Trading Strategies for Cryptocurrencies:

Are Technical Indicators Useful for Trading Cryptocurrencies?

IS713: Foundations for Data Analytics

18 November 2021

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1. Introduction

In today's fast paced and constantly growing world, inflation has become a constant reality that constantly depreciates the value of money. Inflation is borne from three key drivers:

I. Excess aggregate demand over supply from a consumerist world.

II. Cost-push effects resulting from monopolies and oligopolies in different markets, rising unit labor cost, diminishing supply of raw materials for production and transport, increasingly unpredictable and extreme weather.

III. The autoregressive cycles of economic expansion and contraction through socio-political intervention by governing bodies and unions in the form of revisions of prices, wages and rents that manipulate inflation according to their market objectives[2]. Relying on wage increments alone and bank interest rates to cope with inflation is no longer a feasible strategy in most contexts and the global population has noticed this, resulting in a rise in retail trading as a tool for the average working adult to ensure their money keeps abreast with growing prices[3].

To reduce the effects of inflation, many take to investment in order to increase their capital [18]. Traditional forms of investment [19] can include equities, commodities, and bonds among many others. Furthermore, depending on the risk appetite, traders can adopt many different strategies, from long term fundamental based trading to day-trading, or even leveraged trading.

There are many mechanisms which a trader can use to invest to grow their money. Most commonly, the direct buying and selling of an instrument is used. When a trader believes that the value of an instrument - foreign currency exchange, equities, or commodities - is undervalued and expects the price to increase, a buy order is made at the current price in anticipation that the price will increase. This is known as a 'long' order. Conversely, when the price of an instrument is expected to drop, a trader will make a sell order, effectively borrowing a stock at the current price with the intention of buying it later at a lower price. The decision as to whether a price is expected to rise, or fall, can be based on either fundamental analysis, technical analysis or intuition and experience. Fundamental analysis, as earlier discussed, focusses on the company's presumed fundamental value. In contrast, technical analysis typically uses the movements, patterns, and history of prices to make trading decisions. The tools and systems which a trader uses to analyze the movements and history of prices and make trading decisions is known as their trading strategy.

In recent years, the introduction of Bitcoin [1] in 2009, has led to the creation of a new market, the cryptocurrency market. This market has seen huge adoption and interest from the public, with thousands of cryptocurrencies available for traders to trade and an overall market capitalization in the trillions of dollars. The price of Bitcoin has also risen exponentially since its inception, and many people have earnt a fortune – and an unlucky few have lost their life savings – betting on Bitcoin. Although Bitcoin has seen an exponential price increase, there has been several waves in the Bitcoin market so far, with the bitcoin market gaining – and losing up to a trillion dollar in market value within the course of a week. Bitcoin prices do not move like the stock market, it is

more volatile and driven by events and investor sentiment. In fact, many have likened Bitcoins to bubbles in the stock market, where prices increase rapidly due to speculative investment, followed by a crash where sell-offs cause the price to decline dramatically, leaving speculative investors in the lurch.

While the less informed trader might simply follow market hype when entering the Bitcoin market, some more informed investors have taken to using various methods to try and gain profits from trading Bitcoin or other cryptocurrencies. Among those methods is the use of technical analysis in predicting future cryptocurrency prices. **The goal of this paper is thus to examine whether technical indicators are useful for trading in the Cryptocurrency Market.**

A brief introduction to the technical indicators that are used for the technical analysis and trading strategies is provided to better understand the application of these indicators for making trading decisions (see Annex A). The selected indicators and their corresponding trading strategies are some of the most used indicators that are accessible and understood by most traders. This was intentionally done to ensure the impact of the conclusion affects as many traders as possible.

The structure of the paper is as follows: Section 2 briefly discusses how the data was sourced and the processing done to generate the final dataset. Section 3 fits the data to various Autoregressive Distributed Lag (ADL) time series models to determine (i) the variables that are strongly correlated profitable trades, (ii) the lag intervals for specific variables which result in the highest correlation, and (iii) potentially useful interaction terms that indicate marginal increases in trading success conditioned on specific variable states. In Section 4, we dive deep into robustness checks by applying a different time series model (ECM) to determine if previously significant indicators remain so, or if other significant indicators are found. Following which, in Section 5, a full trading strategy is developed based on the insights derived from the earlier models, and this strategy is evaluated against common trading strategies on a different cryptocurrency from the one used in the earlier models to determine its relative performance. Finally, in Section 6, the paper concludes with a summary of the findings and potential improvements that can be made for both the modelling and trading strategy.

BTC-USD (the price of Bitcoin in USD) will be used as the base market for modelling since it is the largest and most popular cryptocurrency. The decision to explore this specific market using technical analysis is because technical analysis is the most quantitative method used to make trading decisions, making it a prime candidate for the application of econometric analysis. Additionally, cryptocurrencies are a nascent market whose true fundamentals have not been established, making fundamental analysis extremely difficult and likely inaccurate. Lastly, Bitcoin's price is highly susceptible to news-induced price action (be it news with a known release date, or sudden news), this makes it a unique challenge for regressive models as the trend is not fixed nor cyclical.

2. Data Collection and Processing

Market data collected for this project is largely from *Yahoo!* finance and *WSJ markets* website. All data is collected on the daily timeframe for the past 5 years. Aside from that, the data used to represent new-based hype for markets is collected from Google Trends by searching for key words, and significant events affecting the Bitcoin market are included as control variables. Market indicators are generated using the TA-Lib Python library, while the common strategies used to apply the market indicators to make trades are consolidated and coded based on information from *Investopedia* and *Wysetrade*.

During the implementation of the strategy, trades made by the strategy were thoroughly checked through visualization and comparison

Figure 1. BTC (2018-2020) RSI Strategy Visualized

against the conditions for making each trade (example seen in Figure 1.). The actions were then plotted against actual market conditions to determine if the strategy was performing as intended. Buy orders are coded as '1' and sell orders are coded as '-1', while a state of '0' indicates that the specific strategy does not recommend making a trade given the conditions. The different variables and their definitions are as follows:
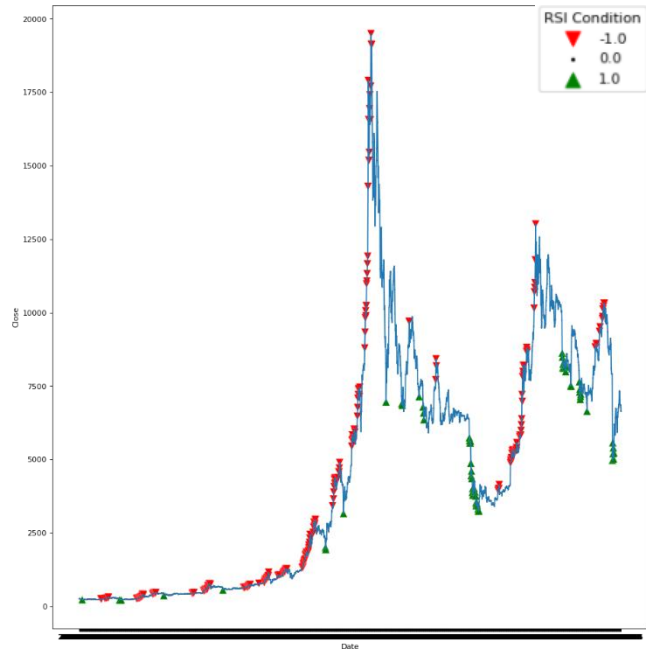
- *Future_Price(x) % Profit/Loss* – The percentage difference in price of the asset x days from the given date.

- *Close* – The closing price of an instrument on a given date.

- *Volume* – The number of trades made for an instrument on a given date.

- *RSI* – The Relative Strength Index of that instrument on a given date.

- *RSI Condition* – The trades made by the RSI based strategy on a given date, when RSI is above 70, a sell trade is made because the instrument is considered to be overbought, when RSI is below 30 a buy trade is made because the instrument is considered to be oversold.

- *MACD Condition* – The trades made by the MACD strategy on a given date, when the MACD line crosses the Signal line from above, a sell trade is made because the shorter term up trend has reversed and caught up with the price of longer-term

- *EMA* - When the MACD line crosses the Signal line from below, the reverse applies and a buy trade is made.

- **EMA Condition** – The trades made by the EMA strategy on a given date, when the price is above the 25EMA, 50EMA, 100EMA and 200EMA, both the short, middle and long-term trend is positive and a buy order is made, when the price is below all aforementioned EMAs, the reverse applies and a sell order is made.

- **Close-EMA200 Price Diff** – The difference in price between the closing price and EMA200 on a given date.

- **Bollinger Band Condition** – The trades made by the Bollinger Band strategy on a given date, when the price touches the upper band, a sell order is made, while a buy order is made when the price touches the lower band.

- **ATR** – The Average True Range on a given date, it is used as a control variable for volatility.

- **Trend** – Takes a value of '1' to represent an uptrend when the price is above the 200EMA and takes a value of '-1' to represent a downtrend when price is below the 200EMA.

- **Forecasted % Profit** – A projection of a linear regression done on the past 14 days to estimate the future price on the next day, it is converted into a percentage by the following equation: $\frac{Forecasted\ Price - Current\ Price}{Current\ Price}$

- **Slope** – The gradient of the 14-day regression line used in Forecasted % Profit.

- **Acceleration** – The rate of change of Slope.

- Certain modifiers are applied to the variables, including

  - *Price Relative* – which indicates that the variable is divided by the closing price

  - *Log()* – which indicates that the log function is applied to the variable.

  - *Interaction Terms* - Lastly, if an x is seen in the variable name like A x B, it indicates that it is an interaction term between variable A and B.

3. Main Models

To derive insights regarding the correlation between the different independent variables and the expected profit from the time series data whilst factoring in additional exogenous factors, an autoregressive distributed lag (ADL) [14] model was used to model the BTC-USD data from 4/4/2015 – 15/4/2020. ADL modelling allows for several different parameters to adjust the based on the context of the problem. These parameters capture (i) whether the relationship between the exogenous and endogenous variables are causal, (ii) the different lags for each variable, and (iii) whether the type of trend the data exhibits.

One key assumption that threatens the validity of the ADL model in this context is stationarity. However, since the data is collected across a relatively short time (5 years), the stationarity

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concerns are not considered to be entirely relevant since the true characteristics of the dataset are still considered to be in flux. Assumptions regarding the true lag length of the model can be further studied but are not considered in this research as we work with only the most data (lag=1) under the assumption that market conditions change quickly and increasing the lag tends to result in increased noise. Large outliers and multicollinearity within regressors were checked for using the Python *statsmodels* library and found to be absent.

Additionally, non-linear terms were added to capture potential non-linear relationships, while interaction terms were added to capture the marginal effects that one variable has, conditioned on the state of another variable.

3.1 Base Autoregressive Distributed Lag Model

The basic ADL model allows for k additional predictors, with q1 lags of the first predictor are included along with q_i lags of the ith predictor takes the following form:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \delta_{11}X_{1t-1} + \delta_{12}X_{1t-2} + \cdots + \delta_{1q_1}X_{1t-q_1} + \cdots$$
$$+ \delta_{k1}X_{kt-1} + \delta_{k2}X_{kt-2} + \cdots + \delta_{kq_k}X_{kt-q_k} + u_t$$

Predictors used include *'Close', 'Volume', ' RSI', 'RSI Condition', 'MACD Condition' 'EMA Condition', 'Close-EMA200 Price Diff', 'BB Condition', ' ATR', 'Trend', 'Forecasted', 'Slope' and 'Acceleration'*, all of which have been defined in Section 2. The lags applied for all predictors and endogenous variables is kept constant within each model for simplicity, although this can be adjusted to better fit the ADL model to the predictors. The performance of each model is captured by both the log-likelihood of the model and the mean squared forecast error final prediction error (MSFE$_{FPE}$) which is given by the following equation:

$$\widehat{MSFE}_{FPE} = \left(\frac{T + p + 1}{T}\right)s_{\hat{u}}^2 = \left(\frac{T + p + 1}{T - p - 1}\right)\frac{SSR}{T}$$

T = Number of observations, p = Number of lag periods applied
SSR = Sum squared residual between predicted and actual values

Results from Table 2. show that assuming the predictors have a causal relationship to the dependent variable decreases the goodness of fit of the model as seen from the higher log-likelihood score, but also decreases the MSFE [15] which indicates that the prediction is more accurate. The causal parameter removes the lags that begin at 0 and only uses predictors lagged by a period of 1 or more. Considering that certain trading signals such as the MACD and RSI [16] can be extremely time sensitive as they use a swing trading strategy and trade at the point of price reversals, lagging these predictors would cause the timing of the reversals to be off. However, it is also important to realize that due to the general effect of having a lower number of predictors when a causal relationship between exogenous and endogenous variables is assumed, the model's decrease in goodness of fit could be simply due to it having significantly fewer predictors as compared to the

model where the causal relationship is not assumed. We tested this assumption and found that the difference in performance is equally pronounced between models with a lag of 1 as compared to models with a lag of 5, indicating that the predictors with a time lag of 0 are equally important in fitting the models with different lags, but in doing so, also causes MSFE to increase. Considering that the conditions in which a trade is made does not a strictly causal relationship with the trade profitability, we decided to proceed with no assumption of a causal relationship.

Table 2: ADL Model Comparison (Causal Parameter)

Model	AR(1)-BH(1)	AR(1)-BH(1)	AR(5)-BH(1)	AR(5)-BH(1)
Causal	False	True	False	True
Log Likelihood	3397.9	3359.0	3441.0	3401.9
MSFE$_{FPE}$	0.001388	0.001346	0.001445	0.001408

AR(x) indicates that x periods of lag are applied to the variables
BH(y) indicates that the profit is based on a trade closed after holding for y days

ADL models are also able to capture trend effects through additional trend parameters. Table 3. captures the different performances of the model under different trend assumptions. Due to the volatility of the BTC-USD market, we expect that there might not be a clear trend. Although it can be said that there is a general overall upward trend with fluctuations in trend for specific periods of time, this is not easily captured by a constant or second order trend across time. This limits the applicability of trend effects captured by the model using the ∂_{itj} parameters, where $j=0$ indicates that there is no trend, $j=1$ indicates a constant trend and $j=2$ indicates a time trend. The model's form is rewritten as follows to capture trend effects:

$$Y_t = \partial_0 + \partial_1 t + \partial_2 t^2 + \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \delta_{11} X_{1t-1} + \delta_{12} X_{1t-2}$$
$$+ \cdots + \delta_{1q_1} X_{1t-q_1} + \cdots + \delta_{k1} X_{kt-1} + \delta_{k2} X_{kt-2} + \cdots + \delta_{kq_k} X_{kt-q_k} + u_t$$

Table 3: ADL Model Comparison (Trend Parameter)

Model	AR(1)-BH(1)	AR(1)-BH(1)	AR(1)-BH(1)	AR(1)-BH(1)
Trend	Constant	No Trend	Time Trend	Constant and Time Trend
Log Likelihood	3397.9	3395.7	3399.6	3402.3
MSFE$_{FPE}$	0.001388	0.001386	0.001397	0.001399

The results show that there is a small increase in fit, but also an increase in MSFE when trend terms are added to the model. Hence, considering that based on the understanding of the USDBTC market being a highly volatile environment, we will work with the assumption that there is no trend in the time series model.

3.2 Variable Modification

Having established that the model's general structure works when (i) assuming a causal relationship between endogenous and exogenous variable, and (ii) having no trend, we proceeded to determine the effects of modifying specific parameters and adding non-linear terms and interaction terms to augment the model. This effort was conducted because the exact relationship between the predictors and the dependent variable is not easily reasoned out for the context of the problem. Price movement is a complex variable that is partly governed by social factors (an agglomeration of decisions made by individuals and institutions) as opposed to mathematical patterns. Numerous researchers have also explored the possibility that price movements can in fact be approximated by using the sentiment of the population as the main predictor [5] and we conduct similar studies in later sections of the paper where we factor in market hype into the model using Google Trends. However, in this section, we work on different variations of the existing predictors to improve the accuracy of the model and discuss the effects of other factors in subsequent sections.

Firstly, we changed the *Forecasted* variable to *Forecasted % Profit*, which we felt is more relevant considering the dependent variable is a function of the percentage profit. Aside from that, we also corrected the *ATR* control variable to become *Price Relative ATR*. Since the *ATR* is affected by the price, the market would appear to be more volatile when the asset is worth a larger price if is not demeaned by the price. This was similarly done for *Volume* although in this context, the correction is partial. Volume of trades in Bitcoin increases steadily over time, but in this model, it is being used as a control variable for the market activity. Since there were fewer traders of Bitcoin in its early stages, the volume of trades required for the market to be considered active in that period should be smaller. We corrected the market activity with the general popularity of Bitcoin, which is a function of the price, revising it to become *Price Relative Volume*. Lastly, we applied the same logic to *Close-EMA200 Price Diff* and revised it to become *Price Relative Close-EMA200 Price Diff* which captures the deviation from the exponential moving average relative to the magnitude of the price. We found that by making these adjustments, the variable's coefficients all increased, indicating that the significance they have on the model has increased. Most notably we noted that the *Close-EMA200 Price Diff* becomes statistically significant at the 1% level of significance when this modification is made. The net effects to the model fit and performance is captured in Table 4. while the changes to the variable's coefficients and statistical significance are captured in Table 5.

