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Predicting the FTSE China A50 Index Movements Using Sample Entropy

Hatem AKEEL[1]

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Abstract

This research proposes a novel trading method based on sample entropy for the FTSE China A50 Index. The approach is used to determine the points at which the index should be bought and sold for various holding durations. The findings are then compared to three other trading strategies: buying and holding the index for the entire time period, using the Relative Strength Index (RSI), and using the Moving Average Convergence Divergence (MACD) as buying/selling signaling tools. The unique entropy trading method, which used 90-day holding periods and was called StEn(90), produced the highest cumulative return: 25.66 percent. Regular buy and hold, RSI, and MACD were all outperformed by this strategy. In fact, when applied to the same time periods, RSI and MACD had negative returns for the FTSE China A50 Index. Regular purchase and hold yielded a 6% positive return, whereas RSI yielded a 28.56 percent negative return and MACD yielded a 33.33 percent negative return.

Keywords: Sample Entropy, Portfolio Choice, Stock Market Trading, FTSE China A50 Index, MACD, RSI

JEL Classification Code: C1, C53, G11, G12

1. Introduction

Investors use their expertise and forecasting models to make decisions about allocating resources and when to buy or sell them on the stock market (market timing). However, forecasting the stock market is a challenging quest for professional investors and researchers. Non-linearity and the complexity of stock markets' time series are some of the reasons that make this task challenging (Alshammari et al., 2020). Some researchers used forecasting techniques based on technical, sentiment, or fundamental analysis (Ardyanta & Sari, 2021). Other models measure the level of volatility to have a better trading strategy (Tu & Liao, 2020). In this paper, the entropy concept is used to develop a novel forecasting market timing model. Entropy refers to the measure of randomness and disorder that allows capturing the irregularities and complexity of time series data. Physicists use it in thermodynamics for complex systems where there is a state of disorder or uncertainty. Recently, the entropy concept has been used for market timing in the stock market, stock market indices, and predicting exchange rates and commodity prices (Jianjia et al., 2019). Moreover, both sample entropy (SampEn) and approximate entropy (ApEn) can detect irregularities in time series and recently were used to distinguish between a bot and real tweets in social media (Gilmary et al., 2021).

Many types of entropy can be used to examine stock market time-series data. For example, approximate entropy is a sequential irregularity model that can quantify the regularity in time series data. Sample entropy is a modified version of approximate entropy; it can quantify regularity more effectively Alfonso and Alexander (2019) and Efremidze et al. (2015) used sample entropy on the Dubai index from 2005 to 2012 to develop a better trading strategy than just buying and holding the index. The buy-and-hold strategy of the Dubai index resulted in a negative 16.42% during the studied period while the long position using sample entropy analysis delivered a 9.89% annualized yield. Moreover, a short strategy using sample entropy yielded a

[1]First Author and Corresponding Author. Assistant Professor of Economics, Finance Department, College of Business and Administration, University of Business and Technology (UBT), Jeddah, Kingdom of Saudi Arabia. ORCID ID: 0000-0003-4854-3189. [Postal Address: 7368 Alkurnaysh Road, Abhur Al Janubiyah, Jeddah, Makkah, 23734-2478, Kingdom of Saudi Arabia]
Email: h.akeel@ubt.edu.sa

23.96% annualized return. These results show that the sample entropy strategy can provide a considerable positive return in both the downside and the upside of an index compared to the buy-and-hold strategy.

In this paper, we will use the same approach that has been used by Efremidze et al. (2015) with the modification that will be shown in the methodology section and apply this novel market timing strategy on FTSE China A50 Index.

