.153

Note: 1) Values in ( ) are standard errors; $^{+}$ and ** denote statistical significance at the 10% and 1% levels, respectively.

2. Test Results

Table 5 presents the outcomes of simulation tests utilizing the RWD model as specified in Equation (8). For instance, the reported average buy return of 0.002% for the momentum rule over the full sample period represents the mean of 16 × 1,000 average buy returns, each derived from 1,000 simulations conducted on the 16 sub-rules. Similarly, the average sell return of 0.004% is calculated by the same methodology, while the buy-sell returns, (A)-(B), highlight the differential between these two returns. The standard deviation of the buy return, reported as 0.402, is based on the mean of the standard deviations computed across the 16 × 1,000 buy returns, which result from 1,000 simulations per sub-rule. The calculation for the standard deviation of the sell return follows an identical approach. Additionally, values enclosed in [ ] denote the mean probability, calculated as follows: for each sub-rule, the probability that the actual average return shown in Table 3 exceeds its simulated counterpart (from 1,000 replications of the RWD model) is found, then averaged across the 16 sub-rules. For example, [0.857] in the average buy return of the momentum rule denotes an 85.7% probability that the actual average return of 0.016 in Table 3 surpasses the 16 × 1,000 simulated average returns. Furthermore, the [0.997] value in the standard deviation column for the momentum rule's buy return suggests a 99.7% probability that the standard deviation of the actual buy return exceeds the 16×1,000 simulated standard deviations. The actual values for buy, sell, and buy-sell returns in Table 3 are 0.016%, -0.009%, and 0.025%, respectively, all of which are greater in absolute magnitude than the corresponding simulated values of 0.002%, 0.004%, and -0.002%. The simulated buy and sell returns—0.002% and 0.004%, respectively—do not show a material difference from the average won/dollar return of 0.003% reported in Table 1. The probability value of 0.911 for the buy-sell return derived from the momentum rule in Table 5 implies that the observed return difference is unlikely to be attributable solely to a random walk model with drift. This result suggests that the excess return from the momentum strategy diverges from that predicted by the random walk with drift model, indicating the possibility of an alternative explanation that may elude detection by standard statistical procedures. The standard deviations of the simulated buy and sell returns are 0.402 and 0.401, respectively, and these do not differ meaningfully from each other. However, as indicated by the probability values of 0.997 and 0.001, the standard deviation of the actual buy return is substantially greater, whereas the standard deviation of the actual sell return is much smaller, lending support to the view that higher returns are associated with periods of increased risk.

Over the entire sample period ('95.01.04–'24.6.28), the probability values associated with the buy-sell returns from the five technical trading rules do not show significant differences and range between 0.805 and 0.942. The results remain consistent for the pre- and post-crisis subsample ('95.01.04–'00.12.29), suggesting that the return differentials in this timeframe are unlikely to be explained by the RWD model on a stochastic basis. In contrast, these probability values exhibit a downward trend throughout the 2000s ('01.01.02–'10.12.30) and approximate the median in the post-2010s, indicating that, during these more recent periods, the RWD model can account for the observed return differentials.

[Table 5] RWD Bootstrap Simulation Tests

Period	Rule	Buy Mean (A)	Buy Std.	Sell Mean (B)	Sell Std.	(A)-(B)
'95.01.04-'24.06.28 (entire period)	Momentum	0.002 [0.857]	0.402 [0.997]	0.004 [0.195]	0.401 [0.001]	-0.002 [0.911]
	Filter	0.003 [0.818]	0.402 [0.923]	0.002 [0.158]	0.402 [0.165]	0.000 [0.942]
	MA	0.003 [0.884]	0.402 [0.998]	0.003 [0.167]	0.402 [0.035]	0.000 [0.939]
	TRB	0.003 [0.893]	0.481 [0.990]	0.002 [0.209]	0.404 [0.538]	0.000 [0.942]
	CB	0.002 [0.890]	0.644 [0.759]	0.026 [0.341]	2.335 [0.005]	-0.023 [0.805]
'95.01.04-'00.12.29 (period prior to and following the currency crisis)	Momentum	0.012 [0.890]	0.632 [0.977]	0.028 [0.170]	+INF [0.001]	-0.017 [0.940]
	Filter	0.019 [0.801]	0.631 [0.917]	0.018 [0.182]	0.636 [0.230]	0.001 [0.899]
	MA	0.018 [0.874]	0.628 [0.980]	0.019 [0.162]	0.630 [0.092]	0.000 [0.928]
	TRB	0.019 [0.950]	0.878 [0.958]	0.017 [0.282]	0.668 [0.688]	0.002 [0.947]
	CB	0.018 [0.849]	+INF [0.626]	0.185 [0.281]	3.663 [0.006]	-0.167 [0.795]
'01.01.02-'10.12.30 (2000s era)	Momentum	-0.011 [0.716]	0.381 [0.989]	-0.006 [0.351]	0.380 [0.002]	-0.005 [0.760]
	Filter	-0.009 [0.765]	0.380 [0.916]	-0.009 [0.218]	0.381 [0.178]	0.000 [0.876]
	MA	-0.009 [0.764]	0.381 [0.993]	-0.009 [0.339]	0.380 [0.043]	0.000 [0.792]
	TRB	-0.008 [0.617]	0.562 [0.860]	-0.009 [0.203]	0.382 [0.600]	0.000 [0.720]
	CB	-0.009 [0.808]	+INF [0.710]	-0.088 [0.528]	2.202 [0.012]	0.079 [0.614]
'11.01.03-'24.06.28 (post-2010 period)	Momentum	0.003 [0.496]	0.261 [0.634]	0.005 [0.579]	0.262 [0.051]	-0.003 [0.472]
	Filter	0.004 [0.466]	0.262 [0.616]	0.004 [0.577]	0.263 [0.196]	0.000 [0.389]
	MA	0.004 [0.414]	0.262 [0.666]	0.004 [0.532]	0.262 [0.138]	0.000 [0.419]
	TRB	0.004 [0.413]	0.454 [0.528]	0.004 [0.650]	0.267 [0.697]	0.000 [0.346]
	CB	0.004 [0.498]	0.587 [0.528]	0.036 [0.471]	1.515 [0.068]	-0.034 [0.566]

Notes: 1) For momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, 16, 84, 144, 96, and 16 sub-rules are employed, respectively, depending on the short- and long-term moving averages or formation periods considered, filter size, holding period.

2) The mean and standard deviation for the momentum rule are averages based on 16 means and 16 standard deviations calculated from 1,000 simulations of the RWD (Random Walk with Trend) model; this methodology is similarly applied to the other rules.

3) Values in [ ] report the average probability that the actual return is greater than the returns simulated 1,000 times from the RWD model for each sub-rule.

Table 6 presents simulation results based on the AR(1) model as specified in equation (9). Consistent with Table 4, AR(1) parameter estimates across the full period ('95.01.04–'24.06.28) are statistically significant and positive, motivating an analysis of whether returns generated by technical trading rules are attributable to daily serial dependence. Similar to the findings with the RWD model, return differentials in the pre- and post-crisis intervals are inadequately explained by the AR(1) model. However, the probability value for buy-sell returns declines progressively over the 2000s, suggesting a greater likelihood that the AR(1) model explains return differentials after 2010.

Table 7 and Table 8 report simulation outcomes for the CAPM and the joint CAPM & AR(1) model. Throughout the full sample period, the CAPM & AR(1) model produces positive buy-sell returns that exceed those generated individually by the CAPM or AR(1) model, though they remain below the actual buy-sell returns reported in Table 3. Notably, as in the simulations involving RWD and AR(1), the likelihood that return differentials are accounted for by the CAPM or CAPM & AR(1) models increases in more recent sample periods.

