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A Study on the Effectiveness of SPY ETF Prediction Based on Signal Trading

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Abstract: *An exchange-traded fund (ETF) is a popular trading tool in today's stock market, known for its low cost, low risk, and high liquidity. Enhancing the accuracy of predicting ETF future prices using quality trading strategies is of interest. This study selects the widely traded SPY ETF in the U.S. market as a representative. It utilizes market signal theory and panel data of daily closing prices of five major international stock indices from 2012 to 2021. Python Jupiter notebook is used as the programming tool to construct a multiple regression model and conduct a series of predictive analyses. The aim is to track SPY price changes by measuring the fluctuations in other stock indices, thereby predicting SPY prices. Following regression predictions, a time series prediction model is employed, and the market signal predictions are compared with a Buy-and-hold strategy. Lastly, using metrics like R2, Adj-R2, Sharpe ratio, and Maximum drawdown as evaluation criteria, empirical results are observed. The findings indicate that the Signal-based trading strategy outperforms Buy-and-hold, yet the impact of several stock index prices on ETF regression is not significant. Investors should adhere to cautionary principles, consider market signals, and diversify investments to mitigate risks.*

Keywords: *Signal-based Trading, Multiple Linear Regression, Sharpe Ratio, Maximum Drawdown*

1. Introduction

An exchange-traded fund (ETF) is an open-ended fund listed and traded on an exchange with variable basic shares. As an investment vehicle, an ETF combines the diversification benefits of a mutual fund with the convenience of stock trading. This dual functionality allows investors to both subscribe or redeem fund shares from the fund management company in the primary market and buy and sell them at market prices in the secondary market. The basic operation mode of an ETF involves the fund provider, who owns the underlying assets, designing a fund to track their performance and then selling shares of that fund to investors. Investors can purchase a basket of shares and trade them on an exchange during trading hours just as they would buy shares in a company. Typically, an ETF is structured to track the performance of a specific market index, sector index, or other combination of assets [1]. In addition to these benefits, the innovative structure of ETFs allows investors to short the market, gain leverage, and earn a return on their investment [2]. According to Gary Gastineau, author of "The ETF Trading Funds Manual," the first ETF was the S&P 500 Shares, introduced in 1989 [3]. This ETF has since become a foundational tool for many investors and will be utilized in the model analysis below.

In this paper, we will develop a multivariate linear regression model to predict the daily price changes of SPY using time series data from a series of global indices. SPY is an ETF that tracks the S&P 500 Index[4], making it a representative proxy for the overall performance of the U.S. stock market. By leveraging data from other major indices such as the S&P 500 (SP500), Australia's All Ordinaries Index (AOrd), Hong Kong's Hang Seng Index (HSI), Germany's DAX, and the Nasdaq Composite, we aim to construct a signal-based trading strategy for SPY. This approach involves identifying patterns and trends in the historical data that can inform trading decisions, thereby enhancing the potential for profitable investments[5-6].

2. Establishment of multiple regression model based on signal trading

2.1 Data preprocessing

The data used in this study include SPY_lag1, SP500, AOrd, HSI, DAX, and Nasdaq indices. This research collected daily closing prices of these six stock indices from 2012 to 2021, representing stock

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markets from the United States, Australia, Hong Kong, and Germany. The data were sourced from Yahoo Finance, ensuring a certain level of authority and reliability.

The dataset was randomly divided into two equal groups of 1000 data points each for training and testing purposes. This random split is essential for evaluating the model's performance, as it ensures that the training and testing datasets are independent of each other, providing an unbiased assessment of the model's predictive power.

2.2 Correlation analysis

A scatter-matrix plot was generated to visualize the relationships between the predictor and response variables as shown in Figure 1. The analysis indicated that the correlations between the predictors (SP500, AOrd, HSI, DAX, Nasdaq) and the response variable (SPY_lag1) were not particularly strong. This suggests that while these indices are relevant, their individual contributions to the model's predictive accuracy might be limited. Further analysis showed that the indicators had a slight negative correlation with SPY, but the values were minimal and could be considered insignificant for the model.