Table 4: ADL Model Comparison (Effects of Modification of Terms)

Model	AR(1)-BH(1) Pre-Modified	AR(1)-BH(1) Post-Modified
Causal	False	False
Trend	No Trend	No Trend
$MSFE_{FPE}$	0.001392	0.001401

Table 5. Effects of Modification of Terms					
Pre-Modified Variable	Pre-Modified Coefficient	Pre-Modified P>|z|	Post-Modified Variable	Post-Modified Coefficient	Post-Modified P>|z|
Volume.L0	-3.77E-13	0.358	Price Relative Volume.L0	-1.59E-10	0.955
Volume.L1	3.12E-13	0.435	Price Relative Volume.L1	8.22E-10	0.765
Close-EMA200 Price Diff.L0	0.0009	0.477	Price Relative Close-EMA200 Price Diff.L0	-0.2212	0.001***
Close-EMA200 Price Diff.L1	-0.0009	0.476	Price Relative Close-EMA200 Price Diff.L1	0.2141	0.001***
ATR.L0	0.0001	0.082	Price Relative ATR.L0	0.0051	0.176
ATR.L1	-9.33E-05	0.119	Price Relative ATR.L1	-0.0039	0.295
Forecasted.L0	0.0001	0.507	Forecasted % Profit.L0	-0.0575	0.579
Forecasted.L1	-0.0001	0.527	Forecasted % Profit.L1	0.0845	0.354

*= significant at 10%, ** = significant at 5%, *** = significant at 1%*

3.3 Non-Linear Terms

Following the term modifications, non-linear terms [17] were also added to the model to capture potential non-linear relationships between variables. *Price Relative Volume, Price Relative Close-EMA200 Price Diff* and *Price Relative ATR* were identified as variables that may have a non-linear relationship with profit, specifically, it is suspected that the effects of market activity, deviation from mean and price volatility has a decreasing level of impact as their magnitudes increase, suggesting a possible log-linear relationship with profit levels. While *Log(Price Relative Volume)* and *Log(Price Relative ATR)* may be generated by applying the logarithmic function to the variables directly, due to the negative values in *Price Relative Close-EMA200 Price Diff* it is necessary to first convert the values to positive floats with a value greater than 1 before applying the logarithmic function and reinstating the original signs to the floats. Table 6 shows the performance of the models with different non-linear term combinations.

Table 6. ADL Model Comparison (Effects of Non-Linear Terms)			
Model	**AR(1)-BH(1)**	**AR(1)-BH(1)**	**AR(1)-BH(1)**
Replaced Non-linear Terms	None	log(*Price Relative Volume)*	log(*Price Relative Volume)* log(*Price Relative ATR* *log(Price Relative Close-EMA200 Price Diff)*
Log Likelihood	3404.5	3405.2	3399.6
MSFE$_{FPE}$	0.001401	0.001401	0.1400

Table 7. Effects of Non-linear Terms					
Pre-Modified Variable	**Pre-Modified Coefficient**	**Pre-Modified P>|z|**	**Post-Modified Variable**	**Post-Modified Coefficient**	**Post-Modified P>|z|**
Price Relative Volume.L0	-1.59E-10	0.955	log(Price Relative Volume).L0	0.0025	0.482
Price Relative Volume.L1	8.22E-10	0.765	log(Price Relative Volume).L1	-0.0032	0.355
Price Relative Close-EMA200 Price Diff.L0	-0.2212	0.001***	log(Price Relative Close-EMA200 Price Diff).L0	-0.3833	0.009***
Price Relatively Close-EMA200 Price Diff.L1	0.2141	0.001***	log(Price Relative Close-EMA200 Price Diff).L1	0.3539	0.015**
Price Relative ATR.L0	0.0051	0.176	log(Price Relative ATR).L0	0.0174	0.338
Price Relative ATR.L1	-0.0039	0.295	log(Price Relative ATR).L1	-0.0132	0.467

* = significant at 10%, ** = significant at 5%, *** = significant at 1%

As seen in Table 7. the log-linear relationship between *Price Relative Volume* and expected profits holds as the statistical significance of the variable increases. However, the same cannot be said for *Price Relative Close-EMA200 Price Diff* and *Price Relative ATR*. Hence the model will

only be adjusted to include an additional *Log(Price Relative Volume)* term to capture this potential non-linear relationship with the percentage profits.

3.4 Interaction Terms

Interaction terms are useful for determining if the marginal effects of a variable conditioned on another variable are significant. Typically, we would expect that the signal-based indicators that make swing trades tend to perform better when the direction of the trade is following the trend, so we added interaction terms for all possible combinations of swing trade indicator variables, and conditioned them on both the *Trend* and the *Price Relative Close-EMA200 Price Diff*. The log likelihood of the model increases while the MSFE decreases minimally, indicating that the interaction terms do indeed contribute to the model performance. Table 8. shows the performance of the model with and without the interaction terms and Table 9. shows the coefficients and statistical significance of the interaction terms. While it is noted that the interaction terms are all not statistically significant at the 10% level of significance, the improvements across both the log likelihood and MFSE suggest it is beneficial to keep the terms for the model.

Table 8: ADL Model Comparison (Effects of Interaction Terms)		
Model	AR(1)-BH(1)	AR(1)-BH(1)
Interaction Terms	Absent	Present
Log Likelihood	3405.2	3409.7
MSFE$_{FPE}$	0.001401	0.001400

Table 9. Interaction Term Coefficients and Statistical Significance		
	Coefficient	P>|z|
RSI x Trend.L0	-0.0003	0.33
RSI x Trend.L1	0.0001	0.58
RSI x Price Relative Close-EMA200 Price Diff.L0	0.0015	0.33
RSI x Price Relative Close-EMA200 Price Diff.L1	-0.0017	0.22
RSI Condition x Trend.L0	-0.0002	0.97
RSI Condition x Trend.L1	-0.0062	0.37
RSI Condition x Price Relative Close-EMA200 Price Diff.L0	-0.0099	0.64
RSI Condition x Price Relative Close-EMA200 Price Diff.L1	0.002	0.93
MACD Condition x Trend.L0	-0.0016	0.8
MACD Condition x Trend.L1	0.0031	0.63
MACD Condition x Price Relative Close-EMA200 Price Diff.L0	0.0156	0.49
MACD Condition x Price Relative Close-EMA200 Price Diff.L1	-0.0086	0.7

3.5 Determining Optimum Lag

Previous sections have identified which regressors are statistically significant in the model, however the optimal number of lags to be applied for the model have yet to be determined. By using Bayes' Information Criteria (BIC) and Akaike's Information Criteria (AIC), we can assess a model's goodness-of-fit at different lags. BIC and AIC are given by the following formula:

$$\text{BIC}(p) = \ln\left[\frac{SSR(p)}{T}\right] + (p+1)\frac{\ln(T)}{T}$$

$$\text{AIC}(p) = \ln\left[\frac{SSR(p)}{T}\right] + (p+1)\frac{2}{T}.$$

T = Number of observations, p = Number of lag periods applied
SSR = Sum squared residual between predicted and actual values

The lags tested range from 1-10 and we found that the lag which gives the most negative BIC and AIC is the lag of 1. AIC favors having more lags as it reduces the effects of the number of observations by having a constant second term. Both criteria balance between the model-fit and regressor coefficients. Model performance for the different lags is shown in Table 10. below:

Table 10. Model Fit at Different Lags						
Model Lag / Performance	Lag = 1	Lag = 2	Lag = 4	Lag = 6	Lag = 8	Lag = 10
BIC	-6577	-6478	-6327	-6159	-5965	-5827
AIC	-6738	-6715	-6718	-6705	-6665	-6681

Considering that the ADL model contains lags for each indicator, yet each indicator has different lags for price impact, we set different lags for the ADL model for comparison and found that *RSI*, *MACD* Condition and *Price Relative Close-EMA200 Price* were statistically significant across different models. Moreover, the MSFE_{FPE} decreases with increase of the lag. This is probably because ADL with lag = 10 has more parameters, so the model can better fit the function between indicator and price. However, the highest statistical significance for lag varies from indicator to indicator as seen in Table 11.

For RSI indicator, when the lag range is extended, RSI.L9 and RSI.L10 increases in statistical significance compared with RSI.L0 and RSI.L1. The RSI indicator is based on the principle of supply and demand equilibrium, by measuring the total increase in stock prices in a certain period as a percentage of the past 14-day average of the total change in stock prices, RSI assesses the strength of long and short forces, and then suggests specific operations. Based on the above facts, RSI only describes momentum and does not directly give a suggestion to buy or sell

but should be combined with other indicators to make a proper trading decision, so it is understandable that RSI is statistically significant with a larger lag as it relies on trend change (which is slower) in response to the change in momentum.

For MACD Condition indicator, when the lag range is extended, MACD Condition.L0 and MACD Condition.L4 become most statistically significant. MACD is a technical indicator that uses the convergence and divergence between the short-term (12-day) exponential moving average and the long-term (26-day) exponential moving average of the closing price to make a judgment on the timing of buying and selling. Because MACD signals the instant of buying or selling, the MACD Condition.L0 having the highest statistical significance across all MACD lag terms is not surprising.

Table 11. Highest Statistical Significance for Terms at Different Lags								
ADL-Lag1	Coeff	P>|z|	ADL-Lag5	Coefficient	P>|z|	ADL-Lag10	Coeff	P>|z|
RSI.L0	0.0012	0.015 **	RSI.L0	0.0014	0.009 ***	RSI.L9	0.0018	0.011 **
RSI.L1	-0.0009	0.050 **	RSI.L1	-0.0013	0.060 *	RSI.L10	-0.0018	0.001 ***
Price Relative Close-EMA200 Price Diff.L0	-0.1575	0.119	Price Relative Close-EMA200 Price Diff.L1	0.5211	0.003 ***	Price Relative Close-EMA200 Price Diff.L2	-0.5403	0.005 ***
Price Relative Close-EMA200 Price Diff.L1	0.1625	0.118	Price Relative Close-EMA200 Price Diff.L2	-0.5788	0.001 ***	Price Relative Close-EMA200 Price Diff.L10	0.3985	0.003 ***
MACD Condition.L0	0.0254	0.000 ***	MACD Condition.L4	0.0107	0.011 **	MACD Condition.L0	0.0283	0.000 ***
MACD Condition.L1	0.0006	0.888	Price Relative Close-EMA200 Price Diff.L3	0.4786	0.006 ***	MACD Condition.L4	0.0109	0.017 **

*= significant at 10%, ** = significant at 5%, *** = significant at 1%*

3.6 Results and Conclusions

Based on all the models above, we noted that the *RSI, MACD Condition* and *Price Relative Close-EMA200 Price Diff* were consistently statistically significant across most of the models. This indicates that these variables are likely to play a critical role in determining the profitability of a trade and will be useful in the development of a more advanced trading strategy that outperforms the basic strategies. Additionally, we noted that the lag of 1 is most suitable for our model, producing the highest BIC and AIC score between lags 1-10.

4. Robustness Checks

In addition to the model robustness checks conducted via variable modification, additional non-linear and interaction terms and testing the model with different lags, further checks were conducted to ascertain the significance of the regressors. One of the key methods used is the

exploration of additional control variables based on hypothesis. The two key hypotheses are (i) market hype affects the trading price of Bitcoin and (ii) major events can affect the trading price of Bitcoin are explored in Section 4.1 - 4.2 and fully detailed in Annex B. We also conducted a different form of robustness checks by fitting the data to an ECM to determine if the results are statistically significant which will be discussed in Section 4.3.

4.1 Market Hype - Google Trends

Researchers have conducted empirical studies [6,7,8,9] to demonstrate that the investors may have a "herd mentality" when making investment decisions, i.e., other investors' actions may affect one investor's own decision. For example, if one investor finds that many people (e.g., their friends) on the Internet are discussing cryptocurrency, they are more likely to start investing in cryptocurrency.

In the current society where social media is well-developed, retail investors are not only affected by people around them (e.g., friends or colleagues). They also receive instant information from the Internet or social media. Suppose investors see that people on the Internet are all talking about Bitcoin. In that case, they may not be able to resist the temptation to search Bitcoin and seek potential investment opportunities. Google is currently one of the most widely used search engines in most of the countries in the world. Google trends are some aggregated data showing that how frequently Google users search certain keywords. Such data can be used to understand and predict financial [10] and even public health events [11]. For example, researchers use the abnormal increase of Google search trends of keywords like "headache", "cough", etc., to estimate whether Covid-19 has been spread in certain regions [1].

In this section, we plan to analyze whether Google Trends data can help our model perform the changes in Bitcoin price. The following two intuitions motivate us to perform such an analysis. On the one hand, Google Trends, to some extent, can reflect the new investors into the cryptocurrency market. A surge in the frequency of a cryptocurrency-related keyword being searched can mean that more investors are paying attention to it, and as a result, they may eventually become investors, which leads to a rise in the Bitcoin price. On the other side, Google Trends may reflect some important events in cryptocurrency investments. An example would be, big companies announcing that they accept Bitcoin for payment or the reward for mining bitcoin transactions is cut in half (Bitcoin halving events).

After pre-processing these weekly data into daily data, we add the Google Trends data as an additional independent variable and got the following statistical results related to the Google Trend as shown in the Table 12.:

Table 12. Statistical Significance of Google Trends						
Variable	Coeff	Std err	z	p > |z|	[0.025	0.975]
GTrend-L0	0.0002	0.001	0.288	0.773	-0.001	0.001
GTrend-L1	0.00017	0.001	0.033	0.974	-0.0001	0.001

As we can observe from Table 12, the significance for both trend-L0 and trend-L1 is not high, which means that the Google Trend data on "Bitcoin" does not contribute to making a better model. Based on the analysis of using Google Trend as an additional independent variable, we conclude that there is no strong evidence suggesting the strong correlation between Google Trend data and the Bitcoin price change.

4.2 Major Events – Bitcoin Upgrade (SegWit) and Halving

Since Bitcoin was introduced in 2009, it has gone through several bull runs – in 2011, 2013, 2017 and, in 2021, is currently going through another. The meteoric increase in prices during Bitcoin's bull runs have garnered Bitcoin a huge amount of interest from the public and have most commonly been attributed to an upgrade of Bitcoin's technology, and the halving of rewards for Bitcoin miners. From the table below, it can clearly be seen that there is some sort of correlation between Bitcoin's bull runs and the halving dates/bitcoin upgrade.

Bitcoin Upgrade	Halving Dates	Bitcoin Bull Runs
		2011
15 May 2013	November 2012	2013
24 August 2017	9 July 2016	2017
November 2021	May 2020	2021

In this section, we use the 2017 Bitcoin upgrade (SegWit) as a control variable to determine its statistical impact on the price of Bitcoin and *Future_Price(x) % Profit/Loss*, as described in Section 3. First, by using a dummy variable to run ARDL, the results show that the event is not statistically significant when regressed on *Future_Price(x) % Profit/Loss*. Additionally, running ARDL on different time frames show that the event becomes even less statistically significant as the as time frame increases.

ARDL REGRESSION TABLE						
VARIABLE	Coeff	Std err	z	p > |z|	[0.025	0.975]
Segwit.L0	56.5812	298.567	0.190	0.850	-528.989	642.151
Segwit.L1	59.2099	299.140	0.198	0.843	-527.485	645.905

Next, performing the Chow test on Bitcoin's *Close* price to USD and the SegWit event dummy variable, yields a Chow score of 0.053 and a p-value of 1.68e-12, which is statistically significant. This also matches with what is seen on the BTC-USD chart, where the trend in Bitcoin prices after the SegWit event was much steeper than before the event. Performing the Chow test on *Future_Price(1) % P/L* to *Close* price and the SegWit event yields a p-value of 0.00029, which is statistically significant. However, Performing the Chow test on *Future_Price(3) % P/L* yields a p-value that is not statistically significant. Additionally performing ARDL regression on the dummy variables with each of the indicators give a statistically insignificant p-value and performing the Chow test on all mentioned indicators give a statistically insignificant result.

This shows that there is a significant trend change in *Future_Price(1) % P/L* as compared to *Close* price upon the SegWit event occurring, however, the trend change becomes insignificant as a result of the structural break if the projection of *Future_Price(x) % P/L* were to be increased. The structural break also does not affect the effect of technical indicators on future prices. Running the Chow test on the 2016 Bitcoin reward halving produces similar results, with a statistically significant p-value of 0.0035 for BTC-USD price, and 1.32e-18 for *Future Price(1)-Close* price. Similarly, using the dummy variable directly for ARDL regression produces statistically insignificant results.

4.3 Error Correction Model (ECM)

For unstable time series, it can be transformed into a stable series by difference method, and a classic regression analysis model can be established. For example, we may establish a regression model between per capita consumption level (Y) and per capita disposable income (X):

$$Y_t = \alpha_0 + \alpha_1 X_t + \mu_t$$

If Y and X have a common upward or downward trend, then we can differentiate X and Y so that they will become a stationary series, and the difference regression model is established:

$$\Delta Y_t = \alpha_1 \Delta X_t + v_t \qquad where \qquad v_t = \mu_t - \mu_{t-1}$$

However, this approach will cause two problems: (1) If there is a long-term stable equilibrium relationship between X and Y, $Y_t = \alpha_0 + \alpha_1 X_t + \mu_t$, but there is no serial correlation in the term μ_t. Then v_t in the differential formula $Y_t = \alpha_0 + \alpha_1 X_t + \mu_t$ is a first order moving average time series, so it is serially correlated; (2) If the estimation is done in differential form, important information about the level values of the variables will be ignored, when the model only expresses the short-run relationship between X and Y, but does not reveal the long-run relationship between them. This is because from a long-run equilibrium point of view, the change in Y in period t depends not only on the change in X itself, but also on the state of X and Y at the end of period t-1 and on the degree of imbalance between X and Y in period t-1. Also, the use of differential variables tends to yield unsatisfactory regression equations.

For example, when using the $\Delta Y_t = \alpha_1 \Delta X_t + v_t$ regression, it is rare that the intercept term is significantly zero, i.e., we often obtain an equation of the following form:

$$\Delta Y_t = \hat{\alpha}_0 + \hat{\alpha}_1 \Delta X_t + v_t \quad \hat{\alpha}_0 \neq 0 \tag{1}$$

With X held constant, Y will also keep its long-run equilibrium value constant if the model has a static equilibrium (static equilibrium). However, if we use equation (1), Y will be in a long-run up or down process even if X remains constant, which means that there is no static equilibrium between X and Y. This is inconsistent with most economic theory hypotheses that have static equilibrium. Hence the error correction models come into being.

Based on the above facts, ECM can be used to model the USDBTC data while accounting for the instability in the time series. From Table 13. it is apparent that both models have a similar log-

likelihood, however the ADL has a significantly smaller MSFE, making it a better model for predicting Bitcoin price. Overall, as seen in Table 14., it is still the *RSI, MACD Condition and Price Relative Close - EMA200 Price Diff* which are the three indicators most statistically significant with prices. However, for the ECM model, *Close.L1* and *Accelerate.L1* become more significantly correlated with prices compared to the ADL model. Even more interestingly, we find that *Price Relative ATR* is statistically significant at the 1% level of significance in the ECM but is not statistically significant in the ADL. Hence, we decided to test it as part of the trading strategy in Section 5. to determine if can benefit trading performance.

Interestingly, it is the volatility related indicators such as *Acceleration* and *ATR* that seem to demonstrate an increased statistical significance with the profitability of trades for the ECM. This may be because once the long-term trend has been removed from the data, it is the shorter timeframe volatility that accounts for most of the price action – and hence trade profitability.