The decline in the explanatory or predictive power of technical trading rules over time relative to null models can be attributed to several factors. First, in episodes such as the currency crisis and global financial crisis, when the won/dollar exchange rate experiences pronounced increases, technical trading strategies like momentum and TRB tend to yield abnormal excess returns that are not easily explained by standard null models, whereas such effects are less prominent in stable periods.

Second, as capital flows become fully liberalized and information disseminates swiftly—enabling investors to form rational expectations—it becomes increasingly challenging to achieve excess returns from investments in other foreign currency assets, as implied by UIP. Since the first quarter of 2001, Korea has maintained its status as a net external creditor, accumulating more external credit than external debt, owing to a persistent current account surplus following the 1997 currency crisis. According to the International Investment Position (IIP), Korea transitioned to a net foreign asset position in the third quarter of 2014, as its overseas investment (external financial assets) surpassed inbound foreign investment (external financial liabilities). Consequently, domestic pension funds, utilizing rational investment strategies in their overseas investments, have emerged as key participants in the won/dollar exchange market. This shift has contributed to a more efficient foreign exchange market compared to previous periods, distinguishing their activity from that of overseas speculators.

Furthermore, Korea's portfolio of trade partners has broadened, with a particularly significant increase in trade with China. Since 2003, China has overtaken the United States as Korea's primary export destination, and since 2007, it has surpassed Japan as Korea's leading source of imports. However, these emerging economies have not adopted exchange rate systems determined purely by market

[Table 6] AR(1) Bootstrap Simulation Tests

Period	Rule	Buy Mean (A)	Buy Std.	Sell Mean (B)	Sell Std.	(A)-(B)
'95.01.04- '24.06.28 (entire period)	Momentum	0.002 [0.852]	0.404 [0.998]	0.003 [0.200]	0.400 [0.001]	-0.001 [0.906]
	Filter	0.005 [0.786]	0.406 [0.928]	-0.001 [0.188]	0.401 [0.164]	0.006 [0.919]
	MA	0.006 [0.848]	0.407 [0.999]	0.000 [0.202]	0.400 [0.033]	0.006 [0.909]
	TRB	0.020 [0.887]	0.531 [0.991]	-0.001 [0.235]	0.401 [0.543]	0.020 [0.934]
	CB	0.014 [0.904]	0.661 [0.754]	0.017 [0.373]	2.320 [0.004]	-0.003 [0.767]
'95.01.04- '00.12.29 (period before and after the currency crisis)	Momentum	0.017 [0.871]	0.650 [0.982]	0.025 [0.165]	0.619 [0.001]	-0.008 [0.931]
	Filter	0.035 [0.754]	0.671 [0.920]	-0.003 [0.239]	0.631 [0.231]	0.038 [0.857]
	MA	0.039 [0.803]	0.674 [0.981]	-0.001 [0.233]	0.611 [0.093]	0.040 [0.863]
	TRB	0.137 [0.924]	1.337 [0.952]	0.003 [0.309]	0.643 [0.708]	0.135 [0.916]
	CB	0.070 [0.794]	+INF [0.609]	0.085 [0.357]	3.535 [0.006]	-0.015 [0.711]
'01.01.02- '10.12.30 (2000s period)	Momentum	-0.012 [0.718]	0.382 [0.988]	-0.006 [0.349]	0.380 [0.002]	-0.005 [0.760]
	Filter	-0.008 [0.758]	0.381 [0.918]	-0.010 [0.225]	0.382 [0.177]	0.002 [0.869]
	MA	-0.008 [0.753]	0.381 [0.993]	-0.009 [0.345]	0.380 [0.043]	0.001 [0.783]
	TRB	-0.006 [0.617]	0.563 [0.862]	-0.009 [0.204]	0.383 [0.599]	0.003 [0.720]
	CB	-0.004 [0.802]	+INF [0.711]	-0.091 [0.532]	2.201 [0.012]	0.088 [0.608]
'11.01.03- '24.06.28 (post-2010 period)	Momentum	0.002 [0.494]	0.261 [0.640]	0.005 [0.584]	0.262 [0.051]	-0.002 [0.467]
	Filter	0.004 [0.464]	0.262 [0.616]	0.004 [0.584]	0.263 [0.197]	0.000 [0.382]
	MA	0.004 [0.411]	0.262 [0.664]	0.004 [0.535]	0.262 [0.136]	0.000 [0.414]
	TRB	0.005 [0.412]	0.456 [0.527]	0.004 [0.647]	0.267 [0.697]	0.001 [0.345]
	CB	0.005 [0.496]	0.594 [0.525]	0.033 [0.482]	1.515 [0.068]	-0.028 [0.556]

Notes: 1) For momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, 16, 84, 144, 96, and 16 sub-rules are implemented, respectively, depending on the short- and long-term moving averages or the respective formation periods considered, filter size, holding period, etc.

2) The mean and standard deviation for the momentum rule represent averages of 16 means and 16 standard deviations calculated from 1,000 simulations of the AR(1) model; the same approach is taken for the other rules.

3) Values in [ ] represent the average probability that the actual return exceeds the returns simulated 1,000 times from the AR(1) model for each sub-rule.

[Table 7] CAPM Bootstrap Simulation Tests

Period	Rule	Buy Mean (A)	Buy Std.	Sell Mean (B)	Sell Std.	(A)-(B)
'95.01.04-'24.06.28 (entire period)	Momentum	0.003 [0.840]	0.405 [0.997]	0.003 [0.209]	0.401 [0.001]	0.000 [0.890]
	Filter	0.005 [0.788]	0.407 [0.919]	0.001 [0.180]	0.402 [0.161]	0.004 [0.919]
	MA	0.008 [0.810]	0.408 [0.998]	-0.002 [0.230]	0.401 [0.032]	0.010 [0.870]
	TRB	0.019 [0.858]	0.526 [0.987]	0.000 [0.226]	0.401 [0.544]	0.018 [0.912]
	CB	0.009 [0.907]	0.650 [0.751]	0.018 [0.362]	2.336 [0.004]	-0.009 [0.775]
'95.01.04-'00.12.29 (period pre- and post-currency crisis)	Momentum	0.018 [0.862]	0.633 [0.982]	0.031 [0.152]	0.643 [0.001]	-0.013 [0.936]
	Filter	0.018 [0.801]	0.639 [0.918]	0.019 [0.168]	0.640 [0.225]	-0.002 [0.912]
	MA	0.022 [0.850]	0.634 [0.982]	0.018 [0.160]	0.634 [0.084]	0.004 [0.917]
	TRB	0.039 [0.947]	0.951 [0.957]	0.029 [0.242]	0.676 [0.676]	0.011 [0.950]
	CB	0.002 [0.877]	+INF [0.617]	0.219 [0.261]	3.670 [0.006]	-0.216 [0.824]
'01.01.02-'10.12.30 (2000s period)	Momentum	-0.012 [0.731]	0.390 [0.988]	-0.008 [0.377]	0.377 [0.002]	-0.003 [0.751]
	Filter	-0.004 [0.732]	0.392 [0.903]	-0.011 [0.233]	0.380 [0.173]	0.007 [0.856]
	MA	-0.006 [0.765]	0.403 [0.990]	-0.009 [0.326]	0.377 [0.037]	0.003 [0.801]
	TRB	0.011 [0.505]	0.639 [0.818]	-0.011 [0.201]	0.377 [0.607]	0.022 [0.611]
	CB	-0.010 [0.774]	+INF [0.696]	-0.123 [0.610]	2.187 [0.011]	0.114 [0.532]
'11.01.03-'24.06.28 (post-2010 period)	Momentum	0.003 [0.484]	0.263 [0.594]	0.006 [0.568]	0.261 [0.047]	-0.003 [0.464]
	Filter	0.006 [0.411]	0.264 [0.560]	0.003 [0.610]	0.263 [0.179]	0.003 [0.322]
	MA	0.008 [0.291]	0.265 [0.593]	-0.001 [0.665]	0.259 [0.145]	0.009 [0.242]
	TRB	0.017 [0.345]	0.471 [0.521]	0.000 [0.703]	0.263 [0.707]	0.017 [0.264]
	CB	0.017 [0.425]	0.643 [0.515]	0.049 [0.439]	1.522 [0.063]	-0.032 [0.549]

Notes: 1) For momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, 16, 84, 144, 96, and 16 sub-rules, respectively, are used based on the selections of short- and long-term moving averages or formation periods, filter size, and holding period.

