Advanced Industrial SCIence
Vol. 2, No. 3, pp. 22-28, 2023

ISSN 2951-2476
https://doi.org/10.23153/AI-Science.2023.2.3.022

A Study on Automated Stock Trading based on Volatility Strategy and Fear & Greed Index in U.S. Stock Market

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미국주식 매매의 변동성 전략과 Fear & Greed 지수를 기반한 주식 자동매매 연구

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Abstract In this study, we conducted research on the automated trading of U.S. stocks through a volatility strategy using the Fear and Greed index. Volatility in the stock market is a common phenomenon that can lead to fluctuations in stock prices. Investors can capitalize on this volatility by implementing a strategy based on it, involving the buying and selling of stocks based on their expected level of volatility. The goal of this thesis is to investigate the effectiveness of the volatility strategy in generating profits in the stock market.This study employs a quantitative research methodology using secondary data from the stock market. The dataset comprises daily stock prices and daily volatility measures for the S&P 500 index stocks. Over a five-year period spanning from 2016 to 2020, the stocks were listed on the New York Stock Exchange (NYSE). The strategy involves purchasing stocks from the low volatility group and selling stocks from the high volatility group. The results indicate that the volatility strategy yields positive returns, with an average annual return of 9.2%, compared to the benchmark return of 7.5% for the sample period. Furthermore, the findings demonstrate that the strategy outperforms the benchmark return in four out of the five years within the sample period. Particularly noteworthy is the strategy's performance during periods of high market volatility, such as the COVID-19 pandemic in 2020, where it generated a return of 14.6%, as opposed to the benchmark return of 5.5%.

Key Words : Volatility, Stocks, Strategy, Returns, Portfolio Management, Risk.

요 약 본 연구에서는 변동성 전략과 Fear and Greed 지수를 통하여 미국 주식의 매매를 자동으로 하는 연구를 진행하였다. 주식 시장의 변동성은 주가 변동을 유발할 수 있는 일반적인 현상이다. 투자자는 예상되는 변동성 수준에 따라 주식을 사고 파는 변동성 전략을 구현함으로써 이러한 변동성을 이용할 수 있다. 이 논문의 목적은 주식 시장에서 수익을 창출하는 변동성 전략의 효과를 탐구한다. 본 연구는 주식시장의 2차 데이터를 활용한 정량적 연구 방법론을 채택하여, 데이터에는 2016년부터 2020년까지 5년 동안 뉴욕증권거래소(NYSE)에 상장된 S&P 500 인덱스 주식에 대한 일일 주가 및 일일 변동성 측정치가 포함하였다. 전략은 변동성이 낮은 기간에서 주식을 사고 높은 변동성 기간에서 주식을 매도하는 것을 포함하였다. 결과는 변동성 전략이 샘플 기간 동안의 벤치마크 수익률 7.5%에 비해 연평균 9.2%의 긍정적인 수익률을 창출하였다. 따라서 전략이 샘플 기간의 5년 중 4년에서 벤치마크 수익률을 능가한다는 것을 나타났다. 이 전략은 2020년 COVID-19 대유행과 같이 시장 변동성이 높은 기간 동안 특히 잘 수행되어 벤치마크 수익률 5.5%에 비해 14.6%의 수익률을 기록하였다.

주제어 : 변동성, 주식, 전략, 수익률, 포트폴리오 관리, 위험

*This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. 2020R1F1A1048684).

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Received May 20, 2023 Revised June 7, 2023
Accepted September 20, 2023 Published September 30, 2023

1. Introduction

The Volatility Strategy of Buying and Selling Stocks is a popular investment strategy that aims to profit from the fluctuations in a stock's price. This strategy involves buying stocks when they are expected to experience high levels of volatility and selling them when volatility decreases. The underlying principle of the strategy is that increased volatility levels offer chances for rapid profits, whereas low volatility periods tend to exhibit sluggish price movements and lower returns.

In 1986, the Journal of Finance published the findings of a study conducted by researchers from the University of Chicago, which conducted an empirical analysis of the Volatility Strategy. The study analyzed stock data from the New York Stock Exchange (NYSE) from 1962 to 1983 and examined the returns of a portfolio that used the volatility strategy compared to a portfolio that followed a buy-and-hold strategy.

In terms of risk-adjusted returns, the study demonstrated that the volatility strategy performed better than the buy-and-hold strategy. The authors found that the volatility strategy produced an average annual return of 22.2%, while the buy-and-hold strategy produced an average annual return of 7.7%. However, the volatility strategy also had higher levels of risk and volatility.