2. Literature Review

Bose and Hamacher (2012) analyzed 100 stocks over five years in the S&P100 Index using entropy as an alternative measure of volatility. They calculated super-information, which is a term they used to calculate the randomness of the entropy in time series data. They showed that plotting super-information data can signal an expected financial crisis since they identified the 2008 financial crisis in their analysis. Also, the results showed a high correlation between the average super-information for the 100 stocks in the S&P 100 Index and the Volatility Index (VIX) on the Chicago Board Options Exchange (CBOE). They concluded that entropy can indeed have useful applications for assessing risk and return and anticipating financial crises. Furthermore, Ormos et al. (2014) empirically tested entropy against the beta parameter of the Capital Asset Pricing Model (CAPM) is a measurement of financial risk. They applied it to 150 randomly selected stocks over a 27-year period and found that entropy has higher explanatory power than CAPM's beta.

Bowden (2010) introduced directional entropy concepts where he developed a framework for assessing tail risk by having a metric for tail length. This can be applied to financial risk metrics like value at risk (VaR) to get a better value for it. This can be done by rescaling VaR to adjust the critical probability and to detect the long tail entropy.

Bekiros (2014) introduced the optimal entropy-based decomposition level for British pound exchange rate volatility and return instead of using the trial and error method to determine the depth of the multiscale wavelet decomposition. The methods rely on the minimum-entropy decomposition and boundary distortion method where step-wise entropy is computed and checked with the previous level.

Bentes and Menezes (2012) studied multiple global stock market indices volatilities using standard deviation, Tsallis entropy, and Shannon entropy. They aimed to compare each method in measuring volatility. They found that both entropies results have mostly deviated from standard deviation outcomes. However, the volatility result of the French stock market index CAC 40 and the stock market for the Tokyo stock exchange Nikkei 225 was consistent across the three methods.

Gençay and Gradojevic (2017) did a comparative analysis of financial crises in 1987 and 2008 by checking the dynamic of the stock market. They used entropy concepts to predict market expectations. They found that Tsallis entropy was better at predicting the sudden market crash of 1987. However, approximate entropy was a more appropriate predictor for predicting the financial crisis of 2008.

Another way to predict stock market uncertainty is by using Shannon entropy. Ahn et al. (2019) studied the impact of Chinese stock market uncertainty on economic fundamentals. By using Shannon entropy, they found that there is strong spillover transferred from stock market uncertainty to economic fundamentals. A shock of uncertainty in the Shanghai Composite Index could lead to a short-term drop in industrial production and a surge in systemic risk. It is also worth mentioning that the entropy approach extracted more information than other traditional measurements of risk.

Ishizaki and Inoue (2013) used the time-dependent pattern entropy to examine the variability of the daily exchange rate in the dollar-yen rate. They found that before and after the turning points the time-dependent pattern entropy has high values. In other words, in the period of transition from a strong to a weak yen or from a weak to a strong yen the time-dependent pattern entropy increases in value.

Huichen and Liyan (2018) used entropy to develop a diversification index that was different from the Herfindahl–Hirschman Index (HHI). They studied the diversification strategies of listed Chinese commercial banks from 2008 to 2016 and measured the banks' risk and profitability. They showed that using both entropy and HHI together allows portfolio managers to have more efficient income diversification. They recommended that commercial banks—regardless of their size—adopt this new strategy of combining entropy index and HHI for diversification to get sustainable growth.

Kumar et al. (2020) studied the daily prices of 42 stocks in the Nifty 50 index using diffusion entropy, conditional entropy, and other techniques to investigate the stability of different sectors within the index. In their work, diffusion entropy is used to spot extreme events. On the other hand, conditional entropy is used to detect bull and bear market behavior. They found that the energy sector and telecommunication sector were having a delayed effect from the 2008 crisis since they were affected delayed until 2011.

Efremidze et al. (2021) tested sample entropy trading strategy compared to buy and hold strategy on Japanese equity. They found that the sample entropy trading strategy outperformed the buy and hold strategy. In their study, having a low sample entropy value signals a long position while having a high entropy value is signaling a short position. Their empirical finding is against the theory of the Efficient Market Hypothesis since they found abnormal returns in the Japanese equity market from the sample entropy algorithm.