2) The mean and standard deviation for the momentum rule are calculated as the average of 16 means and standard deviations derived from 1,000 simulations under the CAPM model. This calculation method is consistently applied to the other rules.

3) Values in [ ] indicate the average probability that the actual return is higher than the returns obtained from 1,000 CAPM model simulations for each sub-rule.

[Table 8] CAPM & AR(1) Bootstrap Simulation Tests

Period	Rule	Buy Mean (A)	Buy Std.	Sell Mean (B)	Sell Std.	(A)-(B)
'95.01.04-'24.06.28 (entire period)	Momentum	0.005 [0.809]	0.413 [0.997]	0.001 [0.237]	0.402 [0.001]	0.004 [0.865]
	Filter	0.007 [0.751]	0.417 [0.891]	-0.002 [0.211]	0.404 [0.150]	0.010 [0.889]
	MA	0.011 [0.765]	0.419 [0.996]	-0.004 [0.271]	0.401 [0.026]	0.015 [0.825]
	TRB	0.034 [0.845]	0.598 [0.988]	-0.003 [0.253]	0.400 [0.540]	0.037 [0.899]
	CB	0.019 [0.878]	0.671 [0.735]	0.008 [0.401]	2.354 [0.004]	0.011 [0.731]
'95.01.04-'00.12.29 (periods before and after the currency crisis)	Momentum	0.025 [0.829]	0.664 [0.980]	0.022 [0.179]	0.619 [0.001]	0.003 [0.905]
	Filter	0.034 [0.755]	0.683 [0.909]	-0.001 [0.226]	0.636 [0.222]	0.035 [0.869]
	MA	0.041 [0.783]	0.685 [0.979]	0.000 [0.225]	0.616 [0.081]	0.041 [0.857]
	TRB	0.149 [0.920]	1.429 [0.946]	0.014 [0.272]	0.650 [0.696]	0.135 [0.918]
	CB	0.052 [0.826]	+INF [0.609]	0.111 [0.336]	3.570 [0.006]	-0.058 [0.740]
'01.01.02-'10.12.30 (2000s sample period)	Momentum	-0.012 [0.728]	0.392 [0.987]	-0.008 [0.369]	0.378 [0.002]	-0.004 [0.755]
	Filter	-0.004 [0.725]	0.394 [0.896]	-0.012 [0.238]	0.381 [0.169]	0.008 [0.849]
	MA	-0.006 [0.759]	0.405 [0.989]	-0.009 [0.329]	0.377 [0.035]	0.004 [0.799]
	TRB	0.012 [0.501]	0.641 [0.817]	-0.011 [0.206]	0.377 [0.603]	0.023 [0.608]
	CB	-0.005 [0.772]	+INF [0.692]	-0.127 [0.614]	2.196 [0.011]	0.122 [0.528]
'11.01.03-'24.06.28 (post-2010 sample period)	Momentum	0.003 [0.487]	0.261 [0.685]	0.006 [0.560]	0.259 [0.071]	-0.003 [0.477]
	Filter	0.006 [0.412]	0.262 [0.649]	0.003 [0.611]	0.261 [0.216]	0.003 [0.323]
	MA	0.008 [0.285]	0.263 [0.671]	-0.001 [0.662]	0.258 [0.172]	0.009 [0.243]
	TRB	0.018 [0.344]	0.480 [0.535]	0.000 [0.702]	0.262 [0.720]	0.018 [0.267]
	CB	0.019 [0.425]	0.654 [0.526]	0.046 [0.450]	1.502 [0.063]	-0.027 [0.544]

Notes: 1) For momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, the number of sub-rules—16, 84, 144, 96, and 16, respectively—depends on parameterizations such as moving average lengths, filter sizes, and holding periods.

2) The mean and standard deviation for the momentum rule are averaged over 16 means and standard deviations obtained from 1,000 simulations of the CAPM & AR(1) model, with similar methodology for the other rules.

3) Values in [ ] provide the average probability that the actual return surpasses the returns produced by 1,000 simulations from the CAPM & AR(1) model across sub-rules.

forces. As a result, the won/dollar exchange rate has become aligned with the dollar index, which weights the dollar's exchange rate against various currencies based on their trade shares with the US, to mitigate exchange rate risk. This alignment suggests that a CAPM specification utilizing dollar index returns as the market portfolio is highly explanatory.