Table 13: Comparison of ADL and ECM

Model	AR(1)-BH(1) ADL	AR(1)-BH(1) ECM
Causal	False	False
Trend	No Trend	No Trend
Log Likelihood	3395.7	3409.735
MSFE$_{FPE}$	0.001392	0.002941

* = significant at 10%, ** = significant at 5%, *** = significant at 1%

Table 14. Comparison between ADL and ECM

ADL-Lag1 Variable	Coefficient	P>|z|	ECM-Variable	Coefficient	P>|z|
RSI.L0	0.0012	0.015**	RSI.L0	0.0012	0.015**
RSI.L1	-0.0009	0.050*	RSI.L1	0.0003	0.133
Price Relative Close-EMA200 Price Diff.L0	-0.1575	0.119	Price Relative Close-EMA200 Price Diff.L0	-0.1575	0.119
Price Relative Close-EMA200 Price Diff.L1	0.1625	0.118	Price Relative Close-EMA200 Price Diff.L1	0.0051	0.900
MACD Condition.L0	0.0254	0.000***	MACD Condition.L0	0.0254	0.018**
MACD Condition.L1	0.0006	0.888	MACD Condition.L1	0.0259	0.000***
Price Relative ATR.L1	-0.0037	0.377	Price Relative ATR.L1	0.0014	0.005***
Close.L1	-6.549e-06	0.308	Close.L1	-7.357e-07	0.053*
Acceleration.L1	0.0002	0.678	Acceleration.L1	-0.0002	0.071*

5. Evaluating Model Performance

Having derived insights from the different models generated, we are now ready to test out different trading strategies. To summarize, the ADL model identified the *RSI*, *MACD Condition and Price Relative Close-EMA200 Price Diff* as statistically significant indicators, while the Error Correction Model (ECM) model identified *Price Relative ATR* as a significant regressor. In Section 5.1. we will construct a strategy that uses these regressors to make trading decisions and compare the results against common trading strategies. In Section 5.2. the model will be applied to trading data on the hourly timeframe to determine if the strategy works for intraday trading. In Section 5.3. we will adjust the holding times of the best performing strategy to determine if the profit can be improved by simply closing the trades more than 1 period after the trade is made. Lastly, in Section 5.4, we apply the best strategy, with the best holding time across different major cryptocurrency markets and compare the performance to determine if the strategy is feasible outside of Bitcoin.

5.1 Trading Strategies

Since the raw RSI values and MACD based trading strategy were identified as significant indicators, it is worthwhile to determine if the common RSI or MACD based trading strategy has any success. The results of the tests are shown in *Annex – Strategy Performance*. Each strategy is tested on two instruments from each type of market, and the average percentage profit per trade is captured in a chart. The RSI based trading strategy was found to perform poorly initially, barely profitable at 0.00045% profit per trade. However, with strategies that used additional trend and volatility indicators such as *Trend, Price Relative Close-EMA200 Price Diff* and *Price Relative ATR*, we found that the RSI trading strategy can be profitable, making an average of 4.49% returns per trade. Interestingly, setting a limit to the volatility in the market by using *Price Relative ATR* seemed to be able to filter out losing trades for the RSI strategy which on hindsight makes sense because when the price fluctuates wildly, it is possible to trigger RSI based trades even though there might not be a clear sign of a reversal.

For the MACD trading strategy, the starting point greatly differed from RSI in that its profitability was clear (1.77% average per trade) across all instruments even with the basic strategy. By conducting similar augmentations from the RSI strategy to the MACD strategy, we were able to bring the average trade profitability to 6.71% per trade. Again, we noticed that controlling for the volatility was critical for increasing the quality of the trades, suggesting that reversal-based trading strategies can greatly benefit from a volatility filter. Based on the above findings, it is apparent that the regressors identified by the different models have greatly contributed to enhancing basic strategies that typically consider only the general trend and a signal.

5.2 Trading Timeframes

For a given trading strategy, different trading timeframes can have different success. In this section, we randomly sample a period of USDBTC hourly data and compare the trading performance of our current best strategy based on the MACD indicator, trend and volatility. The preliminary results in Table 15. showed that trading on the hourly timeframe strategy was significantly more profitable than the daily timeframe, with an average profitability of around 12% per long trade. The short trade performance on both timeframes were relatively similar, losing about 0.1% per trade on average. Having success at the lower timeframe indicates that the strategy has the potential to be highly profitable as it will be able to make more trades in each period of time.
Additional research could be done to determine if the strategy still holds at the 1-minute, 15-minute and even the ticker level timeframe.

Table 15: Trading on Different Timeframes				
Trading Timeframe	BTC Daily Long Trades	BTC Daily Short Trades	BTC Hourly Long Trades	BTC Hourly Short Trades
% Profit/Loss	2.58	-0.36	12.34	-0.62

5.3 Trade Holding Times

Exiting a trade is just as important entering a trade. For the trading strategies employed thus far, the holding time has been set to one day after the trade is made, however, given that the market takes time to respond to signals, it may be possible that a longer holding time can result in increased profits, although it is equally true that once a trade is held for too long, the conditions of the market may have changed beyond the expectations of the trading strategy. In this section, we conduct a preliminary study on the effects of holding on to the trade for different periods of time and determine its effect on profits. Note that the model being used in this section is the MACD trading strategy with only considerations for *Price Relative Close-EMA200 Price Diff*. This is because the earlier model allows for more trades and across more instruments, allowing for a better general understanding of the

Table 16. Mean Profit for Different Holding Times						
Holding Time (Days)	1	3	5	10	15	30
Instrument	Mean % Profit					
BTC Long	2.37	3.36	4.07	7.00	9.37	14.21
BTC Short	-0.42	-1.22	-1.91	-3.47	-5.18	-10.64
DOGE Long	6.06	8.64	10.98	10.89	6.15	-13.26
DOGE Short	3.8	3.53	3.34	-0.29	-0.59	-4.73
Oil Long	2.16	2.13	2.47	2.63	1.12	0.36
Oil Short	1.63	2.51	3.57	4.72	5.39	11.4
Gold Long	1.3	1.29	1.06	0.57	0	-1.01
Gold Short	0.85	0.93	1.09	0.77	1.52	2.06
SP500 Long	0.3	-1.07	-1.16	-1.38	-3.55	-2.18
SP500 Short	0.68	0.37	0.48	0.72	0.65	1.23
STI Long	0.71	0.78	0.89	1.12	1.1	1.12
STI Short	0.73	0.84	1.26	0.93	0.29	1.21
All Instruments	1.68	1.84	2.18	2.02	1.36	-0.02

effects of extending the holding times. Based on the results from Table 16., it is obvious that the optimal

holding time for the trades may not be 1 day, in this instance, for the specific strategy, increasing the holding time to 5 days increases average profits by 29.7% per trade, which is substantial. This confirms the criticality of considering holding times when applying a trading strategy.

5.4 Alternative Cryptocurrency Markets

Cryptocurrencies outside of Bitcoin are potentially untouched markets for profit. The best performing strategy was applied to other major cryptocurrencies such as Dogecoin (DOGE), Binance Coin (BNB), Solana (SOL), Cardano (ADA), Ripple (XRP) and Ethereum (ETH). All the cryptocurrencies aside from SOL demonstrated profitability from the trading strategy, averaging 15.94% profit per trade on average across all markets. The dramatic increase in profits is due largely to the change in holding time to 3 days as the previous analysis suggested. When the exact same strategy is applied with a holding time of 1 day, the returns averaged at 8.34% per trade. Using the extended holding strategy, BNB was found to have an average of 7.86% profit per long trade and an average 6.21% profit per short trade. ADA returned an average of 6.38% per short trade. ETH demonstrated great potential for both long and short trades, returning 11.5% and 8.73% returns for each category respectively. Lastly, XRP demonstrated DOGE levels of profitability for long trades, at 83.0% per long trade – which is a surprising result because it is a relatively stable cryptocurrency market, while DOGE returns improved significantly to 40.5% per long trade after increasing the holding time. It was noted that the ADA long trades failed to trigger because the market did not trend upward strongly historically, hence potential trades did not meet the *Price Relative Close-EMA200 Price Diff* threshold to make trades. In the case of SOL, it only started trading in April 2020 resulting in much fewer data points as compared to the other cryptocurrencies, compounded with the requirement for 200 periods to pass before the 200EMA generates readings, SOL can be treated as an empty dataset.

6. Conclusion

In this research, we have progressively developed multiple ADL and ECM time series models to determine variables that are statistically significant to the profitability of trades. Through Section 3, the process of ensuring that the variables make sense in the context of the objective (trade profitability), and the process of exploring additional regressors (modified terms, non-linear terms, interaction terms) that could improve the model is critical in ensuring that regressors are properly represented. In this aspect, the price relativity of indicators played the biggest role by adjusting the indicators by the price at which the asset was worth at a given point in time. Following this, in Section 4, we had a pool of indicators which we repeatedly tested for statistical significance with (i) different models, (ii) different lags, (iii) different types of instruments, and considered (iv) the effects of events that tend to have a large impact on price. We found that hype, represented by *Google Trends* and major Bitcoin events were not statistically significant to the time series models despite the observation that these regressors seemed to influence on price. Most importantly, we found that *RSI, MACD Condition, Price Relative Close-EMA200 Price Diff* and *Price Relative ATR* were proven to be robustly significant across most of the above situations.

Using the knowledge gleaned from the above process, a few simple and logical trading strategies were developed using the chosen technical indicators in Section 5. Since each indicator was included with a specific intention from the start, the joint effects of these intentions allowed us to come up with trading strategies relatively quickly. The first strategy attempts to use *RSI* as a momentum indicator to make trades, it is important to note that while *RSI* had statistical significance to profit levels, the trading strategy based on *RSI* which is represented by *RSI Condition* was not statistically significant, indicating that it may not be functional on its own. Hence, we combined it with *Trend* to quickly determine if making trades that followed the trend were useful and found that the RSI strategy worked better when the trades were made following the overall trend. We then took this a step further by using *Price Relative Close-EMA200 Price Diff* to determine the strength of the trend, trading only when the trend is strong and this improved profitability further. *Price Relative ATR*, which is a volatility indicator was then used to filter out trades during periods when the price was volatile, this was found to have a further positive impact on trade returns. Having confirmed that the process of (i) confirming the strength of the trend and aligning trades with the direction of the trend and (ii) avoiding trades during highly volatile periods was beneficial, we applied the same methodology to improving the *MACD Condition* trading strategy and received similarly improved results.

Considering the above, time series models can be useful for identifying technical analysis indicators that affect trade profitability, and that these indicators can be used to construct profitable trading strategies. These strategies can then be further improved by adjusting basic trading parameters such as the timeframe on which the trades are made and the holding time of each trade. Note that because the RSI and MACD are momentum indicators used for swing trading during trend reversals, during market crashes, the strategy remains entirely feasible – this is important to note because certain trading strategies assume that market prices only go up as is the case of what we have seen for cryptocurrency in recent times.

Another important point to note is that while the usage of indicators that indicate trend strength and market volatility, appear to filter out poor trades, increasing trade quality and average returns, it also reduces the number of trades made. Finding the optimum point between trade quality and quantity is an aspect of this research that can be further developed. Additionally, the variance in success of a trading strategy between different categories of markets – and even within instruments belonging to a same market category is significant. It appears that the tendency for strong trends to occur in cryptocurrency markets is larger than in equities (SP500 and STI) and commodities (Oil and Gold) hence we see the reversal compounded with strong trend strategy conducting a higher quantity of trades at a higher quality when in the cryptocurrency market. This insight points towards the requirement for a careful selection of items in a trading portfolio that are specifically catered to a trading strategy. In sum, the ground has already been laid for demonstrating the effectiveness of using econometric analysis to develop a trading strategy based on technical analysis, and we are excited to see these strategies applied under real market conditions.

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Annex A – Popular Technical Indicators (Formula and Application)

Popular Technical Indicators (Formula and Application)		
Name	**Formula**	**Application**
Average True Range (ATR)	$TR = \text{Max}[(H - L), \text{Abs}(H - C_P), \text{Abs}(L - C_P)]$ $ATR = \left(\dfrac{1}{n}\right) \sum_{(i=1)}^{(n)} TR_i$ **where:** TR_i = A particular true range n = The time period employed	Measures the daily volatility of an asset. The indicator does not indicate the price direction; rather it is used primarily to measure volatility caused by gaps and limit up or down moves.
Bollinger Band (BB)	$\text{BOLU} = \text{MA(TP}, n) + m * \sigma[\text{TP}, n]$ $\text{BOLD} = \text{MA(TP}, n) - m * \sigma[\text{TP}, n]$ **where:** BOLU = Upper Bollinger Band BOLD = Lower Bollinger Band MA = Moving average TP (typical price) = (High + Low + Close) ÷ 3 n = Number of days in smoothing period (typically 20) m = Number of standard deviations (typically 2) $\sigma[\text{TP}, n]$ = Standard Deviation over last n periods of TP	The closer prices move to the upper band, the more overbought the market, and the closer the prices move to the lower band, the more oversold the market.
Exponential Moving Average (EMA)	$EMA_{\text{Today}} = \left(\text{Value}_{\text{Today}} * \left(\dfrac{\text{Smoothing}}{1 + \text{Days}}\right)\right)$ $\qquad + EMA_{\text{Yesterday}} * \left(1 - \left(\dfrac{\text{Smoothing}}{1 + \text{Days}}\right)\right)$ **where:** EMA = Exponential moving average	The 200-day EMA is used as an indicator for long-term trends. When a stock price crosses its 200-day moving average, it is a technical signal that a trend reversal has occurred.
Moving Average Convergence Divergence (MACD)	$\text{MACD} = 12\text{-Period EMA} - 26\text{-Period EMA}$ Signal Line = MACD 9-Period EMA	Traders may buy the instrument when the MACD crosses above its signal line and sell the security when the MACD crosses below the signal line.
Relative Strength Index (RSI)	$RSI_{\text{step one}} = 100 - \left[\dfrac{100}{1 + \frac{\text{Average gain}}{\text{Average loss}}}\right]$ $RSI_{\text{step two}} = 100 - \left[\dfrac{100}{1 + \frac{(\text{Previous Average Gain} \times 13) + \text{Current Gain}}{((\text{Previous Average Loss} \times 13) + \text{Current Loss})}}\right]$	RSI values of 70 or above indicate an instrument is overvalued and primed for a trend reversal. An RSI reading of 30 or below indicates an undervalued condition.

Annex B – Robustness Checks

Effect of Google Trends

The term "herd mentality" [6] refers to a phenomenon where people join groups and follow the actions of others under the assumption that other individuals have already done their research. Herd instincts are common in all aspects of society, even within the financial sectors, where investors follow what they perceive other investors rather than rely on their own analysis. Researchers have conducted empirical studies [6,7,8,9] to demonstrate that the investors may have a "herd mentality" when making investment decisions, i.e., other investors' actions may affect one investor's own decision. For example, if one investor finds that many people (e.g., their friends) on the Internet are discussing cryptocurrency, they are more likely to start investing in cryptocurrency.

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Figure 2 The trends of how frequently the keyword "bitcoin" is searched in the past five years. The data is collected worldwide and normalized.

Figure 3 The trends of how frequently the keyword "cryptocurrency" is searched in the past five years. The data is collected worldwide and normalized.
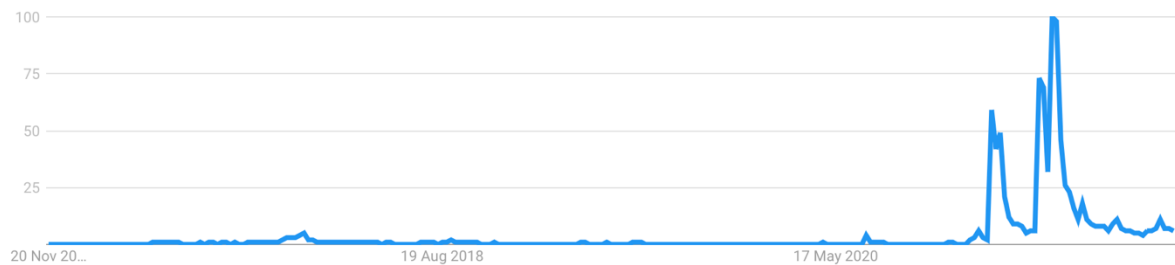

Figure 4 The trends of how frequently the keyword "dogecoin" is searched in the past five years. The data is collected worldwide and normalized.

We first introduce how we collect and process the Google Trends data on cryptocurrency-related keywords. Figure 2 illustrates the trends depicting how frequently the keyword "Bitcoin"

has been searched in the past five years (worldwide search data), and Figure 3 shows the trends depicting how frequently the keyword "cryptocurrency" is searched in the past five years (worldwide search data). As we can observe from the two figures, the two trends are quite similar to each other. However, we also collected the search data for "dogecoin", which was previously a non-mainstream cryptocurrency but has soared in the recent year. We can observe that its search trend is greatly different from the trends of either "Bitcoin" or "cryptocurrency". Since we investigate the trends in a period of 5 years, we use the Google trends data for more commonly used and representative keywords like "Bitcoin".

After downloading Google Trends data as a CSV file, we perform some pre-processing. More specifically, when we request data for a more extended period (e.g., one year or longer), Google only returns weekly data. It uses the average search data for each week. We also need to point out that the search trends data is normalized. We do not have the exact times of a Google being searched per week, but we can see the relative trends between two-week data. So sample data is shown in Table 1. To make the data can be used in our previously built model. We expand these weekly data to daily data by assigning the single weekly search data to each day in that week.

Table 1 Sample data pints from the Google Trends data.

WEEK	BITCOIN (WORLDWIDE)_
20/11/16	3
27/11/16	3
4/12/16	4
11/12/16	5
18/12/16	6

After pre-processing these weekly data into daily data, we add the Google Trends data as an additional independent variable, and run the model again. We display the statistical results related to the Google Trend variable in the following table:

Variable	Coef	Std err	z	p > |z|	[0.025	0.975]
Trend-L0	0.0002	0.001	0.288	0.773	-0.001	0.001
Trend-L1	0.00017	0.001	0.033	0.974	-0.0001	0.001

As we can observe from this table, the significance for both trend-L0 and trend-L1 is not high, which means that the Google Trend data on "Bitcoin" does not contribute to making a better model. Based on the analysis of using Google Trend as an additional independent variable, we make the following suggestions to the investors: There is no strong evidence suggesting the strong correlation between Google Trend data and the Bitcoin price change. So we suggest the users not follow the trend (i.e., avoid herd mentality) to make decisions.

