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Comparative Study of Automatic Trading and Buy-and-Hold in the S&P 500 Index Using a Volatility Breakout Strategy

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변동성 돌파 전략을 사용한 S&P 500 지수의 자동 거래와 매수 및 보유 비교 연구

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Abstract This research is a comparative analysis of the U.S. S&P 500 index using the volatility breakout strategy against the Buy and Hold approach. The volatility breakout strategy is a trading method that exploits price movements after periods of relative market stability or concentration. Specifically, it is observed that large price movements tend to occur more frequently after periods of low volatility. When a stock moves within a narrow price range for a while and then suddenly rises or falls, it is expected to continue moving in that direction. To capitalize on these movements, traders adopt the volatility breakout strategy. The 'k' value is used as a multiplier applied to a measure of recent market volatility. One method of measuring volatility is the Average True Range (ATR), which represents the difference between the highest and lowest prices of recent trading days. The 'k' value plays a crucial role for traders in setting their trade threshold. This study calculated the 'k' value at a general level and compared its returns with the Buy and Hold strategy, finding that algorithmic trading using the volatility breakout strategy achieved slightly higher returns. In the future, we plan to present simulation results for maximizing returns by determining the optimal 'k' value for automated trading of the S&P 500 index using artificial intelligence deep learning techniques.

Key Words : volatility breakout strategy; auto trading; AI prediction; stock prediction

요 약 본 연구는 미국 S&P 500 지수를 변동성 돌파 전략을 활용하여 Buy and Hold 방식과 비교 분석한 연구이다. 변동성 돌파 전략은 시장의 상대적 안정 또는 집중된 시기 후의 가격 움직임을 활용하는 거래 전략이다. 특히, 낮은 변동성 기간 후에 큰 가격 움직임이 더 자주 발생한다는 것이 관찰된다. 주식이 한동안 좁은 가격 범위에서 움직이다가 가격이 갑작스레 상승 또는 하락하는 경우, 그 주식이 해당 방향으로 계속 움직일 것으로 예상된다. 이러한 움직임을 활용하기 위해 거래자들은 변동성 돌파 전략을 채택한다. 'k' 값은 최근 시장 변동성의 측정값에 곱하는 배수로서 활용된다. 변동성의 측정 방법 중 하나로는 최근 거래일의 최고가와 최저가 차이를 나타내는 평균 진정 범위(ATR)가 있다. 'k' 값은 거래자들이 거래 임계값을 설정하는 데 중요한 역할을 한다. 본 연구는 'k' 값을 일반적인 값으로 연산하여 Buy and Hold 전략과 수익률을 비교 하여, 변동성 돌파전략을 사용한 알고리즘 트레이딩이 약간은 높은 수익률을 이룩하였다. 추후에는 인공 지능 딥러닝 기법을 이용하여 S&P 500 지수의 자동 거래를 위한 최적의 K 값을 구하고, 이를 통해 수익률을 극대화하기 위한 시뮬레이션 결과를 제시할 예정이다.

주제어 : 변동성돌파, 자동매매, 인공지능 예측, 주가예측

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1. Introduction

1.1 Strategies for Stock Prediction

Isaac Newton suffered significant financial losses in the stock market as a part of the South Sea Bubble in 1720. About this, he famously said, "I can calculate the motion of heavenly bodies, but not the madness of people."

Many researchers in the field of artificial intelligence are conducting extensive studies to predict stock prices using AI. They believe that with the vast amount of data available from stock markets and the powerful computational abilities of modern AI systems, there is potential to forecast market movements more accurately. These AI models are trained on historical stock price data, news articles, financial reports, and various other relevant indicators. The hope is that by analyzing patterns and correlations within this data, AI can provide valuable insights and predictions that traditional methods might miss. However, it's worth noting that while AI can enhance the accuracy of predictions, stock markets are inherently volatile and influenced by a myriad of unpredictable factors. As a result, even the most sophisticated AI models cannot guarantee absolute accuracy in their predictions.

Many securities investment firms are now incorporating algorithmic trading into their strategies to some extent. Algorithmic trading, or algo-trading, involves using computer programs and mathematical models to execute trades at high speeds and volumes. These algorithms are designed to identify opportunities for profitable trades based on predefined criteria, often analyzing vast amounts of market data in real-time. By automating the trading process, these firms aim to achieve better trade execution, reduce costs, and potentially capitalize on small market inefficiencies that might be overlooked by human traders. However, it's important to note that while algorithmic trading can offer advantages, it also comes with its own set of challenges and risks.