VII. Rolling Regressions and Out-of-Sample Forecasting

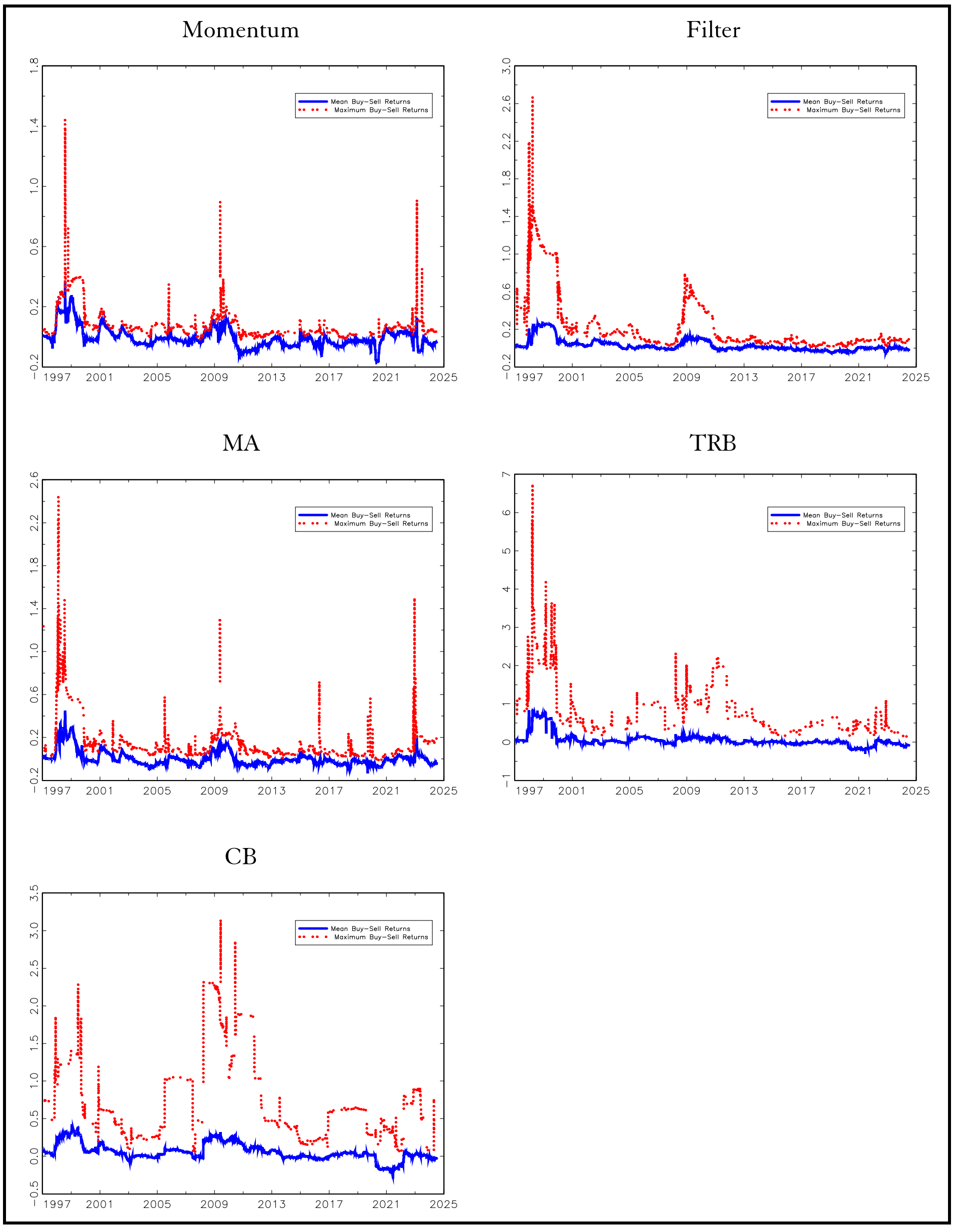
1. Rolling Regressions

In the previous section, I divided the overall period into three main subperiods and demonstrated that returns from technical trading rules diminish over time. However, since major events such as the currency crisis, global financial crisis, and COVID-19 pandemic occurred within each of these intervals, it is worthwhile to further analyze the impact of these crises on the explanatory power of technical trading rules. Therefore, in this section, I first analyze how returns from technical trading rules fluctuate during and after crisis episodes by applying the rolling regressions approach. I then compare the difference between the out-of-sample forecasting ability of technical trading rules, CAPM, and related models and their respective in-sample fits using the same rolling regressions methodology.

Ordinarily, half the total sample is employed for in-sample estimation in out-of-sample forecasting; however, I employ 500 samples for the in-sample estimation within rolling regressions. This approach is preferred because, while technical trading rules utilize at most 200 samples, including the currency crisis period in the initial sample could hinder proper analysis and may cause estimation or forecasting outcomes to be biased by outliers.

In Figure 2, the solid lines represent the average buy-sell returns obtained by each sub-technique across the five technical trading rules, while the short dotted lines display the buy-sell returns for the sub-technique with the highest yield. The initial in-sample buy-sell return estimates for the technical trading rules use 500 samples from January 4, 1995 to January 17, 1997 and are shown first for each technique in Figure 2. The second in-sample estimate employs 500 samples from January 5, 1995 to January 18, 1997, advancing the sample window by one day. This procedure is applied iteratively, and for the 6781st time, the buy-sell return is estimated using 500 samples from June 17, 2022 to June 27, 2024. The buy-sell returns from the 6781st iteration are plotted in the final column of Figure 2 for each technique. Although excess returns rise markedly during periods of the currency crisis, the global financial crisis, and the COVID-19 outbreak, the overall trend shows a decline in excess returns over time.

[Figure 2] Buy-Sell Returns from Rolling Regressions



2. Out-of-Sample Forecasting

The rolling regression results for in-sample estimation largely resemble previous findings, with key differences appearing during crisis periods. While the average excess returns remain positive, they are generally low for most techniques compared to the maximum excess returns identified through data mining. Furthermore, these results likely deteriorate further when applied to out-of-sample forecasts. Accordingly, I assess the predictive performance of both the technical trading rules and CAPM, which serves as the null model, using one-step-ahead out-of-sample predictions. In the first one-step-ahead out-of-sample forecast, the technical trading rules involve either buying or selling foreign exchange on January 18, 1997, determined by the sign of the average excess return calculated from 500 samples spanning January 4, 1995 to January 17, 1997. This process is repeated continuously, and in the 6781st iteration, the decision is to buy or sell foreign exchange on June 28, 2024, drawing on 500 samples from June 17, 2022 to June 27, 2024. For the CAPM, under the static expectations assumption where the market portfolio's forecast at time T+1 (T=500) equals its actual value at time T ($\hat{r}_{T+1} = \alpha_0 + \beta\, \hat{r}_{m,T+1} = \alpha_0 + \beta r_{m,T}$), the return to buy or sell is determined by whether the one-period ahead excess return forecast is positive or negative.

Table 9 presents the buy, sell, and buy-sell returns based on one-day-ahead out-of-sample forecasts. For the total sample period ('97.01.18-'24.06.28), CAPM exhibits the highest level of forecast outperformance. Analyzing by sub-periods, either CAPM or CAPM & AR(1) generally produces the highest buy-sell returns, with the exception of the COVID-19 period. Bold values in Table 9 highlight the maximum absolute return observed. During the COVID-19 crisis, CB outperforms the other models. Although technical trading rules yield higher excess returns when the crisis period is included in the in-sample estimation, this pattern does not extend to the out-of-sample forecasts. During periods with numerous outliers, such as the crisis period, excess returns tend to be highly variable, which can distort the assessment of a model's predictive power. To address this issue, I employ the Henriksson-Merton test (Henriksson and Merton, 1981) to evaluate whether the directional accuracy of the forecast is statistically significant. The Henriksson-Merton test statistic is defined as follows.

$$V = \frac{n_1 - E(n_1)}{\sigma(n_1)} \tag{12}$$

$$E(n_1) = \frac{n N_1}{N}, \qquad \sigma^2(n_1) = \frac{n_1 N_1 (N - N_1)(N - n)}{N^2 (N - 1)}$$

In this expression, n_1 represents the count of instances where both actual and predicted excess returns are negative, and n represents the count of instances where the predicted value is negative, irrespective of the sign of the actual value. N_1 and N refer to the number of cases with a negative actual value and the total number of out-of-sample forecasts, respectively. The Henriksson-Merton test statistic V follows a hypergeometric distribution, which is well approximated by a normal distribution. The outcomes of this test are summarized in Table 10. Within Table 10, P_1 indicates the conditional probability that both actual and predicted excess returns are negative, while P_2 corresponds to the probability that both are positive, and V is the test statistic for whether $P_1 + P_2$ exceeds 1. As indicated in Table 9, $P_1 + P_2$ attains its largest value for CAPM or CAPM & AR(1) in all sub-periods except for the COVID-19 period, where CB demonstrates the strongest predictive ability. Throughout most crisis periods, the directional accuracy of technical trading rules and the random walk with drift (RWD) appears to be biased in one direction. The directional forecasting evidence in Table 9 and Table 10 demonstrates that CAPM or CAPM & AR(1) is superior. Nevertheless, for structural or time series models, metrics such as root mean square error (RMSE) or absolute mean error (AME) are customarily utilized to evaluate forecast error magnitudes.