Effect of Significant Events

Since Bitcoin was developed in 2009, it has gone through several bull runs – in 2011, 2013, 2017 and, in 2021, is currently going through another. The meteoric increase in prices during Bitcoin's bull runs have garnered Bitcoin a huge amount of interest from the public, and have most commonly been attributed to an upgrade of Bitcoin's technology, and the halving of rewards for Bitcoin miners.

From the table below, it can clearly be seen that there is some sort of correlation between Bitcoin's bull runs and the halving dates/bitcoin upgrade.

Bitcoin Upgrade	Halving Dates	Bitcoin Bull Runs
		2011
15 May 2013	November 2012	2013
24 August 2017	9 July 2016	2017
November 2021	May 2020	2021

Using the 2017 Bitcoin upgrade (SegWit) as an example, we will use this event as control variables to determine its impact on the price of Bitcoin, as well as Bitcoin's future prices on the current price, as described in section 3.

Firstly, using a dummy variable to run ARDL, the results show that the event is not statistically significance in terms of the regression of future prices on current price. Additionally, running ARDL on different time frames show that the event becomes even less independent as time frame increases.

ARDL REGRESSION TABLE						
VARIABLE	Coeff	Std err	z	p > |z|	[0.025	0.975]
Segwit.L0	56.5812	298.567	0.190	0.850	-528.989	642.151
Segwit.L1	59.2099	299.140	0.198	0.843	-527.485	645.905

Next, we run ARDL on the Bitcoin *Close* price to the SegWit event and on USD. One would expect the such a major event to have an effect on the price Bitcoin. However, ARDL results also show that the dummy variable of this event has no statistical significance.

This would be because adding a dummy variable changes the coefficient of regressor before and after the event. Upon analysis of the Bitcoin price chart, it can be seen that the price does not

increase outright due to the event. Rather, the trend that the price is following changes. (i.e. the gradient of the line) To measure the impact of the event on the trend, the Chow test, which is used to measure the effects of structural breaks on time-series data, is used.

Performing the Chow test on Bitcoin's Close price to USD and the SegWit event dummy variable, yields a Chow score of 0.053 and a p-value of 1.68e-12, which is statistically significant. This also matches with what is seen on the BTC-USD chart, where trend in Bitcoin prices after SegWit event was that the price increased at a much faster rate than prices before the event. Performing the Chow test on Bitcoin's Future Price (1 day later) to Close price and the SegWit event yields a p-value of 0.00029, which is statistically significant. However, Performing the Chow test on Bitcoin's future Price of 3 days of more yields a p-value that is not statistically significant.

This shows that there is a significant trend change in Bitcoin's 1 day Future Prices as compared to Close price upon the SegWit event occurring, however, the trend change becomes insignificant as a result of the structural break if the time range of future prices were to be increased.

Running the Chow test on the 2016 Halving produces similar results, with a statistically significant p-value of 0.0035 for BTC-USD price, and 1.32e-18 for Future Price 1 to Close price. Similarly, using the dummy variable directly for ARDL regression, produces statistically insignificant results.
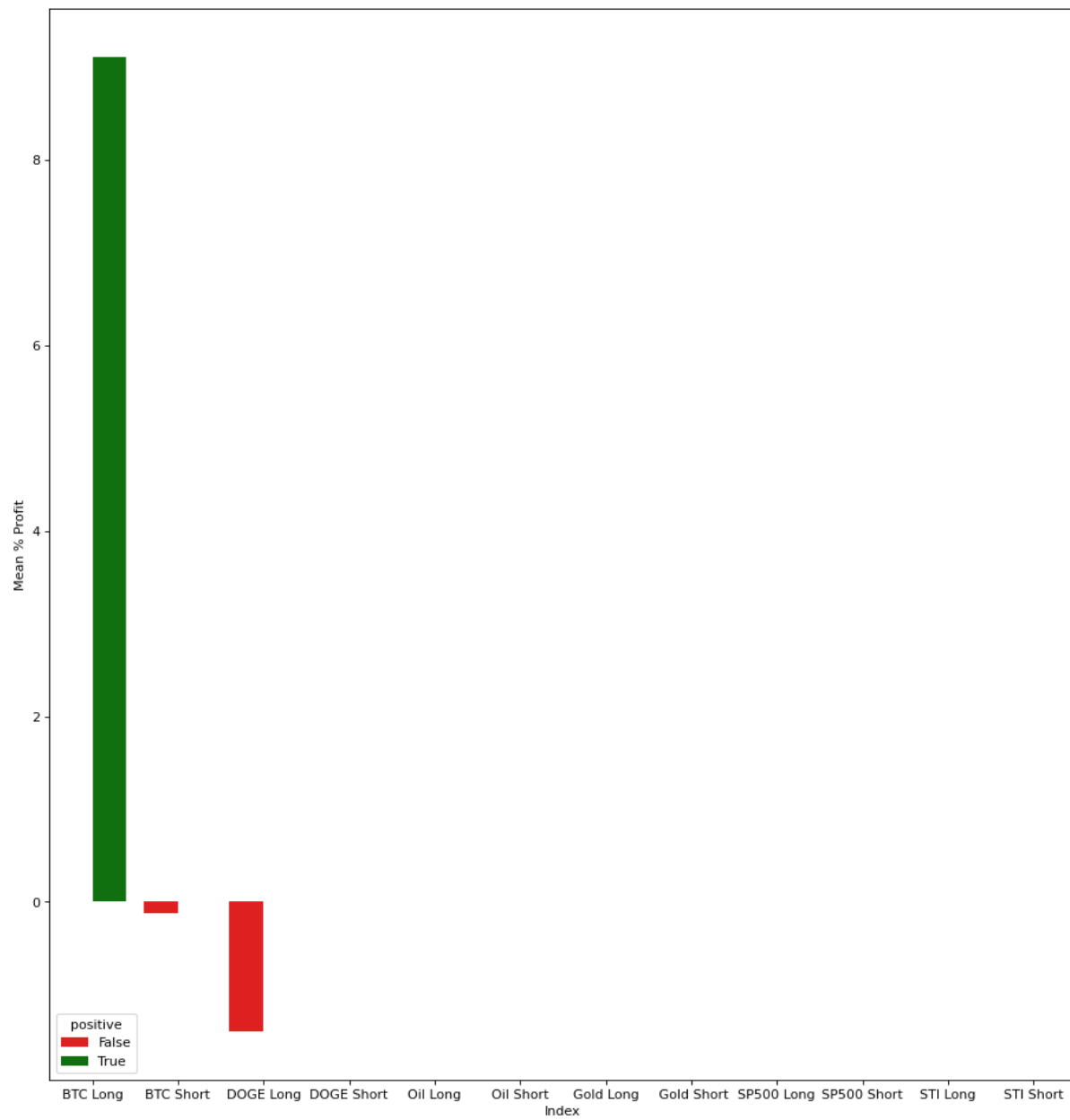
Annex C – Charts and Tables

Basic RSI Trading Strategy (average 0.0045% per trade across all instruments)
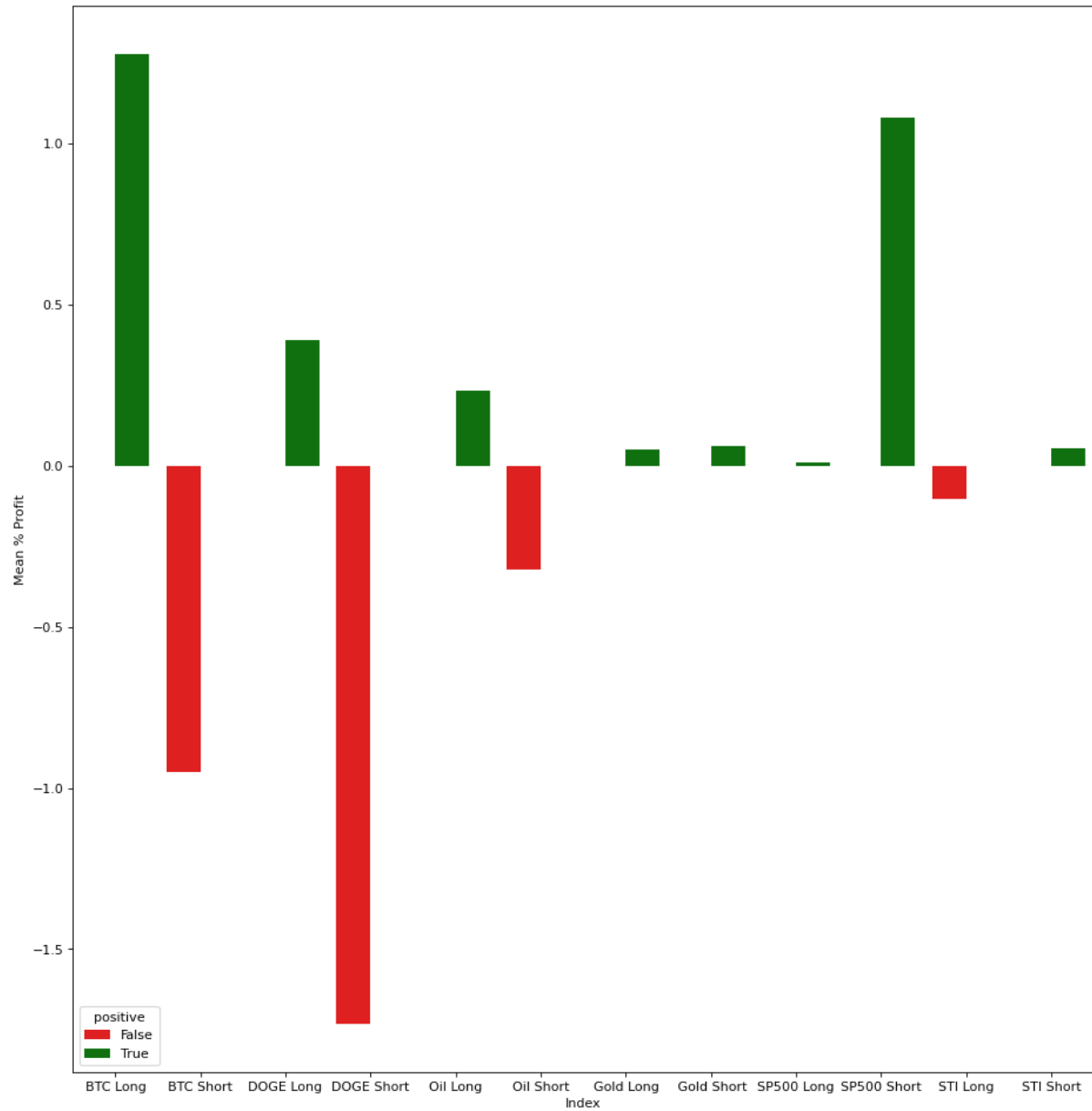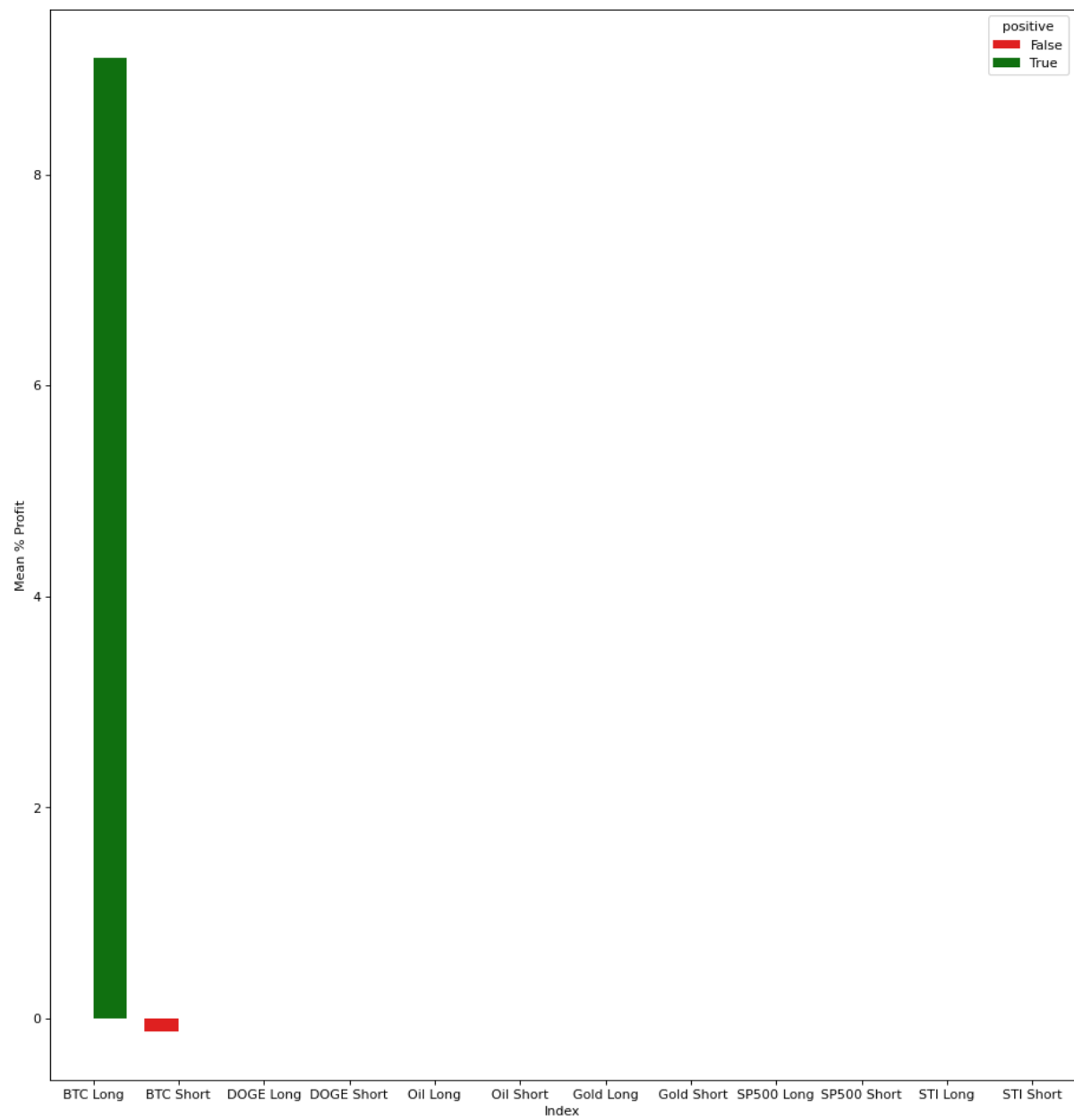
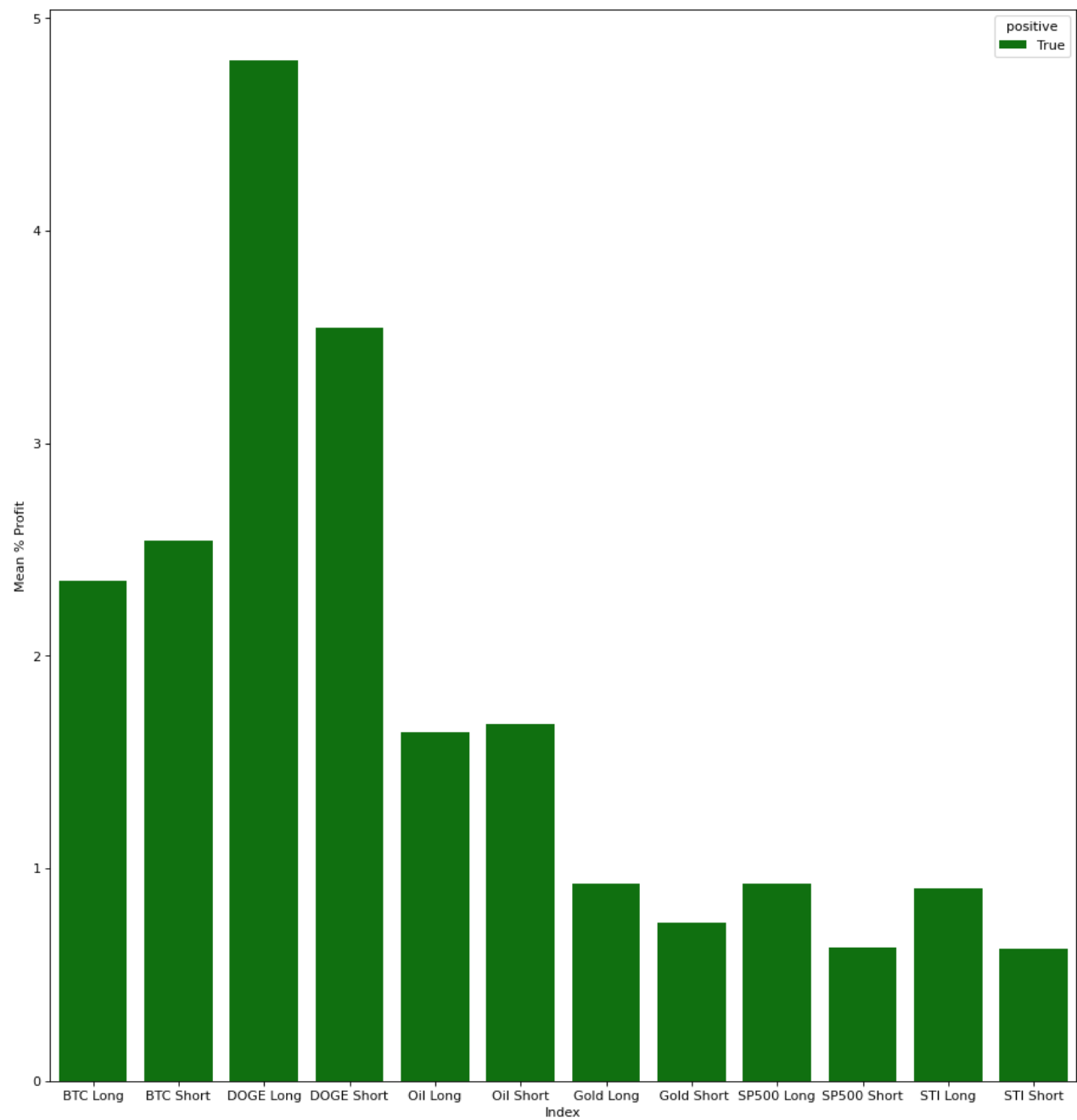**Basic RSI Trading Strategy with Trend (average +0.157% per trade)**
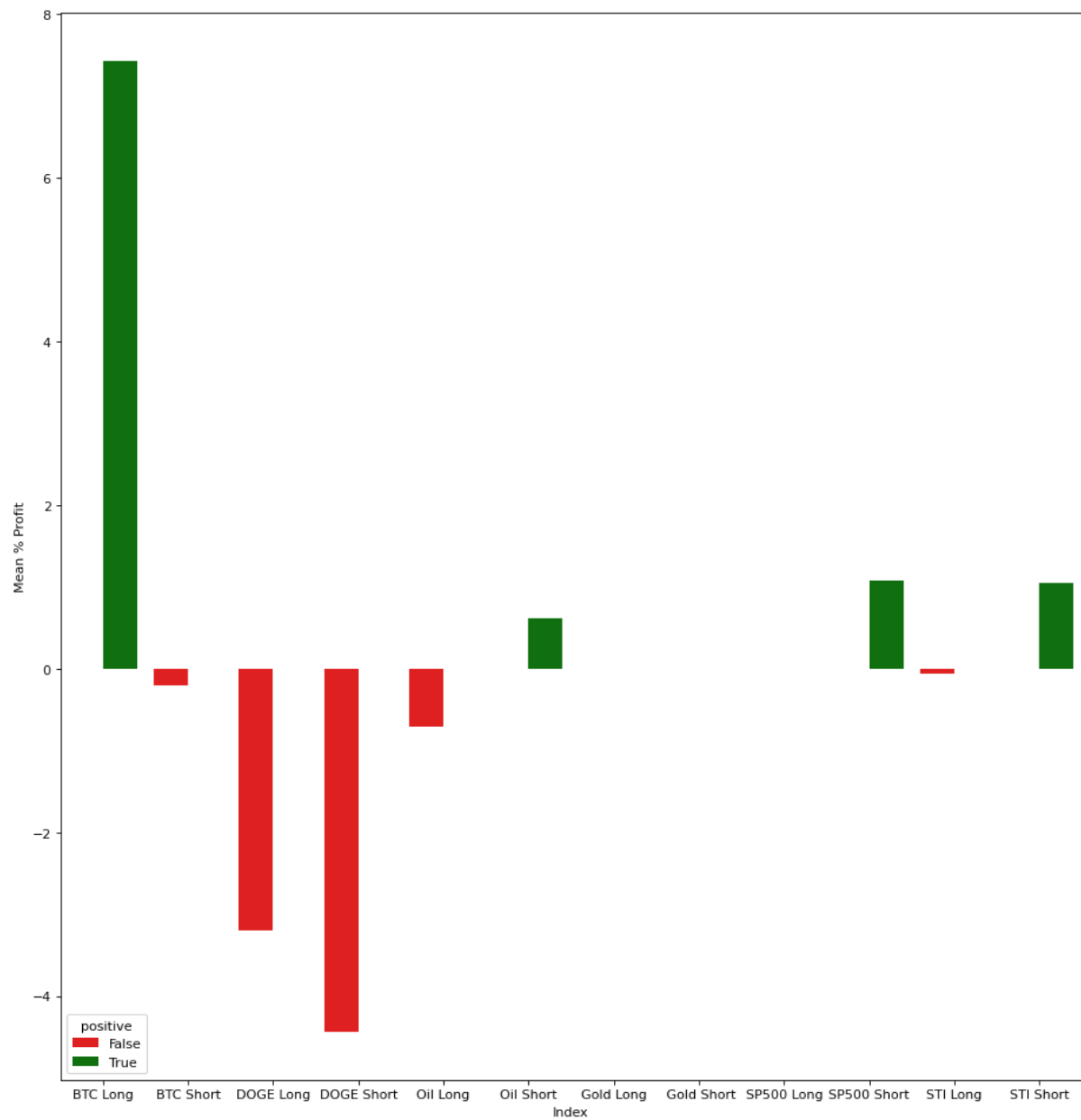
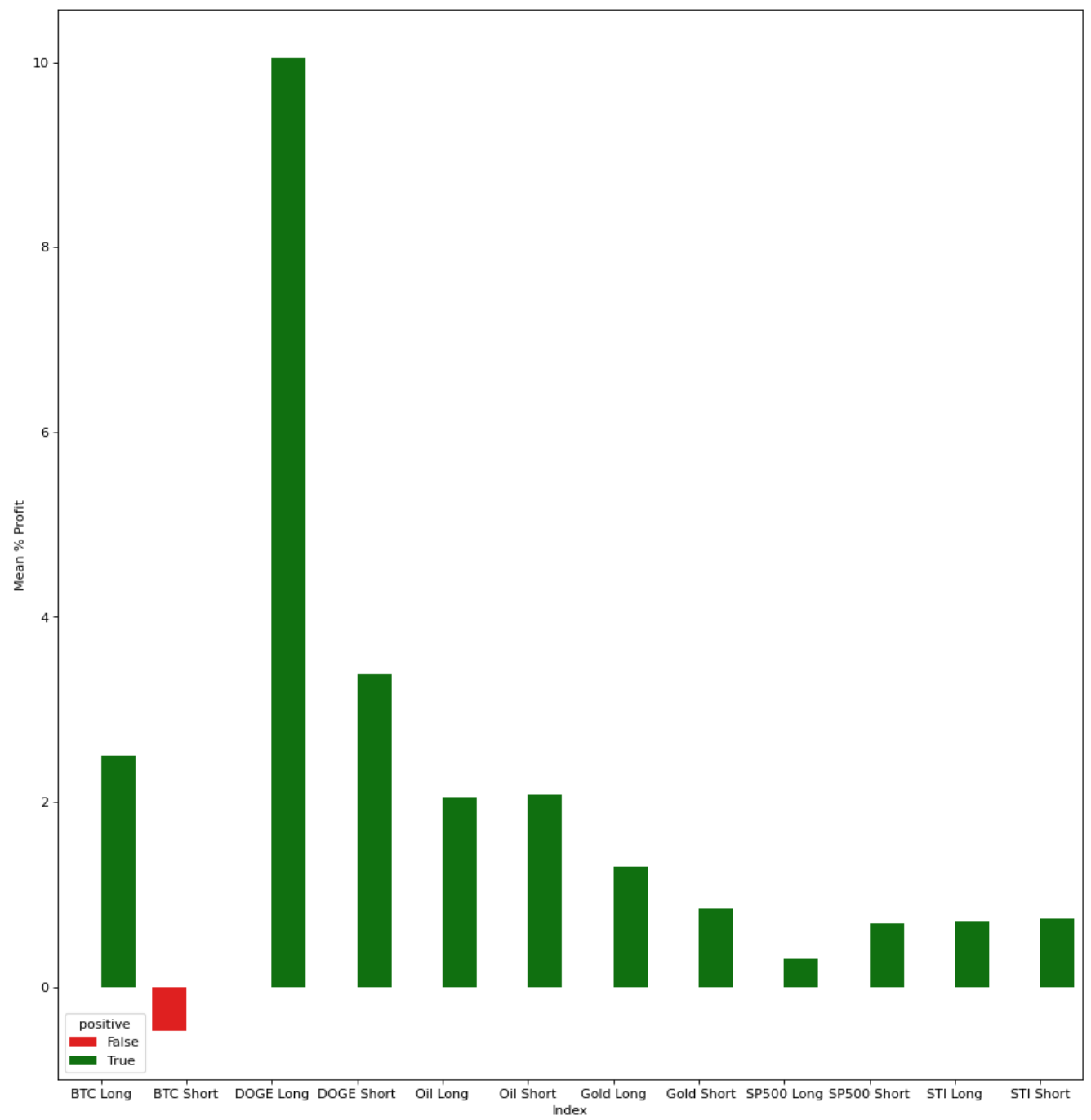**RSI Trading Strategy with Price Diff between Price and EMA200 (average 2.53% per trade)**