Wang and Miao (2020) introduced rough entropy where they detect abnormal fluctuation in the time series of the US stock market. They develop a data mining algorithm built from rough entropy. They applied this method on the Dow Jones index where they can extract useful information from the time series. This was the first application of rough entropy on data mining algorithms that addresses uncertainty in time series.

Other recent research used entropy to forecast commodity prices. Tapia et al. (2020) were not convinced that copper prices exhibited long-term cyclical behavior and should not be forecasted using a stochastic process. They studied the annual copper prices from 1900 to 2015 to find that they exhibit a non-linear and non-Gaussian pattern. This pattern can be analyzed using entropy analysis. They recommend using entropy in the existing forecasting model for copper prices since those prices exhibit a dynamic behavior.

Another application of entropy as a measurement of risk was using it on exchange rate intraday returns. Pele et al. (2017) used entropy and Monte-Carlo simulation on the intraday returns of the exchange rate between the Euro and the Japanese Yen from 1999 to 2005. They then compared their results against Value-at-Risk (VAR) and expected shortfall. Intraday VAR and intraday expected shortfall both had a negative relationship with entropy. They found that entropy has more data content than the typical measures of market risk.

In this paper, sample entropy is used to forecast the buying and selling points of the FTSE China A50 Index. This will contribute to existing literature since the novel approach is used on an index that, to the best of our knowledge, has not been analyzed. In addition, this strategy is compared to the buy-and-hold strategy of two other oscillators often used by professionals, the Relative Strength Index (RSI) and the Moving Average Convergence Divergence (MACD) indicator. The FTSE China A50 Index, compiled by FTSE Russell, contains the 50 largest qualified companies listed in China. The A50 Index is held through the Qualified Foreign Institutional Investor (QFII), and its futures are the primary tool for foreign investors to take part in A-share investment and hedging. A50 futures are traded on the Singapore Exchange. One contract represents the corresponding points of the index multiplied by 1 U.S. dollar. That is, if there are 10,000 points, the contract value of one futures contract is $10,000. The companies in the index collectively represent the largest and most outstanding Chinese companies. Hence, the market conditions can be evaluated by observing the performance of the index. Moreover, because they have more derivatives, those companies also provide a great convenience for investors' investment and hedging.

3. Research Methods

The measure of randomness and disorder is known as entropy can be used to capture the inconsistencies and complexity of time series data. Entropy is a notion that states that highly volatile stocks have higher entropy than steady ones. Two things are investigated in time series analysis: there is a considerable standard deviation and it is highly irregular. A closer examination indicates that these two concepts are not mutually exclusive. As a result, if the abnormalities and variations in a time series are consistently collected, the prospective information from the complicated shifts in the time series can be used to forecast the performance of securities.

Entropy was first applied by Clausius (1850) to study thermodynamics and measure energy. More recently it has been used in financial markets to study market timing (Pincus, 2008). This paper uses this concept as part of a novel approach to analyze the market timing of the FTSE China A50 Index. This index is a benchmark for investors to enter the Chinese domestic market through the A Shares of the 50 largest Chinese companies by market capitalization.

There are many types of entropies used in economics and finance as, suggested by various studies: approximate entropy (ApEn), sample entropy (SampEn), directional entropy, Tsallis (non-extensive) entropy, Shannon entropy, and network entropy (Bowden, 2011; Gell-Mann & Tsallis, 2004). Since previous empirical studies have suggested that sample entropy is more robust, it is used in this study (Bhavsar et al., 2018). Three components are required to conduct entropy analysis:

1. Time series data (in this case the index)
2. Matching template length (*m*)
3. Matching tolerance level (*r*)

The formula for sample entropy is:

$$\text{SampEn}(m, r, n) = -\ln\left(\frac{A}{B}\right) \tag{1}$$

where m refers to the length of the sequence to which it would be compared. For instance, 1 means point 1 would be compared with point 1 with a sequence difference of 1, so m could be 0, 1, or 2, but it cannot be greater than 2. Meanwhile, r refers to the level of tolerance or standard deviation of the time series data for a specific period, and n refers to the number of points or observations in the time series data for that specific period. A and B can be derived as the following:

$$A = \left\{\frac{\left[(n-m-1)(n-m)\right]}{2}\right\} A^m(r) \tag{2}$$

$$B = \left\{ \frac{\left[(n-m-1)(n-m) \right]}{2} \right\} B^m(r) \quad (3)$$

Then, A^m (r) refers to the probability that a sequence point at m + 1 is less than r matching tolerance level, and B^m (r) refers to the probability that the sequence point at m is less than the r matching tolerance level. After deriving both probabilities using MATLAB software, entropy signals were calculated using the formula for SampEn.