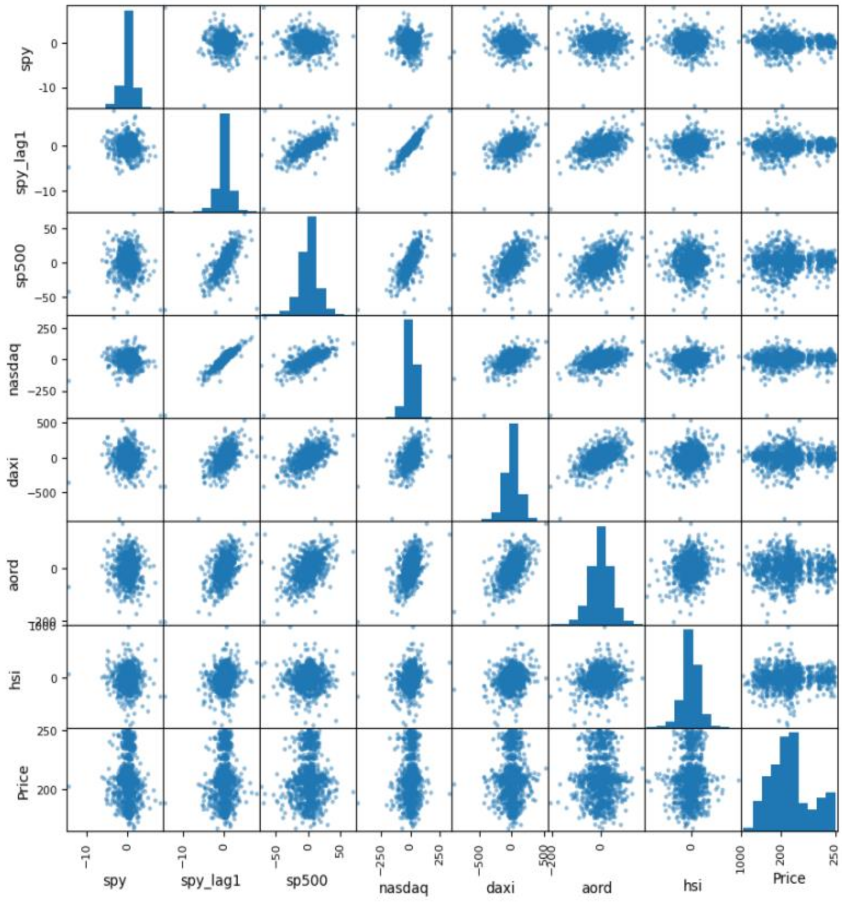

Figure 1: Scatter matrix diagram between variables

2.3 Model fitting

A multiple linear regression model was then fitted to the training data using the least squares method [7]. The initial regression results provided insights into the relationships between the independent variables and the dependent variable. The next step involved comparing the model's performance on both the training and testing datasets to determine its robustness and predictive reliability.

This initial analysis laid the foundation for developing a robust trading strategy based on signal-based trading theory. By leveraging historical data and employing sophisticated regression techniques, this study aims to provide actionable insights and strategies for trading SPY, a key ETF tracking the S&P 500 Index. The results from this stage highlight the importance of thorough data preprocessing and rigorous model validation to ensure the reliability of financial predictions.

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Table 1: Model fitting result

Dep. Variable:		spy		R-squared:		0.010
Model:		OLS		Adj. R-squared:		0.004
Method:		Least Squares		F-statistic:		1.629
Date:		Tue,19 Dec 2023		Prob (F-statistic):		0.136
Time:		11:11:11		Log-Likelihood:		-1853.3
No.Observations:		1000		AIC:		3721
Df Residuals:		993		BIC:		3755
Df Model:		6				
Covariance Type:		nonrobust				
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0879	0.049	1.783	0.075	-0.009	0.185
spy_lag1	-0.1714	0.091	-1.885	0.06	-0.35	0.007
sp500	0.0061	0.005	1.144	0.253	-0.004	0.017
nasdag	0.0016	0.003	0.565	0.573	-0.004	0.007
daxi	-0.0003	0.001	-0.606	0.544	-0.001	0.001
aord	0.0016	0.001	1.077	0.282	-0.001	0.004
his	-8.25E-05	0	-0.285	0.776	-0.001	0.000

As can be seen from the Table.1, both R-squared (0.010) and Adjusted R-squared (0.004) are small and close to 0. Therefore, this regression model is not a good fit. For Prob (F-statistic), the resulting value (0.136) > 0.05. This indicates that we cannot reject the original hypothesis that all variables are not significant. The results in the table also show that the p-value of each variable is greater than 0.05. This indicates that all the selected variables are insignificant. The Durbin-Watson statistic is 1.996 and it is close to 2. This also indicates that to some extent the variables can be considered independent.