In today's rapidly advancing financial landscape, traditional trading strategies often find themselves outpaced by the complexities of modern markets. The S&P 500, representative of the broader US stock market, has always been a focal point for traders and investors. Historically, determining key parameters, such as the 'k' value in volatility breakout strategies, relied heavily on human intuition and rudimentary algorithms. However, the advent of Artificial Intelligence (AI) and its deep learning techniques presents a promising avenue for refining these strategies and enhancing trading profitability. As financial markets become increasingly influenced by myriad factors, the need for sophisticated, data-driven approaches is paramount. This paper delves into an innovative algorithm that harnesses the power of AI to optimize the 'k' value, aiming to capitalize on potential breakout moments in the stock market, particularly within the realm of the S&P 500 index.

This approach signifies a step beyond traditional data sources like historical stock price data, news articles, and financial reports, proposing a more comprehensive data integration that includes IoT-generated information. The paper emphasizes the need for sophisticated, data-driven strategies in the complex financial landscape, highlighting the combined potential of IoT and AI in enhancing the profitability of trading strategies, especially in volatile markets like the S&P 500 [2].

By introducing IoT elements into the discussion, the paper aligns more closely with the themes of IoT convergence research, demonstrating the synergy between IoT technologies and advanced AI applications in the field of stock market analysis and prediction [3].

1.2 Challenges in volatility breakout strategies

In volatility breakout strategies, fixing the K value at 0.5 presents several challenges:

- Lack of Flexibility: A static K value does not adapt to changing market conditions. Different market phases, whether bullish, bearish, or sideways, may require different K values for optimal results.

- Over-Simplification: Markets are complex entities influenced by countless factors. Assuming a one-size-fits-all K value oversimplifies this complexity, potentially leading to missed opportunities or increased risks.
- Reduced Profit Potential: By not adjusting the K value based on recent market data or conditions, traders might miss out on larger breakouts or enter trades that don't have a strong momentum behind them.
- Increased False Signals: A constant K value might lead to more false breakout signals, resulting in potential losses from entering trades that quickly reverse direction.
- Lack of Personalization: Different traders have different risk tolerances and trading objectives. A fixed K value does not allow for individual customization based on a trader's specific needs or goals.
- Underutilization of Data: Modern trading platforms and tools offer a wealth of data that can be used to optimize strategy parameters. By sticking to a fixed K value, traders are not fully leveraging available data to refine their strategies.

In essence, while setting a K value at 0.5 might offer simplicity, it potentially sacrifices the adaptability and precision that can be crucial for trading success in dynamic markets [1, 3-4].

2. Williams %R

Larry Williams' Volatility Breakout Strategy is based on the concept that increases in market volatility, often seen as range expansions, signal potential trend formations [5]. This strategy is popular due to its simplicity, effectiveness in capturing market momentum, adaptability across different time frames and markets, inherent risk management techniques, and objective entry and exit criteria based on measurable factors [6]. It primarily uses the Average True Range (ATR) to assess volatility and determine trading positions [7].

However, the strategy is not without risks. Traders must back-test it under various market conditions and apply solid risk management practices. Alongside, the Williams %R, a momentum indicator developed by Larry Williams, is used to identify overbought and oversold market levels, helping to gauge where the current close stands in relation to past closing prices over a typical period of 14 days. This indicator is crucial for understanding market momentum and making informed trading decisions [8].

Formula: The Williams %R is calculated using the following formula (1):

$$\%R = \frac{Highest\ High - Close}{Highest\ High - Lowest\ Low} \times -100 \quad \text{................(1)}$$

Range: The values of Williams %R range from 0 to -100. A reading above -20 is typically considered overbought, while a reading below -80 is considered oversold [9].

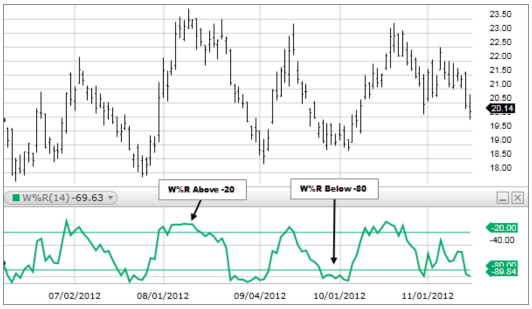
Interpretation: Overbought and Oversold Levels: As with many momentum oscillators, overbought and oversold levels can be used to identify potential market reversals [10].