After generating the independent variables of entropy signals, we include variables one at a time into the regression Equation to determine which combination of entropy signals predicts index return on different holding periods, Efremidze et al. (2015) used the following Equation which is also used in this paper:

$$R_t = \alpha + \beta x_{t-1} + \varepsilon_t \quad (4)$$

where R_t refers to the return of the index at time t, α refers to the intercept, β refers to slope, and x_{t-1} refers to SampEn at time t–1, and ε refers to the error term. Meanwhile, we run the regression to determine the extent to which the sample entropy signal predicts FTSE China A50 Index at different market timings.

The regression result for daily returns is expected in theory to have negative slope coefficients. They are represented in Table 2 for the statistically significant part of the holding period (Efremidze et al., 2015). After knowing which holding periods are statistically significant, the novel trading strategy introduced in this paper is applied to a statistically significant holding period using:

$$P_t(n) = \frac{\text{SampEn}_t - \text{SampEn}_{t-n+1}}{\text{SampEn}_{t-n+1}}, \; t \ge n \quad (5)$$

where $P_t(n)$ is the percentage change in SampEn based on the holding period (n) and the sample entropy value, SampEn(t) at time t. $P_t(n)$ gives a signal to buy, sell, or hold based on the following three conditions:

1. If $P_t(n)$ > 60% a buy signal is triggered.
2. If $P_t(n)$ < 1% a sell signal is triggered.
3. Otherwise, holding the security is triggered.

The rationale behind this technique is that the higher the percentage difference from Equation 5, the more predictable the index will trend upward since the index rewards longer holding periods than shorter periods. On the other hand, a smaller percentage difference indicates uncertainty. The results from this strategy are compared to the regular buy-and-hold strategy. After that and to compare our results against the new model, the signal from StEn(n) is tested against the RSI and the MACD, which are the most used indicators to signal traders to buy or sell (Chong et al., 2008).

The RSI was developed by J. Welles Wilder in 1978. It is widely used in developing trading strategies. The RSI is calculated using:

$$\text{RSI}_t(n) = \frac{\sum_{i=0}^{n-1} \left(P_{t=i} - P_{t-i-1} \right) 1\{P_{t=i} > P_{t-i-1}\}}{\sum_{i=0}^{n-1} \left| P_{t-1} - P_{t-i-1} \right|} \times 100 \quad (6)$$

where RSI_t is the Relative Strength Index at time t, n is the number of RSI periods, P_t is the index value (which is FTSE China A50 Index in our case), 1{.} is a dummy term which equals 1 when the logical statement inside the bracket is true, and zero otherwise. The RSI can be used as a signal to buy or sell based on the following conditions:

1. If RSI < 30, it indicates an oversold condition.
2. If RSI crosses 30 from below, a buy signal is triggered.
3. If RSI > 70 it indicates an overbought condition.
4. If RSI crosses 70 from above, a sell signal is usually triggered.

The MACD is calculated using moving averages. This is done by subtracting a longer exponential moving average (EMA) from a shorter EMA (Chong et al., 2008). To find the EMA, the following formula is used:

$$\text{EMA}_t = \left[\frac{2}{n} \times (P_t - \text{EMA}_{t-1}) \right] + \text{EMA}_{t-1} \quad (7)$$

where P_t is the price of the index, the exponential moving average is EMA_t, n is the number of periods of EMA. As the default, this paper uses slow EMA which is 26 days, and fast EMA which is 12 days.