Table 11 presents the one-period-ahead out-of-sample RMSE and AME.[8] In the case of RMSE, it is notable that the random walk without drift (RW) recorded the lowest RMSE of 0.435 during the period following the currency crisis and preceding the global financial crisis ('99.01.04-'08.08.29).[9] In other time frames, either CAPM & AR(1) or CAPM demonstrated the highest predictive accuracy, consistent with previous periods. Furthermore, it is particularly noteworthy that, based on the AME criterion, RW surpassed both CAPM & AR(1) and CAPM for one-period-ahead out-of-sample forecasts across the currency crisis, post-currency crisis to pre-global financial crisis, and global financial crisis periods. Prior research generally found little distinction between RMSE and AME prioritization when forecasting rate changes or returns, as opposed to volatility. Nonetheless, Table 11 reveals a divergence in the order of the two test statistics, suggesting that models which effectively predict outliers have a lower RMSE, possibly due to the prevalence of outliers during crisis periods.

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[8] RMSE = $\sqrt{\sum_{k=1}^{6781}(r_{500+k} - \hat{r}_{500+k})^2/6781}$, AME = $\sum_{k=1}^{6781}|r_{500+k} - \hat{r}_{500+k}|/6781$. r_{500+k} and $\hat{r}_{500+k}$ denote the actual and predicted values at time 500+k, respectively.

[9] During this period, the out-of-sample R^2 for CAPM & AR(1), CAPM, AR(1), and RWD are all negative values, which are less than 0 for RW: -0.027, -0.037, -0.004, and -0.003, respectively.

[Table 9] One-Period-Ahead Out-of-Sample Returns

Forecasting Period	Returns	Momentum	Filter	MA	TRB	CB	CAPM &AR(1)	CAPM	AR(1)	RWD
’97.01.18	Buy	0.013	0.002	0.015	0.007	0.006	0.137	**0.137**	0.038	0.006
-	Sell	-0.002	0.004	-0.004	-0.002	-0.005	-0.123	**-0.124**	-0.026	0.000
’24.06.28	Buy-Sell	0.015	-0.002	0.018	0.009	0.011	0.259	**0.261**	0.064	0.006
’97.11.03	Buy	0.044	0.044	0.044	0.044	0.044	**0.622**	0.620	0.486	0.044
-	Sell	0.000	0.000	0.000	0.000	0.000	-0.531	**-0.663**	-0.455	0.000
’98.12.31	Buy-Sell	0.044	0.044	0.044	0.044	0.044	1.097	**1.209**	0.941	0.044
’99.01.04	Buy	0.003	-0.006	-0.008	-0.001	0.000	0.066	**0.070**	0.024	0.010
-	Sell	-0.009	0.000	-0.003	-0.016	-0.023	-0.064	**-0.068**	-0.017	-0.013
’08.08.29	Buy-Sell	0.013	-0.006	-0.005	0.014	0.023	0.130	**0.139**	0.041	0.023
’08.09.01	Buy	0.033	0.055	0.055	0.055	0.055	**0.431**	0.385	0.157	0.055
-	Sell	0.584	0.000	0.000	0.000	0.000	-0.449	**-0.452**	-0.270	0.000
’09.06.30	Buy-Sell	-0.550	0.055	0.055	0.055	0.055	**0.881**	0.837	0.427	0.055
’09.07.01	Buy	-0.068	-0.026	-0.010	-0.006	-0.012	**0.119**	0.118	-0.022	-0.022
-	Sell	-0.001	0.005	-0.007	-0.010	0.002	**-0.124**	-0.120	0.003	0.003
’19.12.30	Buy-Sell	-0.066	-0.031	-0.003	0.004	-0.013	**0.242**	0.238	-0.025	-0.025
’20.01.02	Buy	0.000	0.000	0.000	-1.956	**0.137**	0.101	0.040	0.095	0.030
-	Sell	0.030	0.030	0.030	0.063	-0.053	-0.062	0.018	**-0.093**	0.000
’20.06.30	Buy-Sell	-0.030	-0.030	-0.030	-2.019	**0.189**	0.163	0.022	0.188	0.030
’20.07.01	Buy	0.031	0.047	0.031	0.043	0.034	0.151	**0.156**	0.013	0.002
-	Sell	-0.006	-0.005	0.000	0.009	0.003	-0.123	**-0.126**	0.018	0.048
’24.06.28	Buy-Sell	0.036	0.052	0.031	0.035	0.031	0.274	**0.282**	-0.005	-0.047

Notes: 1) For momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, 16, 84, 144, 96, and 16 sub-rules are examined, contingent upon parameters such as moving average specifications and filter or formation settings.
2) Returns for sell, buy, and buy-sell operations are determined from 1-day-ahead out-of-sample forecasts.
3) Bold figures highlight the largest absolute return value.

[Table 10] Henriksson and Merton Test

Forecasting Period	P_1, P_2 & Statistics	Momentum	Filter	MA	TRB	CB	CAPM &AR(1)	CAPM	AR(1)	RWD
'97.01.18 - '24.06.28	P_1	**0.681**	0.396	0.643	0.399	0.297	0.607	0.607	0.569	0.508
	P_2	0.338	0.588	0.384	0.598	**0.716**	0.581	0.581	0.465	0.511
	P_1+P_2	1.018	0.984	1.027	0.997	1.012	1.187	**1.188**	1.033	1.019
	V	2.251^{*}	-1.839^{+}	3.158^{**}	-0.352	1.552	19.905^{**}	19.963^{**}	3.804^{**}	2.144^{*}
'97.11.03 - '98.12.31	P_1	0.000	0.000	0.000	0.000	0.000	**0.597**	0.552	0.506	0.000
	P_2	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.611	0.672	0.573	**1.000**
	P_1+P_2	1.000	1.000	1.000	1.000	1.000	1.208	**1.224**	1.079	1.000
	V	0.000	0.000	0.000	0.000	0.000	4.358^{**}	4.635^{**}	1.743^{+}	0.000
'99.01.04 - '08.08.29	P_1	0.651	0.198	0.620	`0.250	0.229	0.628	0.631	**0.728**	0.673
	P_2	0.387	0.804	0.405	0.773	**0.808**	0.548	0.556	0.321	0.372
	P_1+P_2	1.039	1.002	1.025	1.023	1.036	1.176	**1.187**	1.049	1.046
	V	2.679^{**}	0.191	1.696^{+}	1.805^{+}	2.898^{**}	11.158^{**}	11.800^{**}	3.580^{**}	3.190^{**}
'08.09.01 - '09.06.30	P_1	0.029	0.000	0.000	0.000	0.000	**0.476**	0.437	0.243	0.000
	P_2	0.952	**1.000**	**1.000**	**1.000**	**1.000**	0.619	0.648	0.762	**1.000**
	P_1+P_2	0.982	1.000	1.000	1.000	1.000	**1.095**	1.085	1.005	1.000
	V	-1.130	0.000	0.000	0.000	0.000	1.857^{+}	1.679^{+}	0.110	0.000
'09.07.01 - '19.12.30	P_1	**0.901**	0.569	0.835	0.461	0.297	0.622	0.623	0.577	0.587
	P_2	0.087	0.392	0.182	0.528	**0.700**	0.588	0.575	0.425	0.409
	P_1+P_2	0.988	0.960	1.017	0.989	0.997	**1.210**	1.199	1.003	0.996
	V	-1.440	-2.899^{**}	1.565	-0.770	-0.224	13.593^{**}	12.937^{**}	0.202	-0.316
'20.01.02 - '20.06.30	P_1	**1.000**	**1.000**	**1.000**	0.962	0.642	0.472	0.434	0.396	0.000
	P_2	0.000	0.000	0.000	0.000	0.500	0.600	0.557	0.700	**1.000**
	P_1+P_2	1.000	1.000	1.000	0.962	**1.142**	1.072	0.991	1.096	1.000
	V	0.000	0.000	0.000	-2.514^{*}	2.222^{*}	1.153	-0.150	1.570	0.000
'20.07.01 - '24.06.28	P_1	0.450	0.645	0.555	**0.838**	0.647	0.607	0.620	0.311	0.263
	P_2	0.559	0.386	0.476	0.181	0.388	0.606	0.608	0.707	**0.709**
	P_1+P_2	1.009	1.031	1.031.	1.019	1.035	1.213	**1.228**	1.018	0.971
	V	0.389	1.418	1.381	1.148	1.603	8.700^{**}	9.246^{**}	0.852	-1.486