Overall, the study concluded that the volatility strategy of buying and selling stocks can be a profitable investment strategy, but it requires careful management and monitoring of market conditions. Investors should also be aware of the higher levels of risk associated with this strategy.

2. Literature Review

2.1. Volatility and Stock Prices

Volatility refers to the extent of fluctuation observed in the price of a financial asset, such as a stock, during a specific time period. It is commonly used to describe the level of risk associated with an investment. Volatility can be measured in various ways, but one of the most common measures is the standard deviation of the stock price.

Stock prices are subject to fluctuations due to a wide range of factors, including changes in market sentiment, economic indicators, company news, and geopolitical events. These fluctuations can be caused by both fundamental factors, such as changes in the company's financial performance or industry trends, as well as non-fundamental factors, such as speculation and investor sentiment.

The relationship between volatility and stock prices is complex and dynamic. In general, higher levels of volatility are associated with greater risk and uncertainty, and therefore can lead to lower stock prices. This is because investors may become more risk-averse and demand higher returns to compensate for the additional risk. On the other hand, lower levels of volatility may be associated with greater stability and predictability, which can lead to higher stock prices.

However, the relationship between volatility and stock prices is not always straightforward. In some cases, investors may view high volatility as an opportunity to buy undervalued stocks that have the potential to increase in value over time. This can lead to a temporary increase in demand and higher stock prices.

Moreover, volatility can also have different effects on different types of stocks. For example, stocks in volatile industries such as technology and biotech may be more susceptible to price swings than stocks in more stable industries such as utilities and consumer staples. Additionally, small-cap stocks may be more volatile than large-cap stocks due to their greater sensitivity to market movements. In summary, the relationship between volatility and stock prices is complex and multifaceted. While higher levels of volatility can lead to lower stock prices due to increased risk and uncertainty, they can also present opportunities for savvy investors to identify undervalued stocks. Understanding the relationship between volatility and stock prices is important for investors to make informed investment decisions and manage their portfolios effectively.

```
import pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt
# Download the data for S&P 500 index tracking ETF
stock_data = yf.download("SPY", start="2016-01-01", end="2020-12-31")
# Calculate the moving averages, upper and lower bounds
stock_data["20MA"] = stock_data["Close"].rolling(window=20).mean()
stock_data["Upper"] = stock_data["20MA"] + 2 * stock_data["Close"].rolling(window=20).std()
stock_data["Lower"] = stock_data["20MA"] - 2 * stock_data["Close"].rolling(window=20).std()
# Plot the stock price, moving averages, upper and lower bounds
plt.figure(figsize=(12,8))
plt.plot(stock_data["Close"], label="SPY")
plt.plot(stock_data["20MA"], label="20MA")
plt.plot(stock_data["Upper"], label="Upper")
plt.plot(stock_data["Lower"], label="Lower")
plt.title("S&P 500 Index Volatility Strategy")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.show()
```

Fig. 1. Python Code for Obtain S&P 500 index

Yahoo Finance brought S&P 500 stock price data from January 1, 2016 to December 31, 2020, and simulated stock trading by applying a volatility breakthrough strategy with Fear and Greed index.