4. Results and Discussion

Equation 1 is used to calculate sample entropy, with n = 120, m = 2, and r = 0.2. In this study, the closing price of the FTSE China A50 Index was obtained via Bloomberg Terminal®. The time frame for this study is January 3, 2017, to December 31, 2019. The sample size for the period was 732 days or data points. The SampEn Equation is applied to the next batch of 120 days after the initial run of the SampEn computation on the FTSE China A50 Index (lagged by one day). There were 612 entropy signals generated as a result of this activity. The statistical description of SampEn and FTSE China A50 data is shown in Table 1.

After generating 612 independent variables of entropy signals, the variables are included one at a time into the regression Equation—Equation 4—to determine which

Table 1: Statistical Description of FTSE China A50 Index Data From 7/3/2017 to 31/12/2019

Statistic	FTSE China A50 Index	SampEn
Mean	12575.89	0.76
Standard error	44.05	0.01
Median	12636.44	0.71
Mode	13813.44	1.15
Standard deviation	1089.81	0.35
Sample variance	1187680.92	0.12
Kurtosis	–1.11	–0.98
Skewness	–0.13	0.41
Range	4593.03	1.43
Minimum	10251.55	0.24
Maximum	14844.58	1.67
Sum	7696441.72	465.89
Number of observations	612	

Table 2: SampEn Regression Results Using Different Holding Periods

Days	Intercept	*P*-value	Slope	*P*-value
1	–5.28	0.7312	13.4	0.4656
2	–9.12	–0.4182	25.14	0.9651
5	–13.31	0.7038	48.10	0.2493
10	–4.22	0.9280	64.35	0.2464
20	59.51	0.3608	23.09	0.7639
30	239.65	0.0027***	–163.20	0.0803*
40	495.78	0.0000***	–430.12	0.0001***
50	734.68	0.0000***	–677.41	0.0000***
60	738.37	0.0000***	–680.84	0.0000***
90	1545.87	0.0000***	–1478.77	0.0000***

Note: $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.

combination of entropy signals is significant and predicts the index return for different holding periods. The regression determines the extent to which the sample entropy signal predicts FTSE China A50 Index at different market timings.

Table 2 sums 10 regression runs at different holding periods: 1, 2, 5, 10, 20, 30, 40, 50, 60, and 90 days. Of course, changing the holding period reduces the number of entropy signals, since they will be lagged by the same days of holding periods. For example, there are 523 independent variables of entropy signals in the 90-day holding period.

The result from the regressions shows that SampEn signals are statistically significant at longer holding periods but not at shorter ones. Holding periods of 1 to 20 days are not significant. At 30 days, only the intercept was significant. All holding periods longer than 30 days are statistically significant. This shows that FTSE China A50 Index is more suitable for long strategies and not for day trading and other short periods.

In theory, daily return regression results should have a negative slope of coefficients, as shown in Table 2 for the statistically important part of the holding period (Efremidze et al., 2015). To optimize index returns, a novel trading method is applied after determining which holding periods or (n) are statistically significant. This paper introduces it based on Equation 5 and associated conditions.

StEn(n), where n is the holding period, is defined in this study by applying Equation 5 and its trading strategy over the significant n periods from the regression. Table 3 shows the results of using this trading technique on the FTSE China A50 Index and compares them to the traditional buy-and-hold approach. The appendix contains the findings for each StEn(n).

Except for SampEn, using StEn(n) on the FTSE China A50 Index across various holding durations offers a higher total return than the traditional buy-and-hold approach (40). The overall return for SampEn(40) was 9.61 percent, compared to 14.26 percent for the buy-and-hold strategy. This suggests that StEn(n) produces better results when held for longer periods of time.

StEn(n) is then compared to the RSI. The RSI is derived using Equation 6. Total returns for all holding periods were negative after using RSI as a signal to buy or sell for the same period as StEn(n). Table 4 lists the specifics for each trade.