Since the p-value tests for the predictors all failed, a test of multicollinearity was required. The results are as shown in Table 2.

Table 2: Multicollinearity test result

	spy	spy_lag1	sp500	nasdaq	daxi	aord	hsi
spy	1.000000	-0.080055	-0.029144	-0.067215	-0.036975	-0.007880	-0.028043
spy_lag1	-0.080055	1.000000	0.721292	0.926806	0.523415	0.494887	0.184761
sp500	-0.029144	0.721292	1.000000	0.664921	0.559004	0.472582	0.003067
nasdaq	-0.067215	0.926806	0.664921	1.000000	0.498901	0.485327	0.210020
daxi	-0.036975	0.523415	0.559004	0.498901	1.000000	0.572775	0.189286
aord	-0.007880	0.494887	0.472582	0.485327	0.572775	1.000000	0.181074
hsi	-0.028043	0.184761	0.003067	0.210020	0.189286	0.181074	1.000000

In this case, SPY_lag1 has a positive correlation of 92.68% with the Nasdaq predictor. This will result in the standard error of the coefficients will increase.

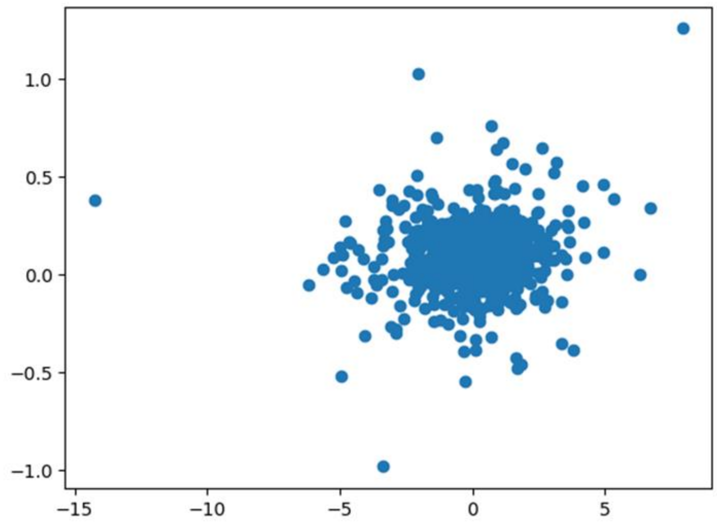

Figure 2: Scatter plot of the actual data against the predicted data for the training set

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After the model was refined, this study used the predict(). method to analyze the training data and test data, and generated a scatter plot of the actual data versus the predicted data for the training set as shown in Figure 2. Since the images do not scatter up and down at the 0 level, this suggests that the regression is not significant.

Ultimately, this study measured the performance of the model based on statistical metrics. The results shows that the adjusted r-squared of the training group and the testing group are still very small and the training group is higher than the testing group. The RMSE of the training group is closer to zero. This means that the predicted value may be close to the actual value. However, the RMSE of the testing is about 3.5 and is much higher than the RMSE of the training, which may indicate that the testing group may be worse than the training group. The reason for this may be that the regression model does not generalise well from the training data to the testing data. As a result, the model is much less suitable for generalisation to a larger real market for predicting daily changes in the price of SPY.

3. Signal-based strategy evaluate model

3.1 Formulation of signal-based strategy

This study devised and assessed a signal-based buy-and-sell strategy for the SPY ETF using a multiple linear regression model. After completing the data pre-importation, data splitting, model fitting, and prediction steps, this study formulated a signal-based strategy and determined profits, as shown in Table 3.