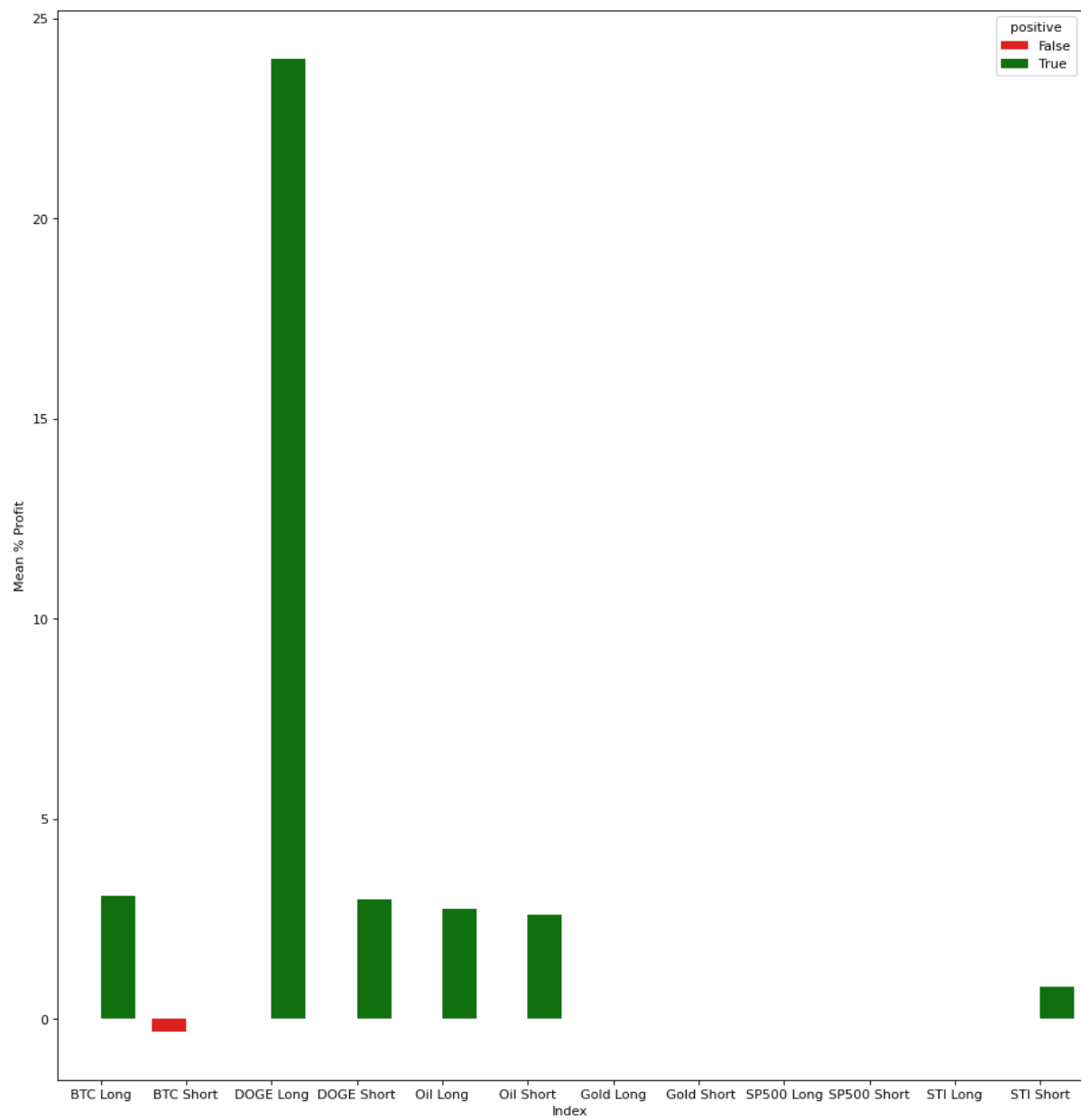**RSI Trading Strategy with Price Diff between Price and EMA200 (>0.1) and Price Relative ATR (<10) (average 4.49% per trade)**

MACD Trading Strategy (average 1.77% per trade)

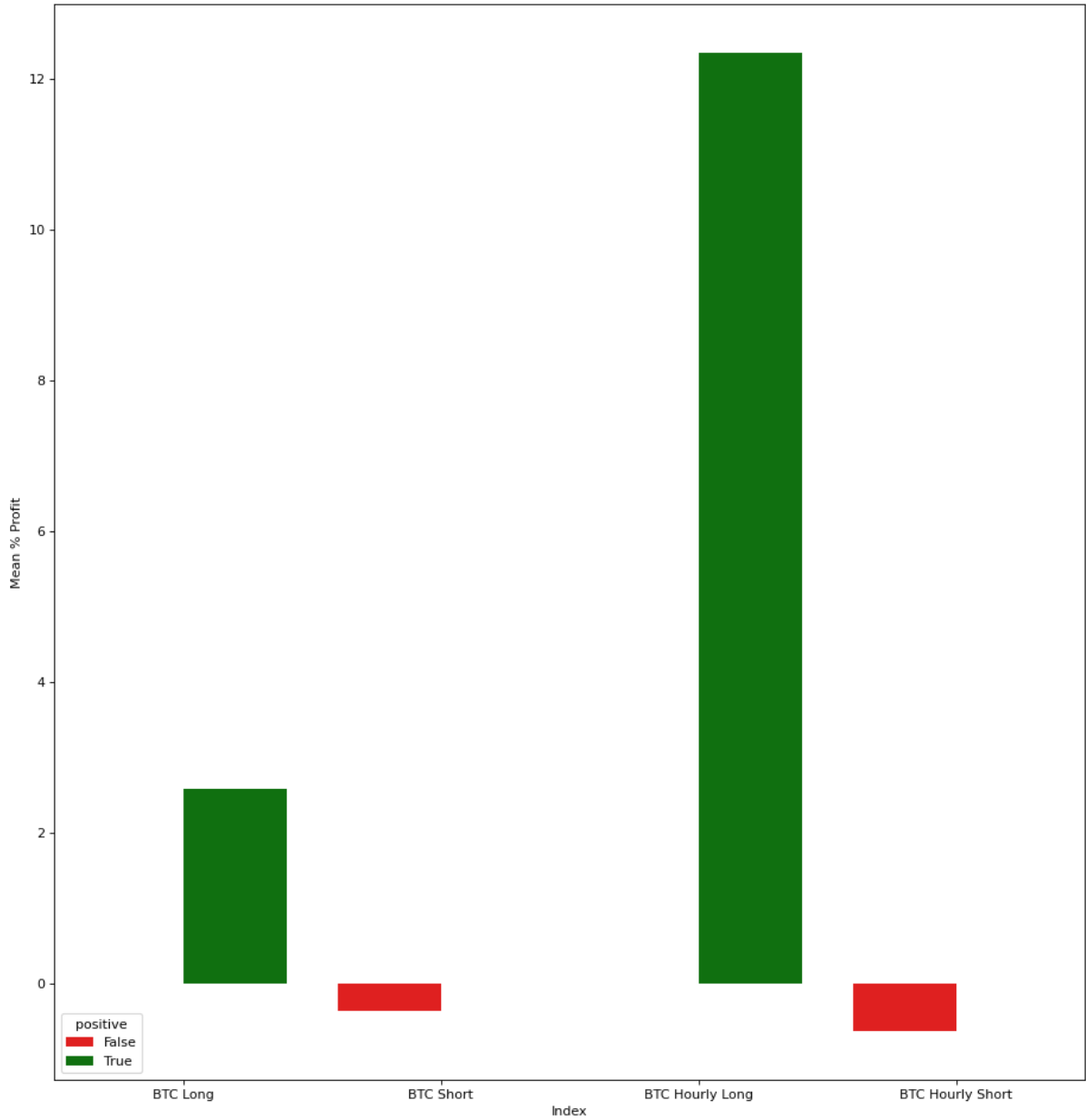**MACD Trading Strategy with Trend (average 2.01% per trade)**