Notes: 1) For momentum, filter, MA (moving average), TRB (trading range breakout), and CB (channel breakout) rules, 16, 84, 144, 96, and 16 sub-rules are included.
2) P_1 (P_2) denotes the conditional probability that both the actual and forecasted values of the excess return are below (or above) zero, and V is the test statistic indicating whether P_1+P_2 exceeds 1. Bold figures the largest value. $^{+}$, *, and ** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[Table 11] One-Step-Ahead Out-of-Sample RMSE and AME

	RMSE					AME				
	CAPM&AR(1)	CAPM	AR(1)	RWD	RW	CAPM&AR(1)	CAPM	AR(1)	RWD	RW
’97.01.18-’24.06.28	0.841	**0.835**	0.852	0.850	0.849	**0.443**	0.445	0.450	0.449	0.448
’97.11.03-’98.12.31	2.854	**2.832**	2.859	2.870	2.867	1.590	1.607	1.550	1.558	**1.550**
’99.01.04-’08.08.29	0.441	0.443	0.436	0.436	**0.435**	0.312	0.314	0.311	0.310	**0.310**
’08.09.01-’09.06.30	2.107	**2.051**	2.147	2.107	2.104	1.450	1.423	1.427	1.396	**1.393**
’09.07.01-’19.12.30	0.535	**0.534**	0.550	0.550	0.549	**0.399**	0.400	0.414	0.414	0.413
’20.01.02-’20.06.30	**0.736**	0.771	0.741	0.757	0.756	**0.551**	0.578	0.538	0.553	0.555
’20.07.01-’24.06.28	**0.513**	0.516	0.556	0.553	0.552	**0.374**	0.377	0.404	0.401	0.401

Notes: 1) Bold values indicate the lowest RMSE and AME.

VIII. Economic Implications

With the extension of foreign exchange market trading hours to 2 a.m. and a rising volume of foreign exchange transactions, leading institutional investors are increasingly adopting algorithmic trading, which could contribute to greater fluctuations in the won/dollar exchange rate irrespective of underlying macroeconomic conditions. Notably, as algorithmic trading has been identified as contributing to sudden fluctuations in both stock and exchange rates, there is a need to analyze technical trading rules, which serve as core strategies within algorithmic trading.

Consequently, this study investigates whether technical trading rules—proposed as empirical grounds for rejecting the weak form of the efficient market hypothesis—can yield superior returns in the won/dollar foreign exchange market. To address issues related to data mining and in-sample estimation, the analysis divides the full sample into three subperiods and applies 436 distinct technical trading rules. The findings indicate that technical trading rules generated substantial positive trading returns in periods surrounding the currency crisis; however, their predictive performance has weakened in recent years, with returns showing zero or negative values post-2010.

Given the limited predictive ability of technical trading rules that challenge the efficient market hypothesis, this study seeks to explore the underlying causes using the RWD model or CAPM, both of which highlight market efficiency, alongside the AR(1) model, a partial adjustment model. The outcomes of the bootstrap tests demonstrate that excess returns associated with technical trading rules exhibit some divergence from the three widely used null models during the pre- and post-currency crisis periods; however, the probability of such divergence has declined notably in recent years. It appears that the technical trading strategies examined here fail to provide alternative explanations that standard statistical tests are unable to capture in the current environment. For instance, most returns attributed to technical trading rules are largely rationalized by the CAPM or its various extensions. The explanatory capacity of technical trading techniques has diminished over time, as the won/dollar foreign exchange market has achieved greater efficiency since the crisis, thanks to a sustained current account surplus and increased rational investment by domestic pension funds abroad.

In addition, I employ rolling regressions to investigate how the buy-sell returns of five technical trading rules evolve across the currency crisis, global financial crisis, and COVID-19 periods by applying 500-sample rolling windows over 6781 iterations, which corroborates earlier findings. The out-of-sample forecasting abilities of the five technical trading rules are also compared in a one-period-ahead forecasting framework, and the results show that the CAPM consistently outperforms both the five technical rules and the alternative null models. Collectively, the bootstrap test outcomes and out-of-sample prediction results demonstrate that excess returns in the won/dollar foreign exchange market are more effectively accounted for and forecasted by the CAPM than by technical trading rules or other null models.

Irrational investors often display herding behavior, a tendency that intensifies during financial crises. The TRB rule exploits the abrupt movements in exchange rates or stock prices resulting from self-fulfilling expectations once resistance or support levels are breached, and empirical findings indicate that the TRB rule generates optimal returns during the periods surrounding the currency crisis. Proponents of the efficient market hypothesis maintain that arbitrage activity safeguards financial market efficiency—even in the presence of herding by irrational investors—while advocates of market inefficiency argue that institutional investors, including pension funds, may similarly act as noise traders because of information asymmetry and a strong focus on short-term outcomes.

On December 19, 2024, following the declaration of a state of emergency, the Bank of Korea and the National Pension Service announced an extension of their foreign exchange swap arrangement until the end of 2025, alongside an increase in the existing ceiling from $50 billion to $65 billion. Additionally, according to the Korea Exchange on January 26, domestic pension funds acted as net purchasers of securities on the exchange every day from December 27 last year through January 24 this year, thereby providing support for domestic equity prices. In the face of financial market shocks, it is essential to prevent the exchange rate or stock prices from breaching critical resistance or support thresholds to help stabilize the financial system; even in cases where such levels are surpassed, the maintenance of market efficiency may still be achieved if pension funds realize arbitrage by engaging in countercyclical transactions.[10]

In summary, as the efficiency of the won/dollar foreign exchange market improves, the predictive power of technical trading rules for won/dollar returns diminishes substantially. Consequently, in such an environment, the large-scale movement of foreign exchange funds utilizing algorithmic trading might destabilize the won/dollar market without generating substantial profits. Furthermore, since Korea operates as a small open economy and its won/dollar exchange rate remains particularly susceptible to both domestic and international shocks, as demonstrated during prior currency crises, the preservation of political and economic stability emerges as a paramount objective.[11]

[10] Lee and Jang (2023) maintained that, as Korea is both a net foreign asset country and a net foreign creditor country, domestic pension funds have the capacity to realize exchange rate gains. In contrast to the scenario during the currency crisis, these funds contribute to the stability of the foreign exchange and stock markets by repatriating overseas investment assets and conducting arbitrage transactions when the won/dollar exchange rate surges sharply.

[11] During the 1997 currency crisis, Korea experienced recession and inflation as a result of a sharp

IX. Summary and Conclusions

This study investigates the capacity of five prominent technical trading rules associated with algorithmic trading to generate excess profits in the won/dollar foreign exchange market by employing daily exchange rate and interest rate data from January 3, 1995, to June 28, 2024. The research further performs a joint assessment of foreign exchange market efficiency through the application of the AR(1) model—a partial adjustment model—as well as the RWD model and CAPM, both of which stress market efficiency. In addition, I reinforce the in-sample bootstrap analysis by utilizing rolling regressions and out-of-sample forecasts.