Table 3: Formulation of signal-based strategy

Date	spy	spy_lag1	sp500	nasdaq	daxi	aord	hsi	price
2011-01-04	-0.750000	0.620003	15.329956	23.210205	6.290039	-9.000000	191.169922	127.330002
2011-01-05	1.110000	-0.750000	-4.169922	-25.950195	-13.600098	-25.200196	107.640625	126.580002
2011-01-06	-0.130004	1.110000	7.510010	30.469971	-16.600098	7.899903	-74.919922	127.690002
2011-01-07	-0.979996	-0.130004	-1.880005	8.370117	42.069825	-12.399902	-57.398438	127.559998
2011-01-10	0.860000	-0.979996	-3.570068	-21.280029	-71.189942	9.200195	-188.210937	126.580002

3.2 Evaluation of signal-based strategy

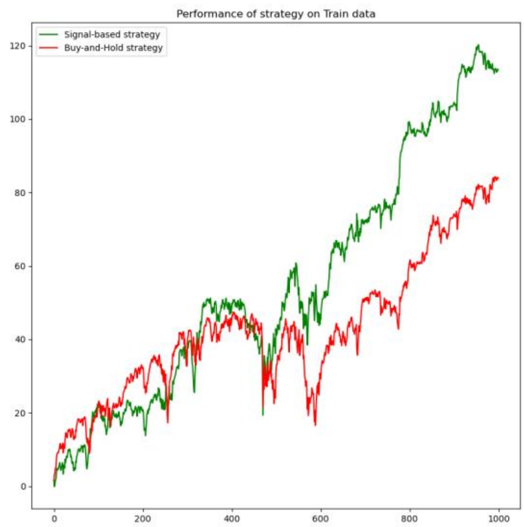

Figure 3: Distinct performance graphs for the training datasets

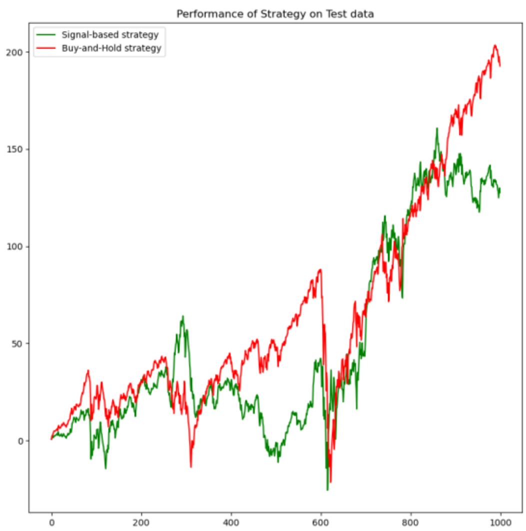

Figure 4: Distinct performance graphs for the testing datasets

By comparing this signal-based strategy to the buy-and-hold strategy, this study generated distinct performance graphs for each strategy based on both the training and testing datasets. The graphs exhibited repetitive fluctuations, indicating that the signal-based strategy did not outperform the buy-and-hold strategy over a period of 1000 units of time. This suggests that the regression model may not be well-suited, and consequently, the strategy derived from it may lack robustness, as shown in Figure 3 and Figure 4.

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The Sharpe ratios for the training and testing data are 1.09 and 0.53 respectively. This result indicates that in the training group, the return is higher than the risk volatility. But the risks of operating in a test group outweigh the rewards. This is unfavourable. In addition, due to the large contrast between the training and testing results, this further suggests that the regression model is poorly fitted.

Maximum reduction is the percentage loss from the peak to the minimum of the investment. From the figure it can be seen that the results for the training and testing data are 14.7% and 28.6% respectively. It is possible that there is a greater investment loss in the test group. It is clear that the results of the testing group are worse than those of the training group under the combined analysis of both criteria. This indicates that the generalization from the training to the testing is not good.

4. Conclusions

Based on the empirical results obtained from the analysis of the multiple linear regression model and the subsequent trading strategies developed, several key observations and conclusions can be drawn. Based on the metrics such as RMSE, r-squared, adjusted r-squared, Sharpe ratio, and maximum drawdown, it is evident that the multiple linear regression model based on historical data is not well-fitted to predict the SPY index. The strategies derived from this model exhibit unsatisfactory performance and are not suitable for real-market application. The model also presents risk issues, as indicated by the suboptimal Sharpe ratio and significant maximum drawdown.

Future research should focus on optimizing and improving the model to enhance its predictive accuracy, reduce risk exposure, and expand its applicability across various market conditions. This may involve refining the selection of independent variables, incorporating additional data sources or alternative modeling techniques, and conducting robustness tests to validate the model's performance under different scenarios.

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