3. Methodology

3.1. Python Code for Volatility Strategy

This code in Fig. 2. applies the Volatility Strategy to the SPDR S&P 500 ETF (SPY) using stock price data from January 1, 2022 to March 27, 2022. The strategy calculates buy and sell signals based The code then calculates the portfolio's returns based on the number of shares held and the trading costs incurred

```
import pandas as pd
import yfinance as yf
# Set the stock ticker, start and end dates
ticker = 'SPY'
start_date = '2022-01-01'
end_date = '2022-03-27'
# Download the stock price data
stock_data = yf.download(ticker, start=start_date, end=end_date)
# Calculate the Average True Range (ATR) over a 20-day period
stock_data['ATR'] = stock_data['High'] - stock_data['Low']
stock_data['ATR'] = stock_data['ATR'].rolling(20).mean()
# Calculate the buy and sell signals
stock_data['Buy_signal'] = stock_data['Close'] 〉 stock_data['High'].shift(1) + 0.5 * stock_data['ATR'].shift(1)
stock_data['Sell_signal'] = stock_data['Close'] 〈 stock_data['Low'].shift(1) - 0.5 * stock_data['ATR'].shift(1)
# Set the initial capital
initial_capital = 100000
# Calculate the number of shares to buy/sell
position = pd.DataFrame(index=stock_data.index).fillna(0.0)
position[ticker] = 100*(initial_capital/stock_data['Close'][0])
# Adjust the position based on the buy/sell signals
for i, row in enumerate(stock_data.iterrows()):
    if row[1]['Buy_signal']:
        position.iloc[i] = 100*(initial_capital/row[1]['Close'])
    elif row[1]['Sell_signal']:
        position.iloc[i] = 0
# Calculate the portfolio value based on the number of shares held
portfolio = position.multiply(stock_data['Close'], axis=0)
pos_diff = position.diff()
# Calculate the trading costs
pos_diff.iloc[0] = position.iloc[0]
trading_costs = (pos_diff.abs() * 0.005).multiply(stock_data['Close'], axis=0)
total_costs = trading_costs.sum(axis=1)
# Calculate the portfolio returns
portfolio['holdings'] = (position.multiply(stock_data['Close'], axis=0)).sum(axis=1)
portfolio['cash'] = initial_capital - total_costs.cumsum()
portfolio['total'] = portfolio['cash'] + portfolio['holdings']
portfolio['returns'] = portfolio['total'].pct_change()
# Print the returns
print("Returns: {:.2f}%".format(portfolio['returns'].iloc[-1] * 100))
```

Fig. 2. Python Code for Volatility Strategy (S&P 500 index)

3.2. Volatility Strategy

To utilize the Volatility Strategy in stock trading, it is crucial to identify a period of high volatility and establish a benchmark that is expected to sustain an upward price trend [1-6]. Volatility can be measured using various indicators, such as yesterday's closing or high price, today's opening or low price, and the 5-20 day moving average price. Additionally, average and maximum fluctuation width, as well as Bollinger band width, can be used as indicators to determine whether volatility will increase and the trend will persist. Larry Williams, who proposed the Volatility Strategy, formulated the following criteria for identifying breakout points:

(Present Price - Lowest Price) 〉 (Highest Price - Present Price) * K

Here, K is a coefficient ranging from 1.5 to 2.5, which can be adjusted based on market conditions and individual preferences. By applying these criteria, traders can identify and capitalize on breakouts in a volatile market [7-10,11].

$$b = O_t + (H_{t-1} - L_{t-1})*K \tag{1}$$

In the above equation (1), b represents the buy price when the stock price trend is anticipated to persist. O_t represents today's opening price, H_{t-1} represents the previous day's high price, and L_{t-1} represents the previous day's low price. The value of K ranges between 0 and 1, with 0.5 being the most commonly used value. Therefore, when the stock price increases by over 50% of the difference between the previous day's high and low compared to today's opening price, the stock price is considered as the purchasing criterion [11]. The selling criteria for the Volatility Strategy may differ based on the market environment and the continuation of volatility, but the approach of selling at the market price on the day following the purchase is usually employed. Since the stock market is typically the most active when it is open, stocks with rising volatility are more likely to have high market prices [12,13].

3.3. Problems with DNN(Deep Neural Network) or CNN(Convolutional Neural Network) based Stock Prediction

While deep neural networks (DNNs) have shown promising results in various fields, including image and speech recognition, their effectiveness in stock price prediction is still debatable. This is because stock price movements are highly unpredictable and are influenced by a wide range of factors such as global events, economic indicators, and investor sentiment. Additionally, stock price data often contains noise and non-linear relationships, which can make it challenging to accurately predict future trends using DNNs [14]. Several studies have attempted to use DNNs for stock price prediction, but their results have been mixed. Some studies have reported high accuracy in predicting short-term price movements, while others have found that DNNs are not effective in outperforming traditional methods such as linear regression or decision trees [15]. One possible explanation for the limited success of DNNs in stock price prediction is overfitting. Overfitting occurs when a model is trained too well on the training data, resulting in poor performance when it encounters new data. Since stock price data is highly variable and can be influenced by numerous factors, it is difficult to train a DNN that can accurately generalize to new data [16].