The empirical results from technical trading strategies applied to the won/dollar foreign exchange market throughout the sample period indicate that buy returns, sell returns, and buy-sell returns attain statistical significance under specific trading rule configurations. Nonetheless, a review of the average expected returns produced by employing a diverse set of technical rules—designed to address concerns about data snooping—demonstrates that the statistical relevance of these trading returns steadily declines from the 1990s to the 2010s.

Furthermore, the results of the bootstrap test utilizing RWD, AR(1), and CAPM models lend support to either the adaptive market hypothesis or the efficient market hypothesis, as evidenced by a diminished predictive capacity of technical trading rules in recent periods compared to the era before and after the 1990s currency crisis, whereas the relevance of CAPM and similar models is observed to increase. The in-sample buy-sell returns generated from five technical trading rules, using a rolling sample of 500 observations across 6781 iterations, display consistent patterns. Notably, the one-period-ahead out-of-sample forecasting results, obtained using the same rolling regression framework, indicate that CAPM—which attributes a significant portion of excess returns to systematic risk—exceeds the five technical trading rules as well as other null models in explanatory power. Thus, the evidence from both the bootstrap analyses and out-of-sample forecasts collectively implies that the excess returns in the won/dollar foreign exchange market are more effectively explained and predicted by the CAPM in comparison to technical trading rules or alternative null models.[12]

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rise in the won/dollar exchange rate and a temporary high interest rate policy. However, the current account deficit of 24.5 billion dollars in 1996 shifted to a current account surplus of 40.1 billion dollars in 1998, largely due to gains in export competitiveness. Furthermore, the real economic growth rate rebounded significantly, rising from -4.9% in 1998 to 11.6% in 1999. However, according to Lee (2024), the positive effects of real effective exchange rate undervaluation on the business cycle and current account have diminished in recent years. This change is attributed to Korea's evolution into a net foreign creditor or net foreign asset country, as well as the expansion of foreign investment, which has not only substituted for exports and domestic employment, but also limited both the appreciation of the won and the growth of imports through increased foreign currency outflows.

[12] Kalemli-Özcan and Varela (2025) decomposed the UIP premium r_{t+1}, as expressed in equation

(6), into an interest rate (IR) differential component and an exchange rate (ER) adjustment component, demonstrating that local and global risk factors exert differing influences on developed and developing economies. For the won/dollar exchange rate, local risk factors such as recession and a current account deficit were predominant during the currency crisis, whereas global risk factors had a greater impact during the global financial crisis. The divergent behavior of the UIP premium components during the currency crisis, compared to the global financial crisis, is largely attributable to the high interest rate policy recommended by the IMF. Thus, it would be pertinent to conduct an analysis of the UIP premium with a similar decomposition, as in Kalemli-Özcan and Varela (2025). Besides the dollar index, additional global risk indicators—such as US stock prices, VIX, and the convenience yield of the dollar (Jiang, Krishnamurthy, Lustig, and Sun, 2024)—may be considered. In the methodology of Kalemli-Özcan and Varela (2025), survey data are employed to proxy expected exchange rates S_{t+1}^{e}. If accessible, survey data for the dollar index could also be utilized, rather than assuming static expectations in out-of-sample forecasting exercises.

Appendix A

This section presents the findings from the estimation of the EGARCH(1,1) model and the two-stage Markov switching model. First, the estimation results of the EGARCH(1,1) model are discussed.

$$r_t = \alpha_0 + \epsilon_t \tag{A1}$$

$$\ln h_t = a_0 + b_1 \ln h_{t-1} + a_1 \frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} + \mathrm{c}\left(\frac{|\epsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right) \tag{A2}$$

where r_t represents the excess return on foreign currency assets and h_t represents the conditional variance. The estimated value of b_1 from the EGARCH(1,1) model is 0.980, indicating that $b_1 < 1$ and that the $\ln h_t$ process is stationary (Table A1). However, when the same dataset is analyzed using the GARCH(1,1) model, the sum of the estimated parameters of h_{t-1} and ϵ_{t-1}^2 exceeds 1, which implies that the conditional variance is nonstationary. The estimate for a_1 is 0.037, suggesting the presence of an asymmetric effect. Specifically, the conditional variance of excess returns increases more in response to positive shocks than to negative shocks. This asymmetric effect is also observed when estimating the GJR model. The results from the bootstrap simulations are omitted for brevity, as they do not differ materially. In contrast to the GARCH-M model, the conditional variance in a GARCH model does not influence the mean return, so the standard approach is to estimate the mean and conditional variance sequentially using a two-step procedure, rather than jointly as previously described. Under this approach, the results are consistent with those of the RWD case. Meanwhile, for the simple GARCH(1,1)-M, EGARCH(1,1)-M, and GJR(1,1)-M models, the maximum likelihood estimation method does not yield convergence even when using the full sample period. It is widely recognized that GARCH-M type models are difficult to estimate and that the risk premium is better explained by the covariance with the relevant market than by its own variance.

[Table A1] EGARCH(1,1) Model Estimation Results

α_0	a_0	b_1	a_1	c
-0.004 (0.004)	-0.016 (0.003)**	0.980 (0.002)**	0.037 (0.006)**	0.237 (0.004)**

Note: 1) ** denotes statistical significance at the 1% level.

Next, assume that the excess return r_t is governed by a basic two-stage Markov switching model, as outlined below.

$$r_t = \mu(s_t) + \sigma(s_t)\epsilon_t \tag{A3}$$

where σ denotes the volatility of the excess return and the residual term ϵ_t is assumed to be i.i.d. s_t is an unobserved state variable, taking the value of 1 when r_t is in a low volatility state and 2 when r_t is in a high volatility state. Specifically, when s_t =1, r_t follows a normal distribution with mean and variance μ_1 and σ_1^2, respectively, whereas when s_t=2, r_t follows a normal distribution with mean and variance $\mu_2$and σ_2^2, respectively. In this setup, the transition probability takes the following form.

$$\begin{aligned} &\mathrm{P}(s_t = 1|s_{t-1} = 1) = P_{11} \\ &\mathrm{P}(s_t = 2|s_{t-1} = 1) = 1 - P_{11} \\ &\mathrm{P}(s_t = 1|s_{t-1} = 2) = 1 - P_{22} \\ &\mathrm{P}(s_t = 2|s_{t-1} = 2) = P_{22} \end{aligned} \tag{A4}$$

The estimation results for the two-phase regime-switching model are presented in Table A2. First, during the low volatility phase, the excess return is -0.005 with a variance of 0.201, whereas in the high volatility phase, the excess return becomes positive at 0.106, and the variance increases by over 30 times to reach 7.542. Similar to the EGARCH model, the findings demonstrate a leverage effect, whereby an increase in excess returns leads to higher volatility, and high volatility phases coincide with periods of crisis. However, in contrast to the variance estimates, the mean parameters do not achieve statistical significance. Consistent with the EGARCH model, the outcomes from the bootstrap simulations do not differ materially; therefore, they are omitted here for brevity.

[Table A2] Estimation Results of the Two-Stage Regime Switching Model

μ_1	μ_2	σ_1^2	σ_2^2	P_{11}	P_{22}
-0.005 (0.006)	0.106 (0.147)	0.201 (0.005)**	7.542 (0.628)**	0.994 (0.001)**	0.910 (0.018)**

Note: 1) ** denotes statistical significance at the 1% level.