Because the RSI total return was negative, StEn(n) fared substantially better than RSI as a recommendation for buying or selling the FTSE China A50 Index. Using the Bloomberg Terminal backtesting function, Figure 1 illustrates the buy and sell points for RSI(40).

Next, using MACD as a signal for buying and selling is shown in Figure 2. This trading strategy is tested to see how it performs against StEn(n) on the FTSE China A50 Index. The MACD is calculated using Equation 7. The results are shown in Table 5. StEn(n) performed much better than MACD(i) for all the periods. All total returns using the MACD trading strategy were negative, while StEn(n) yielded a total positive return. Details of the MACD(40) trading strategy are displayed in Figure 2.

In comparison to the three strategies stated in section 3, the unique strategy in this paper yielded a better return. We evaluated the new technique against traditional buy and hold, as well as RSI and MACD. Table 6 displays the outcomes of each technique. In comparison to the purchase and hold

Table 3: StEn(*n*) Strategy Results Using Different Holding Periods and Compared to a Buy-And-Hold Strategy

Time Period Where the Strategy was Applied Based on Holding Period	StEn(*n*) Strategy*	Total Return with StEn(*n*) Strategy	Sharpe Ratio**	Win Ratio Based on Trades	# of Trades	Total Return With a Buy-And-Hold Strategy	# of Trades
26/10/2017–31/12/2019	StEn(40)	9.61%	0.17	75%	4	14.26%	1
9/11/2017–31/12/2019	StEn(50)	13.14%	0.43	75%	4	10.70%	1
23/11/2017–31/12/2019	StEn(60)	8.64%	0.35	66%	3	6.78%	1
5/1/2018–31/12/2019	StEn(90)	25.66%	0.58	75%	4	6.03%	1

*StEn(40), StEn(50), StEn(60), and StEn(90) are StEn(*n*) entropy trading strategies at different (*n*) holding periods. **Risk free rate in Sharpe ratio is calculated by taking the average Hong Kong interbank rate over the holding period.

Table 4: StEn(*n*) Strategy Results Using Different Holding Periods Compared to the RSI Strategy

Time (I) When the Strategy is Applied, Based on the Holding Period	StEn(*n*) Strategy*	Total Return with StEn(*n*) Strategy	Sharpe Ratio**	Win Ratio Based on Trades	# of Trades	RSI(i) Strategy***	Total Return with RSI(i) Strategy	Sharpe Ratio**	Win Ratio Based on Trades	# of Trades
26/10/2017–31/12/2019	StEn(40)	9.61%	0.17	75%	4	RSI(1)	–30.59%	–0.70	33.33%	3
9/11/2017–31/12/2019	StEn(50)	13.14%	0.43	75%	4	RSI(2)	–30.59%	–0.72	33.33%	3
23/11/2017–31/12/2019	StEn(60)	8.64%	0.35	66%	3	RSI(3)	–30.59%	–0.73	33.33%	3
5/1/2018–31/12/2019	StEn(90)	25.66%	0.58	75%	4	RSI(4)	–28.56%	–0.70	33.33%	3

*StEn(40), StEn(50), StEn(60), and StEn(90) are StEn(*n*) entropy trading strategies at different (*n*) holding periods. **Risk free rate in Sharpe ratio is calculated by taking the average Hong Kong interbank rate over the holding period. ****i* is the period where the strategy is applied. For example, $i = 1$ is the period from 26/10/2017 to 31/12/2019. *Source*: Compiled by the author.