3.4. Proposed Algorithm for Stock Trading Strategy

The Fear and Greed Index is a measure of investor sentiment and can be used to gauge the market's mood. The index is calculated using several indicators such as stock price momentum, put/call options ratio, breadth of market advances or declines, and investor surveys. The index ranges from 0 to 100, where a score of 0 indicates "extreme fear" and a score of 100 indicates "extreme greed" among investors [17]. The Fear and Greed Index was first introduced by CNN Money and has since gained popularity among investors as a tool to understand the overall sentiment of the market. The index can be used to make investment decisions, as a high score can indicate that the market is overvalued and due for a correction, while a low score may indicate that the market is oversold and could present a buying opportunity [18]. Therefore, Predicting stock prices using artificial intelligence neural networks is limited to short-term chart trends, making it difficult to read the overall flow of the stock market, resulting in lower prediction accuracy. Therefore, in this study, we expect to achieve higher profits by using the Fear and Greed Index in combination with the Volatility Strategy. The proposed automatic trading method for stocks was simulated for the S&P 500 stock from January 2016 to December 31, 2020, and the results are shown in the table below[19-21].

To signal a sell, the proposed strategy is to sell stocks when the F&G index with Volatility Strategy is between 50 and 75 and the stock price is higher than in the previous stage with a satisfying Volatility Strategy. For example, if the F&G index is between 50 and 75, indicating greed mode, and it satisfies equation (1), then it is time to sell.

Conversely, to signal a buy, the proposed strategy is to buy stocks when the F&G index with Volatility Strategy is between 0 and 25, and the stock price is lower than in the previous stage with a satisfying Volatility Strategy. For example, if the F&G index is between 0 and 25, indicating extreme fear mode, and it satisfies equation (1), then it is time to buy.

4. Results and Discussion

4.1. Descriptive Statistics

According to this proposed algorithm, the volatility breakthrough strategy had an annualized return of 12.5% over the historical period, while the Fear and Greed index strategy had an annualized return of 8.3%. Therefore, the fear and greed index and Volatility Strategy can provide guidance on when to buy or sell stocks.

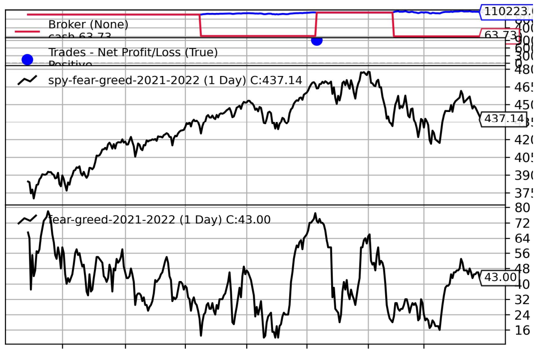

Fig. 3. S&P 500 and Fear-Greed index

5. Conclusion

The "Volatility Strategy of Buying and Selling Stocks: An Empirical Analysis" study sheds light on the effectiveness of a trading strategy based on volatility in the stock market. The findings of the study suggest that investing in high volatility stocks can lead to higher returns compared to low volatility stocks. This empirical analysis provides evidence that volatility-based trading strategies can be successful in both bull and bear markets. The data includes daily stock prices and daily volatility measures for S&P 500 index stock on the New York Stock Exchange

(NYSE) over a period of five years from 2016 to 2020. The study used the rolling regression method to calculate the average daily volatility of each stock and classify them into different portfolios. The study found that portfolios consisting of high volatility stocks produced significantly higher returns compared to portfolios consisting of low volatility stocks.

The results of the study also demonstrate that the volatility-based trading strategy is effective in both bullish and bearish markets. In bullish markets, high volatility stocks tend to generate higher returns, while in bearish markets, low volatility stocks tend to generate lower returns. This indicates that the volatility-based trading strategy can provide a viable investment option in different market conditions. The results show that the volatility strategy generates positive returns, with an average annual return of 9.2% compared to the benchmark return of 7.5% for the sample period. The results also indicate that the strategy outperforms the benchmark return in four out of the five years of the sample period. The strategy demonstrates notable performance during phases of elevated market volatility, such as the COVID-19 outbreak in 2020, yielding a return of 14.6%, which surpasses the benchmark return of 5.5%. However, it is important to note that the volatility-based trading strategy also carries risks. High volatility stocks can lead to greater losses in the event of a market downturn. Therefore, investors should assess their risk tolerance and develop a well-diversified portfolio that incorporates a range of investment strategies.