MACD Trading Strategy with Price Diff between Price and EMA200 (> 0.2) (average 5.15% per trade)
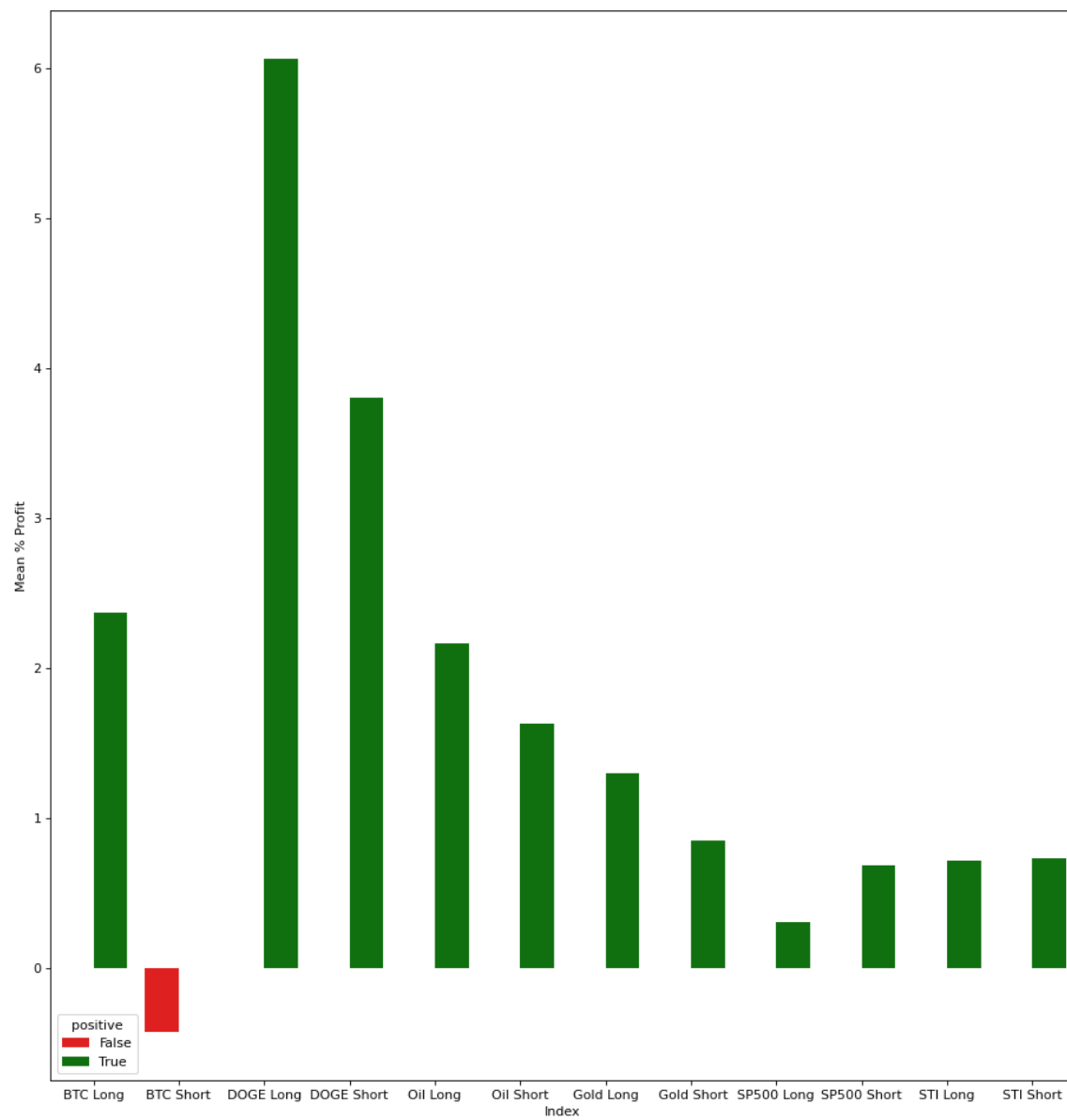
MACD Trading Strategy with Price Diff between Price and EMA200 (>0.5) and Price Relative ATR (<30) (average 6.70% per trade)
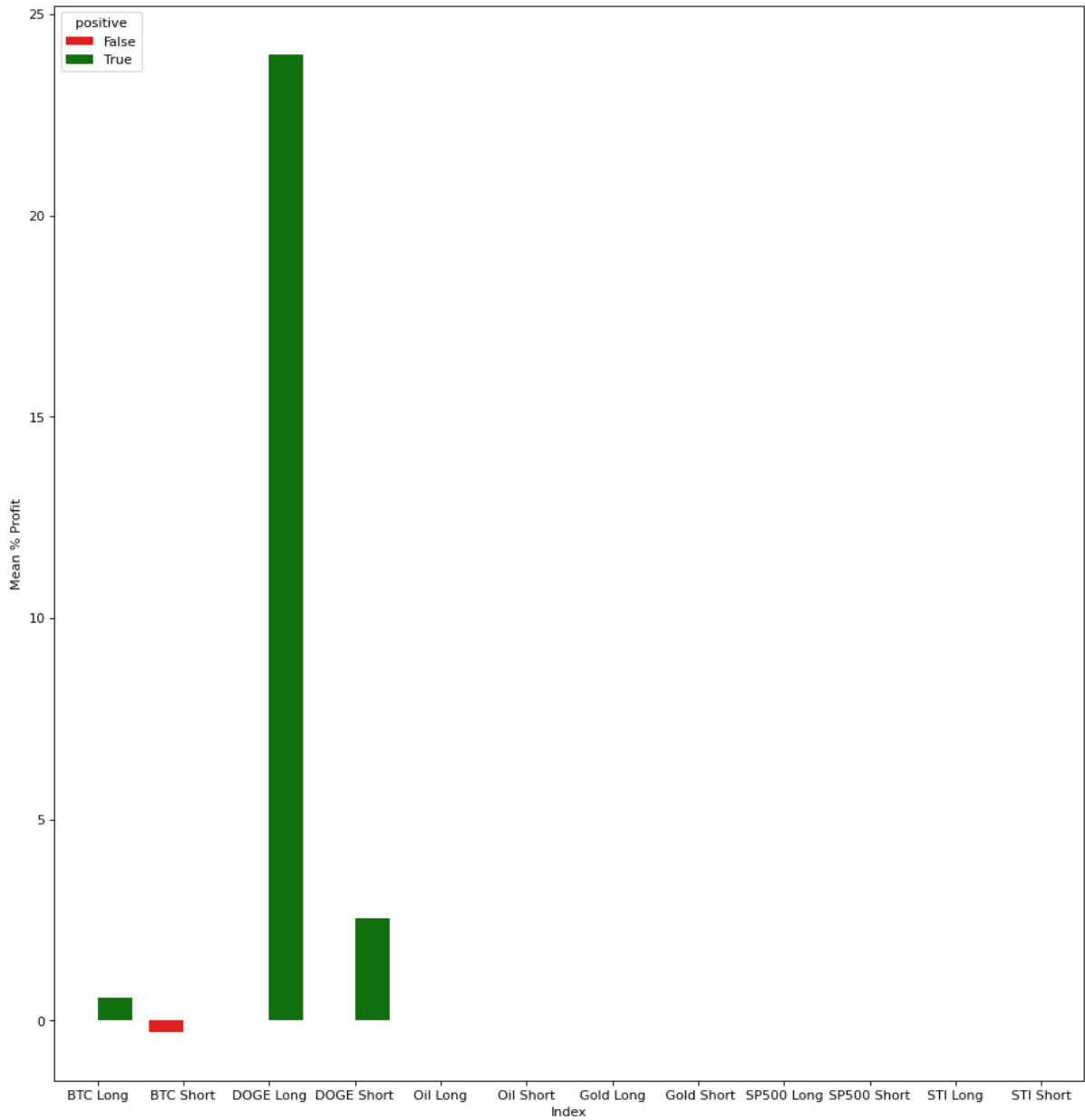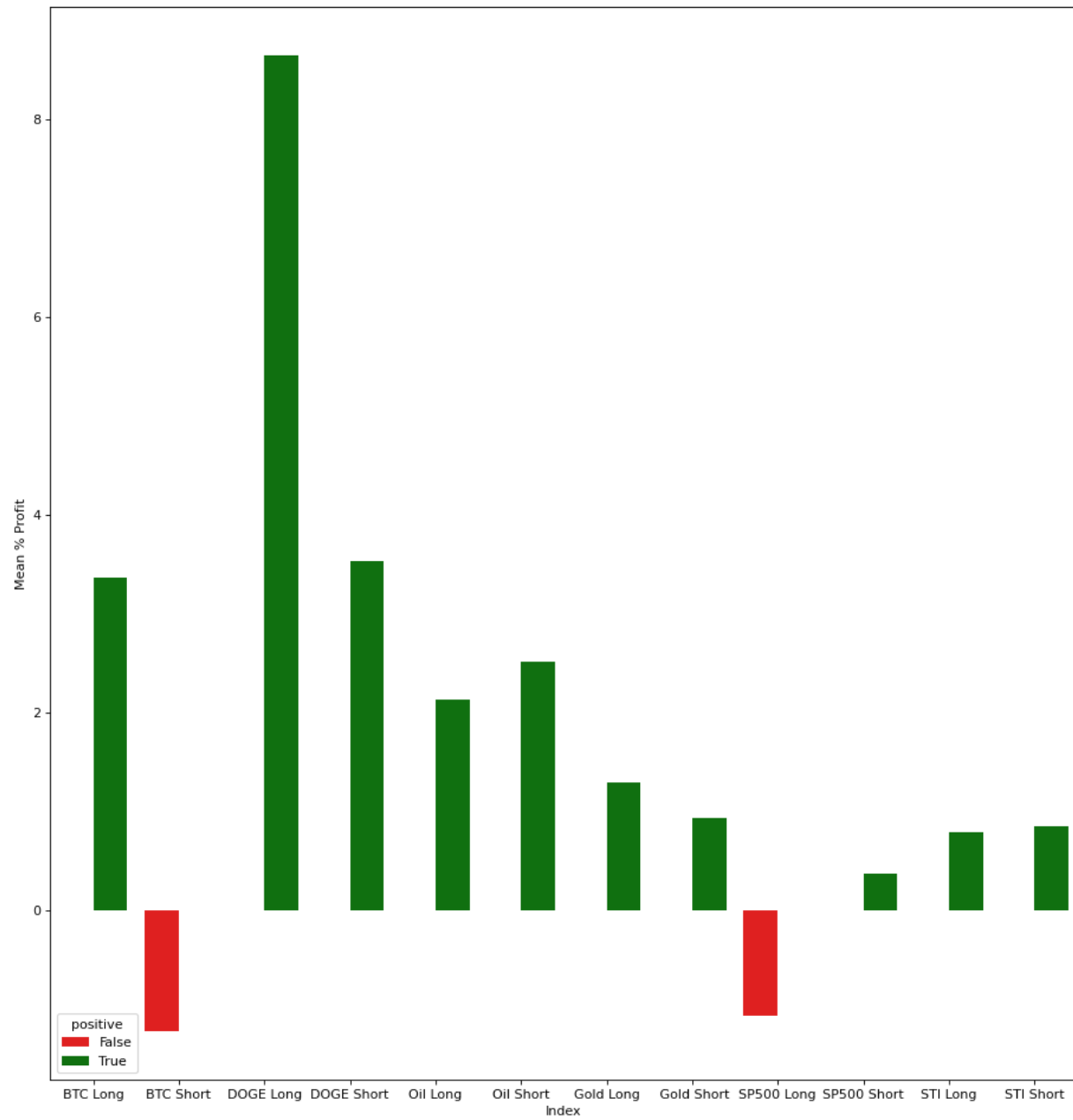
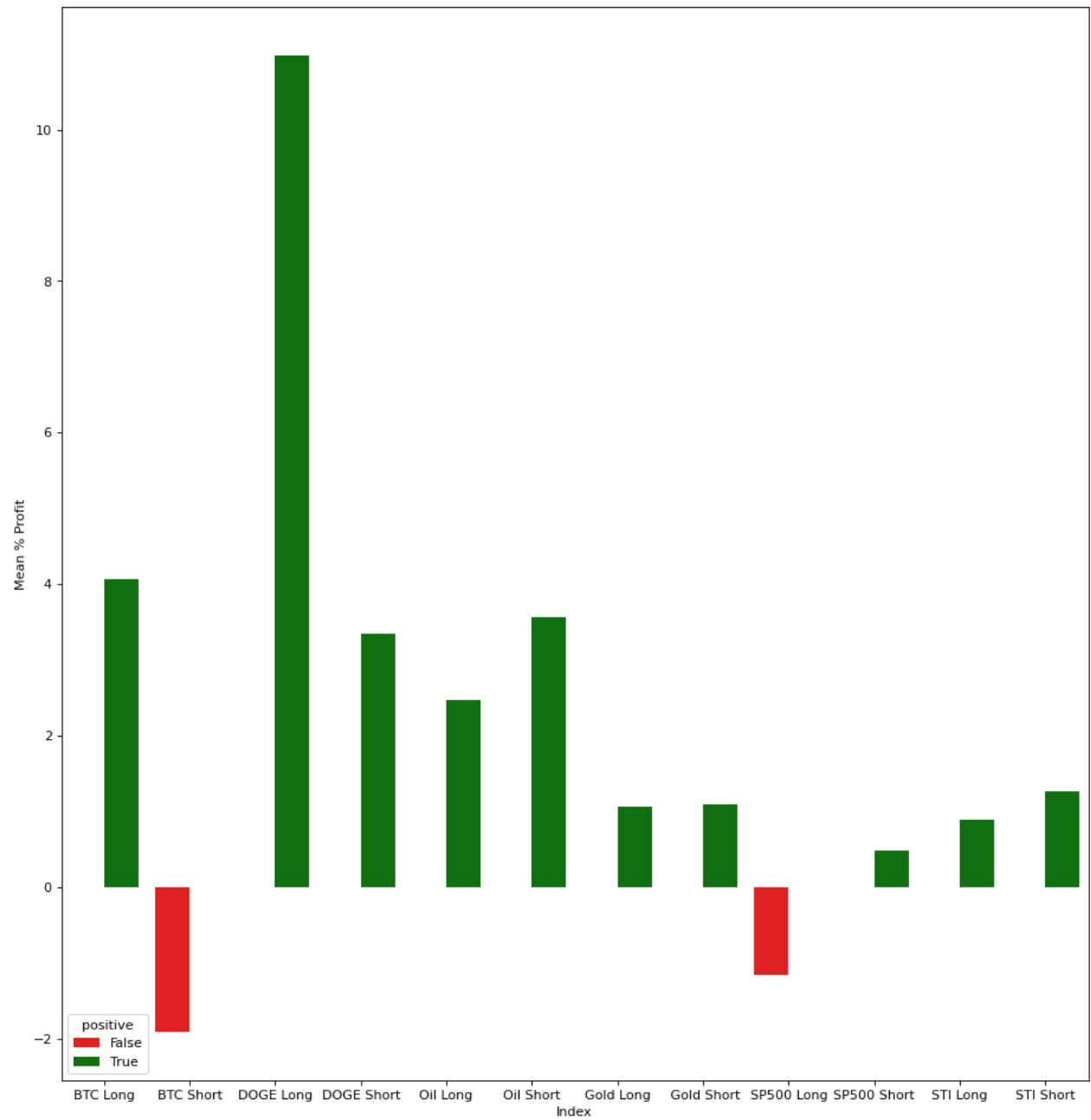**BTC Hourly vs Daily Timeframe Trade Performance**

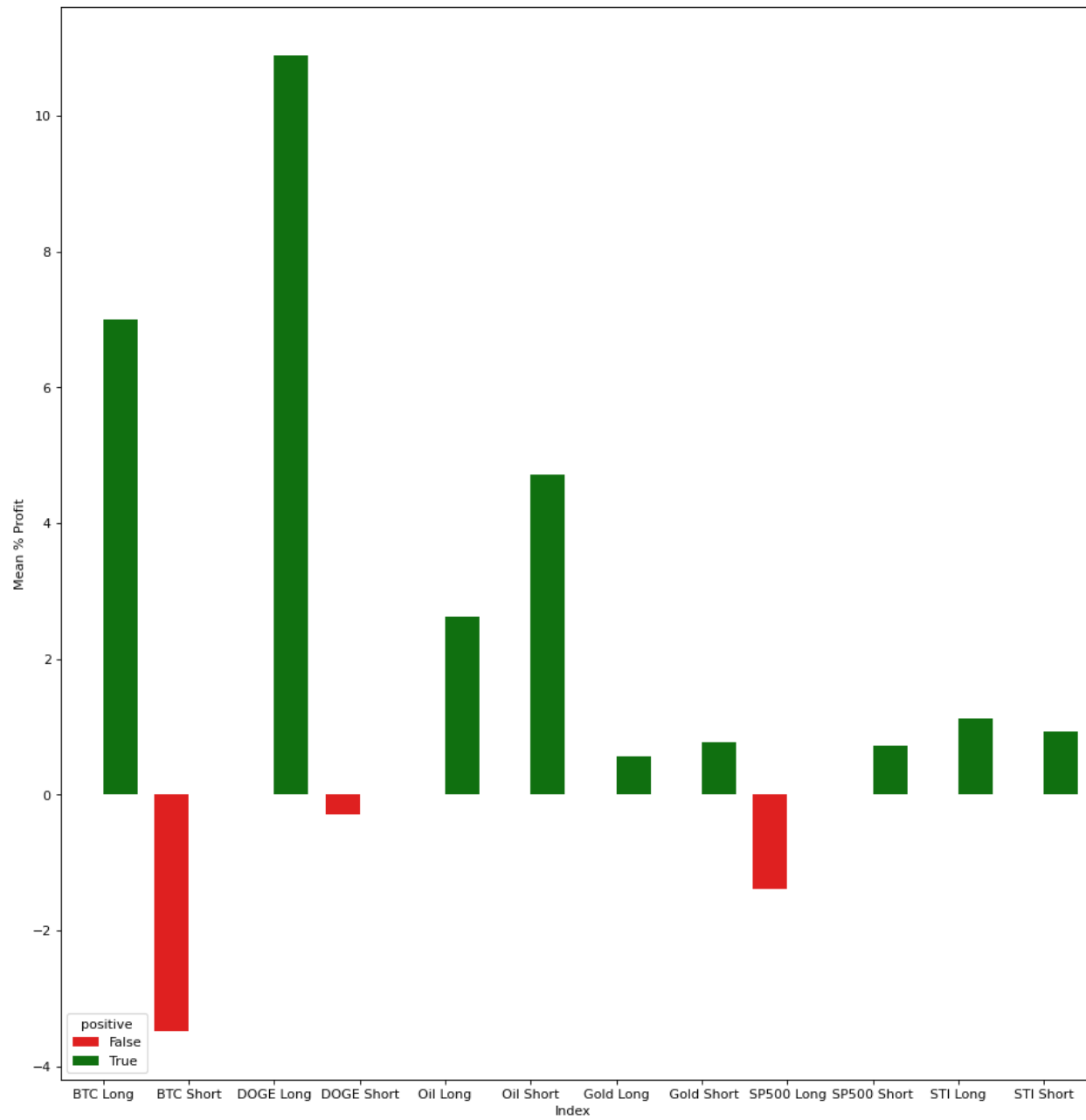**Holding Time = 1 Day (Average +1.68% per trade)**