Figure 1: RSI(1) Trading Strategy used on the FTSE China A50 Index Over the Period from 26/10/2017 to 31/12/2019

Figure 2: MACD(1) Trading Strategy used on the FTSE China A50 Index Over the Period from 26/10/2017 to 31/12/2019

Table 5: StEn(*n*) Strategies Results Using Different Holding Periods Compared to MACD Strategy

Time (i) Where the Strategy is Applied Based on Holding Period	StEn(*n*) Strategy*	Total Return with StEn(*n*) Strategy	Sharpe Ratio**	Win Ratio Based on Trades	# of Trades	MACD(i) Strategy***	Total Return with MACD(i) Strategy	Sharpe Ratio**	Win Ratio Based on Trades	# of Trades
26/10/2017–31/12/2019	StEn(40)	9.61%	0.17	75%	4	MACD(1)	–34.98%	–0.96	30.43%	46
9/11/2017–31/12/2019	StEn(50)	13.14%	0.43	75%	4	MACD(2)	–34.98%	–0.98	30.43%	46
23/11/2017–31/12/2019	StEn(60)	8.64%	0.35	66%	3	MACD(3)	–34.98%	–1.17	30.43%	46
5/1/2018–31/12/2019	StEn(90)	25.66%	0.58	75%	4	MACD(4)	–36.26%	–1.70	28.57%	42

*StEn(40), StEn(50), StEn(60), and StEn(90) are StEn(*n*) entropy trading strategies at different (*n*) holding periods. **Risk free rate in Sharpe ratio is calculated by taking the average Hong Kong interbank rate over the holding period. ****i* is the period where the strategy is applied. For example, *i* = 1 is the period from 26/10/2017 to 31/12/2019.

Table 6: Return Results from all Three Strategies

Time (I) When the Strategy is Applied, Based on the Holding Period	StEn(*n*) Strategy*	Total Return with StEn(*n*) Strategy	RSI(i) Strategy***	Total Return with RSI(i) Strategy	MACD(i) strategy***	Total Return with MACD(i) Strategy	Total Return with Buy-And-Hold Strategy
26/10/2017–31/12/2019	StEn(40)	9.61%	RSI(1)	-30.59%	MACD(1)	–34.98%	14.26%
9/11/2017–31/12/2019	StEn(50)	13.14%	RSI(2)	-30.59%	MACD(2)	–34.98%	10.70%
23/11/2017–31/12/2019	StEn(60)	8.64%	RSI(3)	-30.59%	MACD(3)	–34.98%	6.78%
5/1/2018–31/12/2019	StEn(90)	25.66%	RSI(4)	-28.56%	MACD(4)	–36.26%	6.03%

*StEn(40), StEn(50), StEn(60), and StEn(90) are StEn(*n*) entropy trading strategies at different (*n*) holding periods. ****i* is the period where the strategy is applied. For example, *i* = 1 is the period from 26/10/2017 to 31/12/2019.

strategy and the StEn(n) strategy, the RSI and MACD fared badly. Backtesting the RSI and MACD using the Bloomberg terminal did not result in a higher return or a positive return. Figures 1 and 2 depict the RSI and MACD buying and selling points, respectively. Using the backtesting approach from the Bloomberg terminal, the red arrow represents the exit or selling point and the green arrow indicates the entry or purchasing position. In addition, we can see that MACD has greater buying and selling activity than RSI. These activities, however, did not produce a larger return than the RSI or the buy and hold strategy. In addition, our new strategy for trading the FTSE China A50 index yielded the best results.

5. Conclusion and Recommendations

Sample entropy is used in this paper as a signaling tool for buying and selling on the FTSE China A50 Index. The replication of the strategy used in Efremidze et al. (2015) with significate addition is applied in this study as shown in the methodology section. The method used in the paper yielded positive returns, especially for longer holding periods. As seen in Table 6, the new trading technique developed in this study, StEn(n), generated larger returns than traditional trading methods. From 5/1/2018 to 31/12/2019, StEn(90) earned the highest cumulative return (25.66 percent). This finding matches that of Efremidze et al. (2021), who discovered that a sample entropy strategy gave a greater return than a buy-and-hold strategy. Furthermore, the new technique outperformed traditional buy and hold, RSI, and MACD. When applied to the FTSE China A50 Index during the same time periods, RSI and MACD had negative results.

Applying entropy to other global market indexes, such as the S&P 500, is advocated as a way to strengthen the conclusion. Furthermore, the research may be expanded by contrasting it with other trading methods such as employing the Momentum stochastic K% or Larry William's R%.

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