References

Ahn, C. (2008), "Is Filter Trading Rule Profitable in the USD/KRW Rates? Evidence from *De Facto* Flexible Rate Period (1998-2007)," *Journal of Korean Economic Studies 22*, 81-102 (in Korean).

Allen, H. and M. P. Taylor (1990), "Charts, Noise, and Fundamentals in the London Foreign Exchange Market," *Economic Journal* 100(400), 49-59.

Brock, W., J. Lakonishok, and B. LeBaron (1992), "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns," *Journal of Finance* 47(5), 1731–1764.

Cornell, W. B. and J. K. Dietrich (1978), "The Efficiency of the Market for Foreign Exchange under Floating Exchange Rates," *Review of Economics and Statistics* 6(1), 111–120.

De Bonde, W. F. M. and R. Thaler (1985), "Does the Stock Market Overreact?" *Journal of Finance* 40(3), 793-805.

Dooley, M. P. and J. R. Shafer (1976), "Analysis of Short-Run Exchange Behavior: March 1993 to September 1975," Federal Reserve Board, International Finance Discussion Papers, No. 76.

________________________ (1984), "Analysis of Short-Run Exchange Rate Behavior: March 1973 to November 1981," In: Bigman, D. and T. Taya, Eds., *Floating Exchange Rates and the State of World Trade Payments*, Ballinger Publishing, Cambridge, MA.

Fama, E. F. and M. Blume (1966), "Filter Rules and Stock Market Trading Profits," *Journal of Business* 39, 226-241.

Henriksson, R. D. and R. C. Merton (1981), "On Market Timing and Performance Ⅱ: Statistical Procedures for Evaluating Forecasting Skills," *Journal of Business* 54, 513-533.

Hsu, P.-H., M. P. Taylor, and Z. Wang (2016), "Technical Trading: Is It Still Beating the Foreign Exchange Market?" *Journal of International Economics* 102, 188-208.

Hutchinson, M. C., P. E. Kyziropoulos, J. O'Brien, P. O'Reilly, and T, Sharma (2022), "Technical Trading Rule Profitability in Currencies: It's All about Momentum," *Research in International Business and Finance* 63, 101779.

Ivanova, Y., C. J. Neely, P. Weller, and M. T. Famiglietti (2021), "Can Risk Explain the Profitability of Technical Trading in Currency Markets?" *Journal of International Money and Finance* 110, 102285.

Jegadeesh, N. and S. Titman (1993), "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48(1), 65–91.

Jiang, Z., A. Krishnamurthy, H. Lustig, and J. Sun (2024), "Convenience Yields and Exchange Rate Puzzles," NBER Working Paper No. 32092.

Kalemli-Özcan, S. and L. Varela (2025), "Five Facts about the UIP Premium," NBER Working Paper No. 28923 (Revised January 2025).

LeBaron, B. (1999), "Technical Trading Rule Profitability and Foreign Exchange Intervention," *Journal of International Economics* 49(1), 125–143.

Lee, C. I., M. S. Pan, and Y. A. Liu (2001), "On Market Efficiency of Asian Foreign Exchange Rates: Evidence from a Joint Variance Ratio Test and Technical Trading Rules," *Journal of International Financial Markets, Institutions & Money* 11(2), 199-214.

Lee, K. Y. (2024), "Real Exchange Rate Misalignment and Economic Fundamentals in Korea," *East Asian Economic Review* 28(3), 277-314.

Lee, K. Y. and H. I. Jang (2023), "The Impact of Won/Dollar Exchange Rate Changes on Domestic Prices," *Journal of Money & Finance* 37(2), 2023, 1-41 (in Korean).

Levich, R. M. and L. R. Thomas (1993), "The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach," *Journal of International Money and Finance* 12(5), 451–474.

Logue, D. E. and R. J. Sweeney (1977), "'White Noise' in Imperfect Markets: The Case of the Franc/Dollar Exchange Rate," *Journal of Finance* 32(3), 761–768.

Meese, R. A. and K. Rogoff (1983), "Empirical Exchange Rate Models of Seventies: Do They Fit Out-of-Sample?" *Journal of International Economics* 14(1-2), 3-24.

Menkhoff, L. and M. P. Taylor (2007), "The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis," *Journal of Economic Literature* 45(4), 936–972.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2012), "Time Series Momentum," *Journal of Financial Economics* 104(2), 228–250.

Neely, C. J. (2002), "The Temporal Pattern of Trading Rule Returns and Exchange Rate Intervention: Intervention Does Not Generate Technical Trading Rule Profits," *Journal of International Economics* 58(1), 211–232.

Neely, C. J. and P. A. Weller (2012), "Technical Analysis in the Foreign Exchange Market," In: James, J., I. W. Marsh, and L. Sarno, Eds., *Handbook of Exchange Rates*, John Wiley, Hoboken, NJ.

______________________ (2013), "Lessons from the Evolution of Foreign Exchange Trading Strategies," *Journal of Banking & Finance* 37(10), 3783–3798.

Neely, C. J, P. A. Weller, and J. Ulrich (2009), "The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market," *Journal of Financial and Quantitative Analysis* 44(2), 467–488.

Osler, C. L. and P. H. K. Chang (1995), "Head and Shoulders: Not Just a Flaky Pattern," Federal Reserve Bank of New York Staff Report No. 4.

Ryoo, S. (2001), "Exchange Rate Movement Before and After Free Floating: Efficiency and Technical Trading Profitability," *Economic Papers* 4(1), 160-176.

Serban, A. F. (2010), "Combining Mean Reversion and Momentum Trading Strategies in Foreign Exchange Markets," *Journal of Banking & Finance* 34(11), 2720-2727.

Sweeney, R. J. (1986), "Beating the Foreign Exchange Market," *Journal of Finance* 41(1), 163–182.

Taylor, M. P. and H. Allen (1992), "The Use of Technical Analysis in the Foreign Exchange Market," *Journal of International Money and Finance* 11(3), 304–314.

원/달러 외환시장의 효율성 검증: 기술적 거래기법을 이용한 경우*

이 근 영**

초 록 본 연구에서는 원/달러 환율의 일일 초과수익률을 분석하고 알고리즘 매매의 대표적인 거래방식인 5가지 기술적 거래기법을 활용하여 원/달러 외환시장이 효율적인가를 살펴보았다. 데이터 마이닝 문제를 완화하기 위해 436개 세부거래기법의 수익률을 평균한 결과는 초과수익률의 통계적 유의성이 1990년대, 2000년대, 2010년대 등을 거치면서 점차 낮아짐을 보여준다, 부트스트랩 방법과 기술적 거래기법에 대한 결합검정결과, 이러한 기술적 전략으로부터의 초과수익률은 최근 몇 년 동안 RWD, AR(1), CAPM과 같은 귀무모형에서 생성된 초과수익률과 통계적으로 구별될 수 없었으며, 이는 적응시장가설 또는 효율시장 가설이 점차 설득력을 얻어 감을 시사한다. 500개 표본 창을 6781회 회전 회귀시켜 생성된 5가지 기술적 거래기법의 표본 내 매수−매도 수익률도 유사한 패턴을 보인다. 특히, 동일한 회전 회귀 창을 기반으로 한 1기간 앞 표본외 예측결과는 체계적 위험에 상당 부분의 초과수익률을 귀속시키는 CAPM이 5가지 기술적 거래기법이나 다른 귀무모형보다 더 우수한 성과를 가져온다는 것을 보여준다.

핵심 주제어: 기술적 거래기법, 효율시장가설, 부스트랩 검정, CAPM
경제학문헌목록 주제분류: C1, F3, G1

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