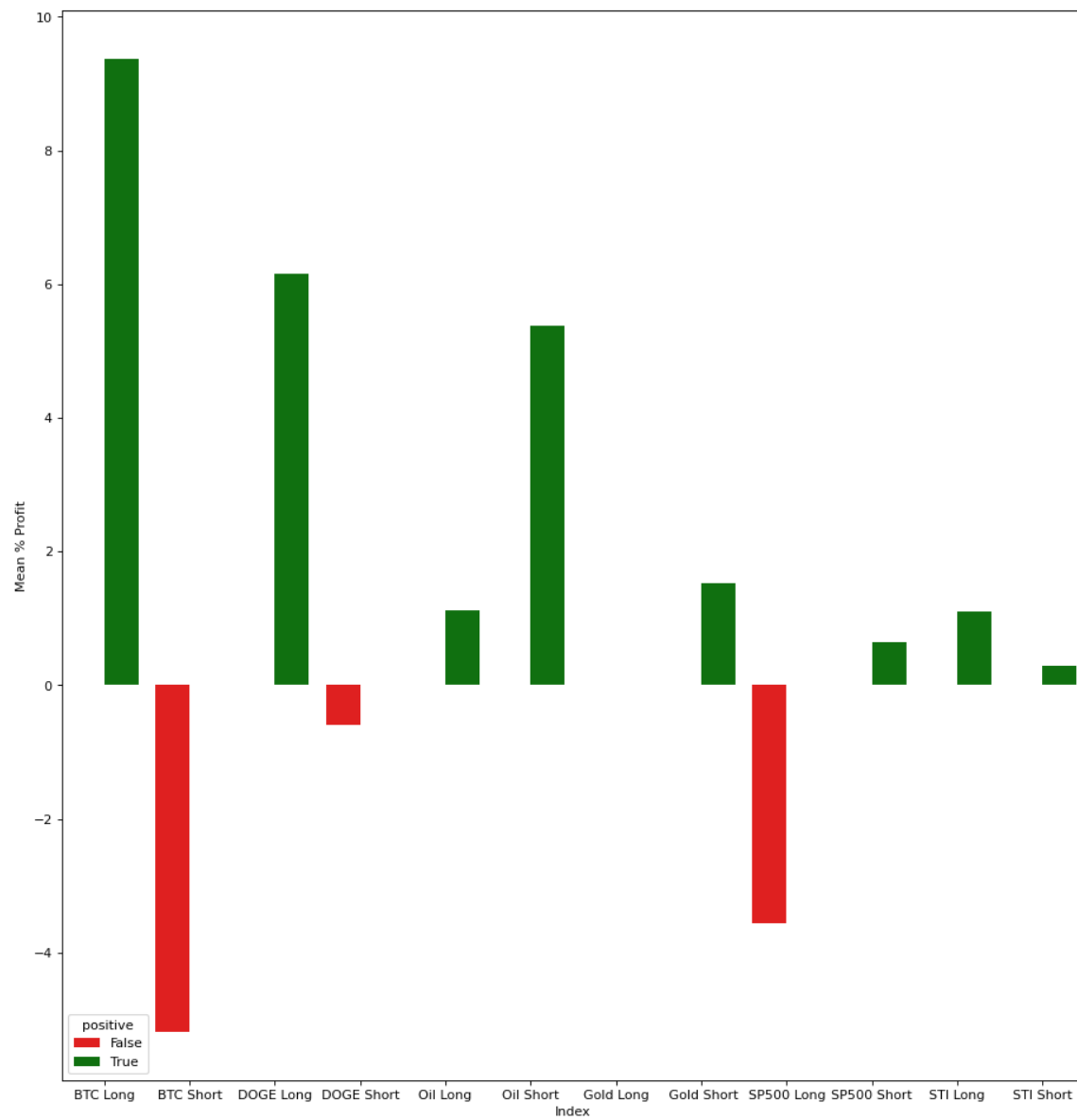**Holding Time = 3 Days (Average +1.84% per trade)**

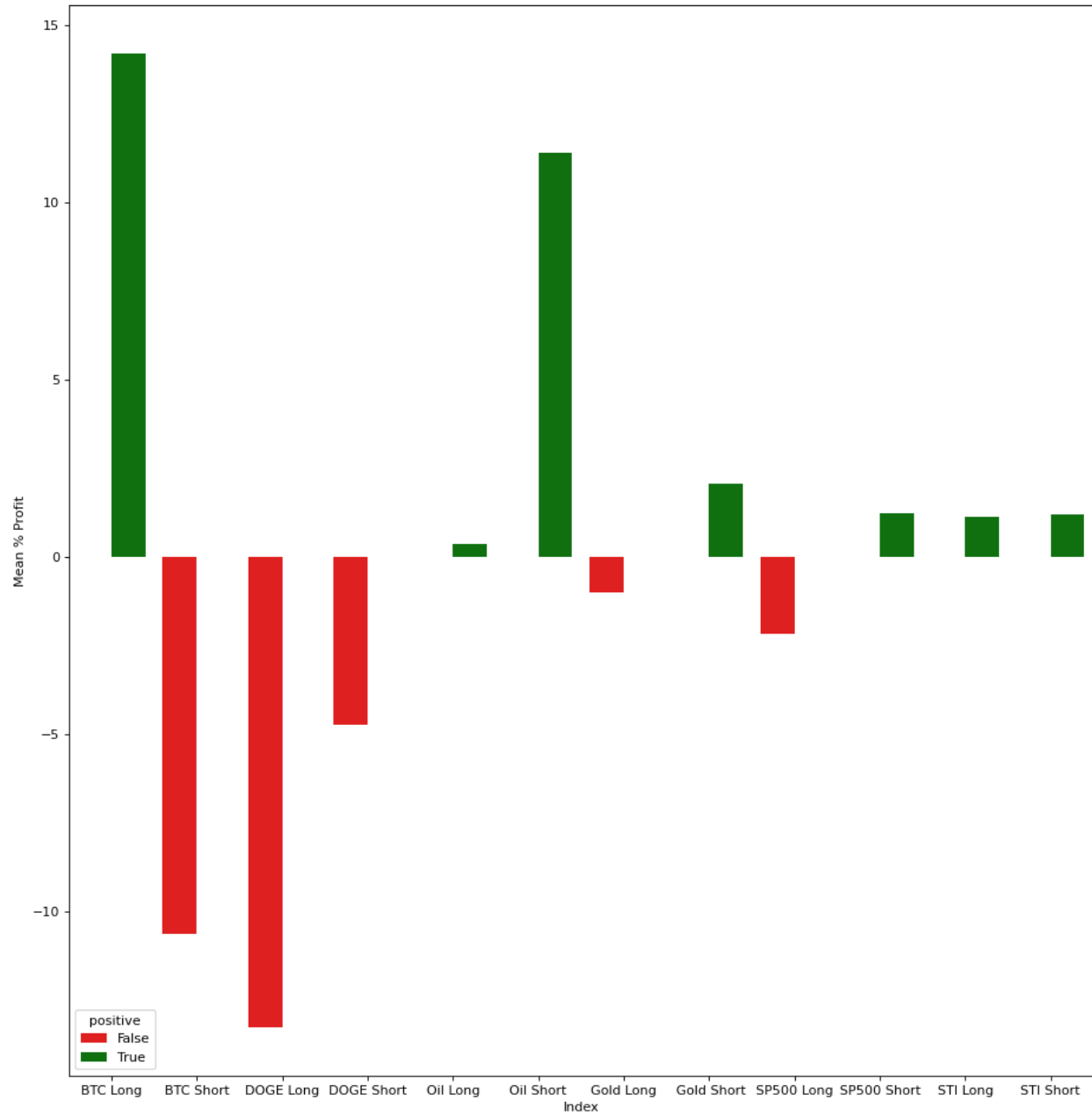**Holding Time = 5 Days (Average +2.17% per trade)**

Holding Time = 10 Days (Average +2.02% per trade)

Holding Time = 15 Days (Average +1.35% per trade)

Holding Time = 30 Days (Average -0.018% per trade)

Model with Lag = 10

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10)	Log Likelihood	3495.555
Method:	Conditional MLE	S.D. of innovations	0.036
Date:	Wed, 17 Nov 2021	AIC	-6681.110
Time:	12:03:16	BIC	-5827.248
Sample:	10	HQIC	-6366.127
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0554	0.017	-3.347	0.001	-0.088	-0.023
future_price1 % P/L.L1	-0.2639	0.070	-3.752	0.000	-0.402	-0.126
future_price1 % P/L.L2	-0.0950	0.071	-1.341	0.180	-0.234	0.044
future_price1 % P/L.L3	-0.0558	0.071	-0.789	0.430	-0.194	0.083
future_price1 % P/L.L4	-0.1137	0.071	-1.605	0.109	-0.253	0.025
future_price1 % P/L.L5	-0.1691	0.071	-2.383	0.017	-0.308	-0.030

future_price1 % P/L.L6	-0.0375	0.071	-0.529	0.597	-0.176	0.102
future_price1 % P/L.L7	-0.0483	0.072	-0.672	0.502	-0.189	0.093
future_price1 % P/L.L8	-0.0541	0.072	-0.755	0.451	-0.195	0.087
future_price1 % P/L.L9	-0.0391	0.072	-0.545	0.586	-0.180	0.102
future_price1 % P/L.L10	-0.1746	0.072	-2.441	0.015	-0.315	-0.034
Close.L0	-0.0022	0.004	-0.515	0.606	-0.011	0.006
Close.L1	0.0038	0.008	0.509	0.611	-0.011	0.019
Close.L2	-0.0048	0.008	-0.589	0.556	-0.021	0.011
Close.L3	0.0034	0.008	0.420	0.674	-0.013	0.020
Close.L4	-0.0074	0.009	-0.818	0.413	-0.025	0.010
Close.L5	0.0258	0.010	2.563	0.010	0.006	0.045
Close.L6	-0.0256	0.010	-2.537	0.011	-0.045	-0.006
Close.L7	0.0118	0.010	1.159	0.247	-0.008	0.032
Close.L8	-0.0088	0.010	-0.864	0.388	-0.029	0.011

Close.L9	-0.0084	0.010	-0.873	0.383	-0.027	0.010
Close.L10	0.0120	0.005	2.310	0.021	0.002	0.022
Volume.L0	-5.313e-13	5.42e-13	-0.981	0.327	-1.59e-12	5.31e-13
Volume.L1	1.386e-12	6.32e-13	2.195	0.028	1.47e-13	2.62e-12
Volume.L2	-1.83e-12	6.31e-13	-2.902	0.004	-3.07e-12	-5.93e-13
Volume.L3	9.682e-13	6.41e-13	1.510	0.131	-2.9e-13	2.23e-12
Volume.L4	-1.682e-12	6.49e-13	-2.590	0.010	-2.96e-12	-4.08e-13
Volume.L5	5.477e-13	6.99e-13	0.784	0.433	-8.22e-13	1.92e-12
Volume.L6	-2.396e-13	7.02e-13	-0.341	0.733	-1.62e-12	1.14e-12
Volume.L7	2.839e-13	7.09e-13	0.401	0.689	-1.11e-12	1.67e-12
Volume.L8	2.303e-13	7.05e-13	0.327	0.744	-1.15e-12	1.61e-12
Volume.L9	-1.278e-13	6.95e-13	-0.184	0.854	-1.49e-12	1.24e-12
Volume.L10	8.297e-13	5.11e-13	1.625	0.104	-1.72e-13	1.83e-12
RSI.L0	0.0014	0.000	2.890	0.004	0.000	0.002

RSI.L1	-0.0006	0.001	-1.029	0.304	-0.002	0.001
RSI.L2	-0.0005	0.001	-0.786	0.432	-0.002	0.001
RSI.L3	0.0010	0.001	1.691	0.091	-0.000	0.002
RSI.L4	1.232e-05	0.001	0.020	0.984	-0.001	0.001
RSI.L5	0.0003	0.001	0.501	0.617	-0.001	0.002
RSI.L6	-0.0007	0.001	-1.043	0.297	-0.002	0.001
RSI.L7	0.0002	0.001	0.276	0.783	-0.001	0.001
RSI.L8	-0.0004	0.001	-0.565	0.572	-0.002	0.001
RSI.L9	0.0014	0.001	2.198	0.028	0.000	0.003
RSI.L10	-0.0010	0.000	-2.244	0.025	-0.002	-0.000
RSI Condition.L0	0.0030	0.004	0.719	0.472	-0.005	0.011
RSI Condition.L1	-0.0029	0.004	-0.670	0.503	-0.012	0.006
RSI Condition.L2	-0.0055	0.004	-1.229	0.219	-0.014	0.003
RSI Condition.L3	0.0135	0.004	3.042	0.002	0.005	0.022

RSI Condition.L4	0.0032	0.004	0.716	0.474	-0.006	0.012
RSI Condition.L5	-0.0023	0.004	-0.516	0.606	-0.011	0.006
RSI Condition.L6	-0.0057	0.004	-1.281	0.201	-0.015	0.003
RSI Condition.L7	0.0045	0.004	1.000	0.317	-0.004	0.013
RSI Condition.L8	0.0039	0.004	0.875	0.382	-0.005	0.013
RSI Condition.L9	-0.0071	0.004	-1.595	0.111	-0.016	0.002
RSI Condition.L10	-0.0010	0.004	-0.238	0.812	-0.009	0.007
MACD Condition.L0	0.0294	0.004	7.506	0.000	0.022	0.037
MACD Condition.L1	0.0057	0.004	1.369	0.171	-0.002	0.014
MACD Condition.L2	0.0094	0.004	2.255	0.024	0.001	0.018
MACD Condition.L3	0.0032	0.004	0.756	0.450	-0.005	0.011
MACD Condition.L4	0.0117	0.004	2.777	0.006	0.003	0.020
MACD Condition.L5	0.0074	0.004	1.749	0.080	-0.001	0.016
MACD Condition.L6	0.0070	0.004	1.674	0.094	-0.001	0.015

MACD Condition.L7	0.0067	0.004	1.606	0.108	-0.001	0.015
MACD Condition.L8	0.0024	0.004	0.579	0.563	-0.006	0.010
MACD Condition.L9	0.0061	0.004	1.507	0.132	-0.002	0.014
MACD Condition.L10	0.0074	0.004	1.905	0.057	-0.000	0.015
EMA Condition.L0	-0.0010	0.003	-0.327	0.744	-0.007	0.005
EMA Condition.L1	2.838e-05	0.003	0.009	0.993	-0.006	0.006
EMA Condition.L2	0.0004	0.003	0.135	0.892	-0.006	0.007
EMA Condition.L3	-0.0068	0.003	-2.163	0.031	-0.013	-0.001
EMA Condition.L4	-0.0001	0.003	-0.032	0.975	-0.006	0.006
EMA Condition.L5	-0.0026	0.003	-0.835	0.404	-0.009	0.004
EMA Condition.L6	0.0011	0.003	0.346	0.729	-0.005	0.007
EMA Condition.L7	-0.0027	0.003	-0.866	0.387	-0.009	0.003
EMA Condition.L8	0.0032	0.003	1.007	0.314	-0.003	0.009
EMA Condition.L9	-0.0040	0.003	-1.295	0.196	-0.010	0.002

EMA Condition.L10	0.0008	0.003	0.276	0.783	-0.005	0.006
Close-EMA200 Price Diff.L0	0.0022	0.004	0.509	0.611	-0.006	0.010
Close-EMA200 Price Diff.L1	-0.0039	0.008	-0.518	0.605	-0.019	0.011
Close-EMA200 Price Diff.L2	0.0047	0.008	0.582	0.561	-0.011	0.021
Close-EMA200 Price Diff.L3	-0.0034	0.008	-0.415	0.678	-0.019	0.013
Close-EMA200 Price Diff.L4	0.0074	0.009	0.825	0.409	-0.010	0.025
Close-EMA200 Price Diff.L5	-0.0257	0.010	-2.564	0.010	-0.045	-0.006
Close-EMA200 Price Diff.L6	0.0256	0.010	2.549	0.011	0.006	0.045
Close-EMA200 Price Diff.L7	-0.0118	0.010	-1.165	0.244	-0.032	0.008
Close-EMA200 Price Diff.L8	0.0088	0.010	0.869	0.385	-0.011	0.029
Close-EMA200 Price Diff.L9	0.0082	0.010	0.858	0.391	-0.011	0.027
Close-EMA200 Price Diff.L10	-0.0120	0.005	-2.312	0.021	-0.022	-0.002
BB Condition.L0	-0.0010	0.004	-0.269	0.788	-0.008	0.006
BB Condition.L1	0.0052	0.004	1.328	0.184	-0.002	0.013

BB Condition.L2	-0.0033	0.004	-0.831	0.406	-0.011	0.004
BB Condition.L3	0.0034	0.004	0.860	0.390	-0.004	0.011
BB Condition.L4	-0.0090	0.004	-2.287	0.022	-0.017	-0.001
BB Condition.L5	0.0045	0.004	1.135	0.256	-0.003	0.012
BB Condition.L6	0.0040	0.004	0.993	0.321	-0.004	0.012
BB Condition.L7	0.0013	0.004	0.323	0.747	-0.007	0.009
BB Condition.L8	-0.0030	0.004	-0.748	0.454	-0.011	0.005
BB Condition.L9	0.0029	0.004	0.740	0.459	-0.005	0.011
BB Condition.L10	-0.0033	0.004	-0.918	0.359	-0.010	0.004
ATR.L0	0.0001	7.33e-05	1.570	0.117	-2.87e-05	0.000
ATR.L1	-0.0002	0.000	-2.099	0.036	-0.000	-1.62e-05
ATR.L2	0.0003	0.000	2.509	0.012	6.56e-05	0.001
ATR.L3	-0.0002	0.000	-1.423	0.155	-0.000	6.52e-05
ATR.L4	0.0002	0.000	1.700	0.089	-3.19e-05	0.000

ATR.L5	-0.0003	0.000	-2.782	0.005	-0.001	-0.000
ATR.L6	0.0004	0.000	3.187	0.001	0.000	0.001
ATR.L7	-0.0002	0.000	-1.441	0.150	-0.000	6.65e-05
ATR.L8	-0.0002	0.000	-1.777	0.076	-0.000	2.37e-05
ATR.L9	0.0003	0.000	2.119	0.034	2.01e-05	0.001
ATR.L10	-0.0001	7.61e-05	-1.594	0.111	-0.000	2.79e-05
Trend.L0	-0.0023	0.004	-0.545	0.586	-0.010	0.006
Trend.L1	0.0038	0.005	0.786	0.432	-0.006	0.013
Trend.L2	0.0074	0.005	1.464	0.143	-0.003	0.017
Trend.L3	0.0066	0.005	1.300	0.194	-0.003	0.016
Trend.L4	-0.0145	0.005	-2.868	0.004	-0.024	-0.005
Trend.L5	-0.0005	0.005	-0.103	0.918	-0.010	0.009
Trend.L6	0.0035	0.005	0.684	0.494	-0.007	0.013
Trend.L7	0.0035	0.005	0.687	0.492	-0.007	0.014

Trend.L8	-0.0015	0.005	-0.290	0.772	-0.011	0.009
Trend.L9	-0.0130	0.005	-2.615	0.009	-0.023	-0.003
Trend.L10	0.0111	0.004	2.645	0.008	0.003	0.019
Forecasted.L0	0.0005	0.001	1.029	0.304	-0.000	0.002
Forecasted.L1	-0.0002	0.001	-0.259	0.796	-0.002	0.001
Forecasted.L2	0.0005	0.001	0.603	0.547	-0.001	0.002
Forecasted.L3	-0.0010	0.001	-1.151	0.250	-0.003	0.001
Forecasted.L4	0.0008	0.001	0.715	0.475	-0.001	0.003
Forecasted.L5	-0.0025	0.001	-2.042	0.041	-0.005	-9.85e-05
Forecasted.L6	0.0024	0.001	1.904	0.057	-7.12e-05	0.005
Forecasted.L7	-0.0007	0.001	-0.599	0.549	-0.003	0.002
Forecasted.L8	0.0005	0.001	0.393	0.695	-0.002	0.003
Forecasted.L9	0.0021	0.001	1.683	0.092	-0.000	0.004
Forecasted.L10	-0.0020	0.001	-3.078	0.002	-0.003	-0.001