Divergences: If the security's price makes a new high, but the Williams %R fails to surpass its previous high and instead moves lower, it might be considered a bearish divergence. Conversely, if the security's price makes a new low, but the Williams %R fails to make a new low and instead moves higher, it could indicate a bullish divergence.

Centerline Crossover: Some analysts look for situations where the Williams %R crosses above or below the -50 level as signals [11].

Comparison with Stochastic Oscillator: Both the Stochastic Oscillator and Williams %R move between 0 and 100, but the Williams %R is upside down, with 0 at the top and -100 at the bottom. This means that overbought readings are below -20, and oversold readings are above -80.

Usage: The Williams %R can be used in various trading strategies, including trend-following and range-bound strategies. Like all technical indicators, it's most effective when used in conjunction with other tools and analysis techniques.



[Fig. 1] Williams %R Chart in Green

Fig. 1 is Williams %R chart. Larry Williams developed Williams %R, a momentum indicator that is the opposite of the Fast Stochastic Oscillator. Readings from 0 to -20 are considered overbought, while readings from -80 to -100 are considered oversold. Williams %R reflects the closing price relative to the highest high over the specified period. It is a bounded oscillator that oscillates between 0 and -100. As a result, the Fast Stochastic Oscillator and Williams %R produce the same lines, but the scaling is different. Williams %R corrects for the inversion by multiplying the raw value by −100 [12-15].

3. Python Code for Volatility Breakout Strategy

Volatility Breakout Strategy is based on the idea that if the price of a stock deviates from its historical volatility, there might be a potential trading opportunity. A commonly used measure of volatility is the Average True Range (ATR). The parameter k determines how many times the ATR will be used to define the breakout level. For instance, if k=1.5 and ATR is 2, the breakout level would be 3 points away from the current price.

The S&P 500 index is comprised of the following Table 1.

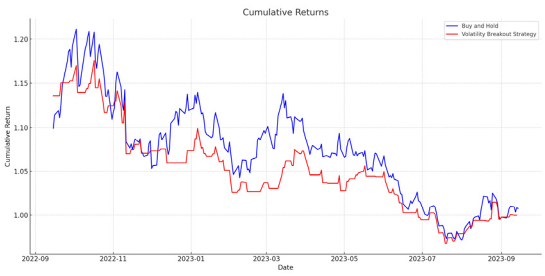
<Table 1> S&P 500 index from Sept. 15, 2022~Sept. 14, 2023

Date	Open	High	Low	Close	Adj Close
14-Sep-23	4,472	4,513	4,470	4,506	4,506
13-Sep-23	4,465	4,481	4,447	4,469	4,469
12-Sep-23	4,488	4,491	4,459	4,465	4,465
11-Sep-23	4,464	4,494	4,459	4,490	4,490
08-Sep-23	4,458	4,478	4,443	4,462	4,462
...	...	...	...	...	...
21-Sep-22	3,879	3,925	3,792	3,806	3,806
20-Sep-22	3,923	3,936	3,843	3,873	3,873
19-Sep-22	3,890	3,927	3,846	3,917	3,917
16-Sep-22	3,889	3,889	3,846	3,871	3,871
15-Sep-22	3,955	3,960	3,888	3,902	3,902

3.1 Experimental Results for Volatility Breakout Strategy with S&P 500 Index Data

Fig. 3 is a python code based on the Volatility Breakout Strategy. Based on the results of the last 5 days, the cumulative return rate following the volatility breakout strategy was 1.13564, indicating a return of approximately 13.56% on the initial investment. Next, let's plot the cumulative return to see the overall trend in Fig. 2.

Looking at Fig. 2, there were periods where the "Volatility Breakout Strategy" had slightly higher returns than the "Buy and Hold" strategy (i.e., the strategy of buying and continuously holding). However, over time, the returns of the two strategies seem to converge. However, during this data period, the volatility breakout strategy showed slightly better results.