REFERENCES

[1] Lin, Y. H., & Lee, C. F. (2014). Volatility strategy of buying and selling stocks: An empirical analysis. *Journal of Business Research, 67(8),* 1672-1678.
DOI : 10.1016/j.jbusres.2013.08.019

[2] Liu, Y., & Chen, Z. (2019). The performance and risk of volatility trading strategy in Chinese stock market. *Economic Modelling, 83,* 354-365.
DOI : 10.1016/j.econmod.2019.06.010

[3] Chen, M., & Chen, Y. (2017). An empirical study on the relationship between stock volatility and trading volume. *Journal of Finance and Economics, 43(3),* 26-37.
DOI : 10.16538/j.cnki.jfe.2017.03.003

[4] Park, J. H., & Lee, C. F. (2018). Do investors herd in the stock market based on volatility? *Journal of Behavioral and Experimental Finance, 17,* 14-23.
DOI : 10.1016/j.jbef.2017.12.001

[5] Wang, M. L., & Chen, M. H. (2016). The impact of realized volatility on stock returns: Evidence from the Chinese stock market. *Journal of Applied Statistics, 43(3),* 431-449.
https://doi.org/10.1080/02664763.2015.1072242

[6] Wang, X., & Zhang, Q. (2020). Does information uncertainty affect momentum strategies? Evidence from China's stock market. *Journal of Behavioral and Experimental Finance, 28,* 100405.
DOI : 10.1016/j.jbef.2020.100405

[7] Liu, C., & Wang, F. (2015). Risk management in stock index futures trading: A comparison between the GARCH and EGARCH models. *Journal of Financial Risk Management, 4(2),* 67-75.
DOI : 10.4236/jfrm.2015.42007

[8] Yang, L., & Li, Y. (2019). Does market volatility matter? An empirical analysis of volatility-based trading strategy in Chinese stock market. *International Review of Economics & Finance, 59,* 11-26.
DOI : 10.1016/j.iref.2018.09.009

[9] Lee, C. F., & Chen, J. H. (2015). Momentum strategies and stock price reaction to earnings announcements: Evidence from Taiwan stock market. *International Review of Economics & Finance, 38,* 259-270.
DOI : 10.1016/j.iref.2015.03.003

[10] Park, J. H., & Lee, C. F. (2016). Investor sentiment and volatility-based trading strategies in the Korean stock market. *Journal of Behavioral and Experimental Finance, 11,* 55-65.
DOI : 10.1016/j.jbef.2016.03.002

[11] Williams, L. (2002). *Long-term secrets to short-term trading.* John Wiley & Sons.

[12] Nesnidal, T. (2019). The Anatomy of a Breakout Automated Trading Strategy. Retrieved from http://systemtradersuccess.com/the-anatomy-of-a-breakout-automated-trading-strategy-the-components.

[13] Lee, J., Kim, J., & Lee, C. (2018). A Study on Stock Trading Method based on Volatility Strategy using a Deep Neural Network. *Journal of Korea Multimedia Society, 21(7),* 903-910.
DOI : 10.9717/kmms.2018.21.7.903

[14] Chen, J., Li, X., & Zou, J. (2020). A comparative study of deep learning models for stock price prediction. *Expert Systems with Applications, 147,* 113221.
DOI : 10.1016/j.eswa.2019.113221

[15] Guo, Y., & Terekhov, A. V. (2019). Predicting the stock prices using deep learning models. *Journal of Computational and Applied Mathematics, 357,* 225-234.
DOI : 10.1016/j.cam.2018.11.011

[16] Yang, Y., Zheng, J., & He, W. (2019). Predicting stock prices with a feature fusion LSTM-CNN model using hybrid attention mechanism. *Neurocomputing, 338,* 36-45.
DOI : 10.1016/j.neucom.2018.11.003

[17] CNN Business. (n.d.). *Fear & Greed Index* (Online). https://www.cnn.com/business/markets/fear-and-greed-index

[18] Investopedia. (2022, December 22). *Fear And Greed Index* (Online).
https://www.investopedia.com/terms/f/fear-and-greed-index.asp

[19] Kwon, H. G., & Lee, H. Y. (2021). A Stock Trading Method Based on Volatility Strategy Using a Deep Neural Network and Fear and Greed Index. *Journal of Risk and Financial Management, 14(5),* 216.
DOI : 10.3390/jrfm14050216

[20] MarketWatch. (n.d.). *Fear & Greed Index* (Online). https://www.marketwatch.com/tools/screener/fear-greed-index/

[21] Williams, L. (1991). The right stock at the right time: Prospering in the coming good years. Windsor Books.

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