[Fig. 2] Buy and Hold vs. Volatility Breakout Strategy

Data Loading: We start by loading the S&P 500 index data from an Excel file. This data contains columns like Date, Open, High, Low, Close*, Adj Close**, and Volume.

Volatility Calculation: The volatility for a given day is calculated as the difference between the previous day's highest price (High) and lowest price (Low). This volatility gives us an idea of how much the price fluctuated on the previous day. Fig. 4 shows ERD based on Fig. 3

```
import pandas as pd
import matplotlib.pyplot as plt
data = pd.read_excel("/path/to/S&P500index.xlsx")
data['Range'] = data['High'].shift(1) - data['Low'].shift(1)
data['Target'] = data['Open'] + data['Range']*0.5
data['Buy'] = data['High'] > data['Target']
data['Return'] = (data['Close*'] / data['Open']) - 1
data['StrategyReturn'] = data['Buy'].shift(1) * data['Return']
data['CumulativeReturn'] = (1 + data['Return']).cumprod()
data['CumulativeStrategyReturn'] = (1 +
data['StrategyReturn']).cumprod()
plt.figure(figsize=(14,7))
plt.plot(data['Date'], data['CumulativeReturn'], label='Buy and Hold',
color='blue')
plt.plot(data['Date'], data['CumulativeStrategyReturn'],
label='Volatility Breakout Strategy', color='red') plt.title('Cumulative
Returns')
plt.xlabel('Date') plt.ylabel('Cumulative Return') plt.legend()
plt.grid(True)
plt.tight_layout() plt.show()
```

[Fig. 3] Python Code of Volatility Breakout Strategy

```
  Data Source ||--o{ Load Data }-» Stock Data
  Stock Data ||--o{ Calculate Metrics }-» Performance Metrics
  Stock Data ||--{ Generate Signal }-» Trade Signal
  Performance Metrics ||--{ Compute Cumulative Metrics }--»
Performance Metrics
  Performance Metrics ||--o{ Plot Data }-» Chart
```

[Fig. 4] ERD based on Fig. 3

The formula used is:

data['Range'] = data['High'].shift(1) - data['Low'].shift (1)

Setting the Target Price: For each day, a target price is set. This target is calculated by adding 50% of the calculated volatility to the opening price (Open) of the current day [9].

The formula used is: data['Target'] = data['Open'] + data['Range']*0.5

Determining Buy Signal: A buy signal is determined for each day based on whether the highest price of the day (High) surpasses the set target price.

If the highest price exceeds the target, it's considered a buying opportunity for the strategy. This is represented as True in the Buy column. Otherwise, it's False.

Calculating Returns: The daily return is calculated as the percentage change between the closing price (Close*) and the opening price (Open) [7].

The formula used is: data['Return'] = (data['Close*'] / data['Open']) - 1

Strategy Return: If we followed the buy signal from the previous day, the strategy's return for the current day is equivalent to the daily return. If we didn't buy, the strategy's return is 0 for the day.

Cumulative Returns: Cumulative returns give us a sense of how our investment would have grown over time. It's calculated by taking the product of all (1 + daily returns) up to the current day.

We calculate cumulative returns for both a simple "Buy and Hold" strategy and the "Volatility Breakout Strategy".

Visualization: Using matplotlib, we plot the cumulative returns over time. The blue line represents the returns from a "Buy and Hold" strategy, while the red line represents the returns from the "Volatility Breakout Strategy".

The x-axis represents the dates, and the y-axis represents the cumulative returns.

This strategy and visualization help in understanding how the "Volatility Breakout Strategy" performs relative to a simple "Buy and Hold" strategy over.

the given period in the S&P 500 index data.

4. Conclusion and Future Work

In conclusion, this comprehensive study underscores the potential merits of the volatility breakout strategy when juxtaposed with the traditional Buy and Hold method for the S&P 500 index. The empirical data suggests that by adeptly harnessing price fluctuations, especially after periods of diminished volatility, traders can achieve marginally superior returns. The 'k' coefficient emerges as a pivotal parameter in this context, influencing trading decisions and outcomes. Furthermore, the promising results obtained by employing this strategy in algorithmic trading accentuate its relevance in contemporary financial markets. As we advance, the fusion of artificial intelligence and deep learning methodologies presents a promising avenue to refine and optimize trading strategies further, potentially revolutionizing the landscape of automated trading.

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