Slope.L0	-0.0031	0.003	-0.957	0.339	-0.009	0.003
Slope.L1	0.0008	0.005	0.169	0.866	-0.009	0.010
Slope.L2	-0.0027	0.005	-0.535	0.593	-0.013	0.007
Slope.L3	0.0051	0.005	1.010	0.313	-0.005	0.015
Slope.L4	-0.0047	0.006	-0.804	0.422	-0.016	0.007
Slope.L5	0.0147	0.007	2.229	0.026	0.002	0.028
Slope.L6	-0.0135	0.007	-2.024	0.043	-0.027	-0.000
Slope.L7	0.0053	0.007	0.784	0.433	-0.008	0.018
Slope.L8	-0.0043	0.007	-0.643	0.520	-0.018	0.009
Slope.L9	-0.0097	0.006	-1.505	0.133	-0.022	0.003
Slope.L10	0.0097	0.003	2.992	0.003	0.003	0.016
Acceleration.L0	0.0039	0.008	0.479	0.632	-0.012	0.020
Acceleration.L1	-0.0016	0.014	-0.114	0.909	-0.030	0.027
Acceleration.L2	-0.0029	0.016	-0.182	0.855	-0.034	0.028

Acceleration.L3	-0.0029	0.016	-0.186	0.853	-0.034	0.028
Acceleration.L4	0.0261	0.016	1.642	0.101	-0.005	0.057
Acceleration.L5	-0.0542	0.016	-3.426	0.001	-0.085	-0.023
Acceleration.L6	0.0542	0.016	3.425	0.001	0.023	0.085
Acceleration.L7	-0.0365	0.016	-2.304	0.021	-0.068	-0.005
Acceleration.L8	0.0367	0.015	2.369	0.018	0.006	0.067
Acceleration.L9	-0.0332	0.012	-2.846	0.004	-0.056	-0.010
Acceleration.L10	0.0122	0.004	2.996	0.003	0.004	0.020

Model with Lag = 8

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8)	Log Likelihood	3459.594
Method:	Conditional MLE	S.D. of innovations	0.036
Date:	Wed, 17 Nov 2021	AIC	-6665.189
Time:	12:21:55	BIC	-5965.434
Sample:	8	HQIC	-6407.069
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0516	0.015	-3.436	0.001	-0.081	-0.022
future_price1 % P/L.L1	-0.2743	0.070	-3.910	0.000	-0.412	-0.137
future_price1 % P/L.L2	-0.0528	0.071	-0.743	0.458	-0.192	0.087
future_price1 % P/L.L3	-0.0560	0.071	-0.786	0.432	-0.196	0.084
future_price1 % P/L.L4	-0.0844	0.071	-1.188	0.235	-0.224	0.055
future_price1 % P/L.L5	-0.1589	0.071	-2.241	0.025	-0.298	-0.020

future_price1 % P/L.L6	-0.0427	0.071	-0.603	0.547	-0.181	0.096
future_price1 % P/L.L7	-0.0297	0.072	-0.412	0.680	-0.171	0.112
future_price1 % P/L.L8	-0.0238	0.072	-0.331	0.741	-0.165	0.117
Close.L0	-0.0051	0.003	-1.548	0.122	-0.012	0.001
Close.L1	0.0076	0.007	1.126	0.260	-0.006	0.021
Close.L2	-0.0063	0.008	-0.796	0.426	-0.022	0.009
Close.L3	0.0019	0.008	0.246	0.806	-0.013	0.017
Close.L4	0.0046	0.006	0.817	0.414	-0.006	0.016
Close.L5	-0.0015	0.005	-0.290	0.772	-0.012	0.009
Close.L6	0.0039	0.007	0.533	0.594	-0.010	0.018
Close.L7	-0.0051	0.008	-0.607	0.544	-0.022	0.011
Close.L8	0.0001	0.004	0.026	0.979	-0.009	0.009
Volume.L0	-5.457e-13	5.36e-13	-1.018	0.309	-1.6e-12	5.06e-13
Volume.L1	1.547e-12	6.21e-13	2.493	0.013	3.3e-13	2.76e-12

Volume.L2	-1.833e-12	6.14e-13	-2.983	0.003	-3.04e-12	-6.27e-13
Volume.L3	1.109e-12	6.33e-13	1.751	0.080	-1.33e-13	2.35e-12
Volume.L4	-1.51e-12	6.51e-13	-2.321	0.020	-2.79e-12	-2.34e-13
Volume.L5	5.39e-13	6.96e-13	0.775	0.439	-8.25e-13	1.9e-12
Volume.L6	-2.871e-15	6.95e-13	-0.004	0.997	-1.37e-12	1.36e-12
Volume.L7	2.698e-13	6.88e-13	0.392	0.695	-1.08e-12	1.62e-12
Volume.L8	1.899e-13	5.06e-13	0.375	0.708	-8.03e-13	1.18e-12
RSI.L0	0.0015	0.000	3.181	0.001	0.001	0.002
RSI.L1	-0.0010	0.001	-1.639	0.101	-0.002	0.000
RSI.L2	-0.0002	0.001	-0.365	0.715	-0.001	0.001
RSI.L3	0.0009	0.001	1.404	0.160	-0.000	0.002
RSI.L4	7.169e-05	0.001	0.115	0.909	-0.001	0.001
RSI.L5	0.0004	0.001	0.659	0.510	-0.001	0.002
RSI.L6	-0.0007	0.001	-1.086	0.278	-0.002	0.001

RSI.L7	0.0002	0.001	0.296	0.767	-0.001	0.001
RSI.L8	-7.64e-05	0.000	-0.164	0.870	-0.001	0.001
RSI Condition.L0	0.0033	0.004	0.800	0.424	-0.005	0.011
RSI Condition.L1	-0.0040	0.004	-0.914	0.361	-0.013	0.005
RSI Condition.L2	-0.0052	0.004	-1.174	0.241	-0.014	0.004
RSI Condition.L3	0.0142	0.004	3.169	0.002	0.005	0.023
RSI Condition.L4	0.0031	0.005	0.684	0.494	-0.006	0.012
RSI Condition.L5	-0.0018	0.005	-0.390	0.697	-0.011	0.007
RSI Condition.L6	-0.0063	0.004	-1.410	0.159	-0.015	0.002
RSI Condition.L7	0.0020	0.004	0.453	0.650	-0.007	0.011
RSI Condition.L8	0.0018	0.004	0.421	0.674	-0.006	0.010
MACD Condition.L0	0.0278	0.004	7.070	0.000	0.020	0.035
MACD Condition.L1	0.0043	0.004	1.037	0.300	-0.004	0.012
MACD Condition.L2	0.0091	0.004	2.174	0.030	0.001	0.017

MACD Condition.L3	0.0023	0.004	0.556	0.578	-0.006	0.011
MACD Condition.L4	0.0121	0.004	2.899	0.004	0.004	0.020
MACD Condition.L5	0.0042	0.004	1.014	0.311	-0.004	0.012
MACD Condition.L6	0.0058	0.004	1.402	0.161	-0.002	0.014
MACD Condition.L7	0.0036	0.004	0.888	0.375	-0.004	0.012
MACD Condition.L8	-0.0012	0.004	-0.317	0.751	-0.009	0.006
EMA Condition.L0	-0.0008	0.003	-0.257	0.797	-0.007	0.005
EMA Condition.L1	0.0002	0.003	0.072	0.943	-0.006	0.006
EMA Condition.L2	-0.0002	0.003	-0.060	0.952	-0.006	0.006
EMA Condition.L3	-0.0071	0.003	-2.260	0.024	-0.013	-0.001
EMA Condition.L4	-0.0002	0.003	-0.076	0.940	-0.006	0.006
EMA Condition.L5	-0.0023	0.003	-0.739	0.460	-0.009	0.004
EMA Condition.L6	-7.363e-05	0.003	-0.023	0.981	-0.006	0.006
EMA Condition.L7	-0.0036	0.003	-1.160	0.246	-0.010	0.003

EMA Condition.L8	0.0026	0.003	0.903	0.367	-0.003	0.008
Close-EMA200 Price Diff.L0	0.0051	0.003	1.540	0.124	-0.001	0.012
Close-EMA200 Price Diff.L1	-0.0076	0.007	-1.135	0.256	-0.021	0.006
Close-EMA200 Price Diff.L2	0.0062	0.008	0.788	0.431	-0.009	0.022
Close-EMA200 Price Diff.L3	-0.0018	0.008	-0.242	0.809	-0.017	0.013
Close-EMA200 Price Diff.L4	-0.0045	0.006	-0.803	0.422	-0.015	0.006
Close-EMA200 Price Diff.L5	0.0015	0.005	0.286	0.775	-0.009	0.011
Close-EMA200 Price Diff.L6	-0.0038	0.007	-0.527	0.599	-0.018	0.010
Close-EMA200 Price Diff.L7	0.0051	0.008	0.607	0.544	-0.011	0.022
Close-EMA200 Price Diff.L8	-0.0001	0.004	-0.026	0.979	-0.009	0.009
BB Condition.L0	-0.0010	0.004	-0.280	0.780	-0.008	0.006
BB Condition.L1	0.0060	0.004	1.534	0.125	-0.002	0.014
BB Condition.L2	-0.0035	0.004	-0.897	0.370	-0.011	0.004
BB Condition.L3	0.0022	0.004	0.568	0.570	-0.006	0.010

	coef	std err	z	P>|z|	[0.025	0.975]
BB Condition.L4	-0.0095	0.004	-2.390	0.017	-0.017	-0.002
BB Condition.L5	0.0036	0.004	0.901	0.368	-0.004	0.011
BB Condition.L6	0.0055	0.004	1.380	0.168	-0.002	0.013
BB Condition.L7	0.0028	0.004	0.714	0.475	-0.005	0.011
BB Condition.L8	-0.0018	0.004	-0.510	0.610	-0.009	0.005
ATR.L0	0.0001	7.26e-05	1.432	0.152	-3.84e-05	0.000
ATR.L1	-0.0002	0.000	-1.925	0.054	-0.000	4.29e-06
ATR.L2	0.0002	0.000	2.089	0.037	1.52e-05	0.000
ATR.L3	-0.0001	0.000	-1.104	0.270	-0.000	0.000
ATR.L4	0.0002	0.000	1.361	0.174	-7.29e-05	0.000
ATR.L5	-0.0003	0.000	-2.170	0.030	-0.001	-2.53e-05
ATR.L6	0.0003	0.000	2.669	0.008	8.84e-05	0.001
ATR.L7	-0.0002	0.000	-1.656	0.098	-0.000	3.83e-05
ATR.L8	-2.269e-05	7.49e-05	-0.303	0.762	-0.000	0.000

Trend.L0	-0.0051	0.004	-1.214	0.225	-0.013	0.003
Trend.L1	0.0063	0.005	1.283	0.200	-0.003	0.016
Trend.L2	0.0088	0.005	1.735	0.083	-0.001	0.019
Trend.L3	0.0064	0.005	1.260	0.208	-0.004	0.016
Trend.L4	-0.0129	0.005	-2.545	0.011	-0.023	-0.003
Trend.L5	-0.0014	0.005	-0.273	0.785	-0.011	0.009
Trend.L6	0.0005	0.005	0.107	0.915	-0.009	0.011
Trend.L7	0.0044	0.005	0.890	0.373	-0.005	0.014
Trend.L8	-0.0029	0.004	-0.691	0.490	-0.011	0.005
Forecasted.L0	0.0008	0.000	1.913	0.056	-2.08e-05	0.002
Forecasted.L1	-0.0007	0.001	-0.883	0.377	-0.002	0.001
Forecasted.L2	0.0009	0.001	0.992	0.322	-0.001	0.003
Forecasted.L3	-0.0009	0.001	-1.113	0.266	-0.003	0.001
Forecasted.L4	-0.0006	0.001	-0.887	0.375	-0.002	0.001

Forecasted.L5	0.0006	0.001	0.773	0.440	-0.001	0.002
Forecasted.L6	-0.0007	0.001	-0.699	0.485	-0.003	0.001
Forecasted.L7	0.0008	0.001	0.752	0.452	-0.001	0.003
Forecasted.L8	-0.0002	0.001	-0.304	0.762	-0.001	0.001
Slope.L0	-0.0046	0.003	-1.821	0.069	-0.010	0.000
Slope.L1	0.0034	0.004	0.773	0.440	-0.005	0.012
Slope.L2	-0.0044	0.005	-0.883	0.377	-0.014	0.005
Slope.L3	0.0043	0.005	0.915	0.360	-0.005	0.014
Slope.L4	0.0033	0.004	0.942	0.346	-0.004	0.010
Slope.L5	-0.0027	0.004	-0.746	0.456	-0.010	0.004
Slope.L6	0.0032	0.005	0.634	0.526	-0.007	0.013
Slope.L7	-0.0037	0.006	-0.647	0.518	-0.015	0.007
Slope.L8	0.0008	0.003	0.294	0.768	-0.005	0.006
Acceleration.L0	0.0077	0.006	1.234	0.218	-0.005	0.020

Acceleration.L1	-0.0096	0.013	-0.726	0.468	-0.035	0.016
Acceleration.L2	0.0035	0.015	0.227	0.821	-0.027	0.034
Acceleration.L3	-0.0006	0.014	-0.044	0.965	-0.029	0.028
Acceleration.L4	0.0053	0.011	0.488	0.626	-0.016	0.027
Acceleration.L5	-0.0096	0.009	-1.097	0.273	-0.027	0.008
Acceleration.L6	0.0052	0.011	0.474	0.635	-0.016	0.027
Acceleration.L7	-0.0004	0.010	-0.036	0.971	-0.021	0.020
Acceleration.L8	0.0002	0.004	0.061	0.951	-0.007	0.008

Model with Lag = 6

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6)	Log Likelihood	3451.582
Method:	Conditional MLE	S.D. of innovations	0.037
Date:	Wed, 17 Nov 2021	AIC	-6705.165
Time:	12:22:05	BIC	-6159.578
Sample:	6	HQIC	-6503.924
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0473	0.013	-3.542	0.000	-0.074	-0.021
future_price1 % P/L.L1	-0.2737	0.070	-3.932	0.000	-0.410	-0.137
future_price1 % P/L.L2	-0.0650	0.070	-0.929	0.353	-0.202	0.072
future_price1 % P/L.L3	-0.0704	0.070	-1.007	0.314	-0.208	0.067
future_price1 % P/L.L4	-0.0840	0.070	-1.199	0.231	-0.221	0.053
future_price1 % P/L.L5	-0.1528	0.070	-2.183	0.029	-0.290	-0.015
future_price1 % P/L.L6	-0.0450	0.070	-0.643	0.520	-0.182	0.092

Close.L0	-0.0027	0.003	-0.919	0.358	-0.008	0.003
Close.L1	0.0021	0.006	0.366	0.714	-0.009	0.013
Close.L2	0.0015	0.005	0.317	0.751	-0.008	0.011
Close.L3	-0.0046	0.003	-1.542	0.123	-0.010	0.001
Close.L4	0.0040	0.004	1.109	0.267	-0.003	0.011
Close.L5	0.0033	0.005	0.704	0.482	-0.006	0.012
Close.L6	-0.0036	0.003	-1.161	0.246	-0.010	0.002
Volume.L0	-6.048e-13	5.14e-13	-1.178	0.239	-1.61e-12	4.02e-13
Volume.L1	1.565e-12	6.04e-13	2.590	0.010	3.8e-13	2.75e-12
Volume.L2	-1.901e-12	6.05e-13	-3.142	0.002	-3.09e-12	-7.14e-13
Volume.L3	8.967e-13	6.2e-13	1.446	0.148	-3.2e-13	2.11e-12
Volume.L4	-1.551e-12	6.31e-13	-2.457	0.014	-2.79e-12	-3.13e-13
Volume.L5	3.872e-13	6.68e-13	0.579	0.562	-9.24e-13	1.7e-12
Volume.L6	9.909e-13	4.93e-13	2.011	0.045	2.43e-14	1.96e-12

RSI.L0	0.0015	0.000	3.170	0.002	0.001	0.002
RSI.L1	-0.0009	0.001	-1.527	0.127	-0.002	0.000
RSI.L2	-0.0002	0.001	-0.395	0.693	-0.001	0.001
RSI.L3	0.0009	0.001	1.504	0.133	-0.000	0.002
RSI.L4	-7.753e-06	0.001	-0.013	0.990	-0.001	0.001
RSI.L5	0.0005	0.001	0.779	0.436	-0.001	0.002
RSI.L6	-0.0007	0.000	-1.622	0.105	-0.002	0.000
RSI Condition.L0	0.0033	0.004	0.802	0.423	-0.005	0.011
RSI Condition.L1	-0.0040	0.004	-0.921	0.357	-0.013	0.005
RSI Condition.L2	-0.0048	0.004	-1.087	0.277	-0.014	0.004
RSI Condition.L3	0.0139	0.004	3.130	0.002	0.005	0.023
RSI Condition.L4	0.0033	0.004	0.747	0.455	-0.005	0.012
RSI Condition.L5	-0.0018	0.004	-0.410	0.682	-0.010	0.007
RSI Condition.L6	-0.0050	0.004	-1.206	0.228	-0.013	0.003

MACD Condition.L0	0.0273	0.004	7.064	0.000	0.020	0.035
MACD Condition.L1	0.0050	0.004	1.238	0.216	-0.003	0.013
MACD Condition.L2	0.0092	0.004	2.261	0.024	0.001	0.017
MACD Condition.L3	0.0014	0.004	0.355	0.723	-0.007	0.009
MACD Condition.L4	0.0120	0.004	2.971	0.003	0.004	0.020
MACD Condition.L5	0.0035	0.004	0.883	0.378	-0.004	0.011
MACD Condition.L6	0.0046	0.004	1.179	0.238	-0.003	0.012
EMA Condition.L0	-0.0008	0.003	-0.275	0.783	-0.007	0.005
EMA Condition.L1	0.0006	0.003	0.179	0.858	-0.006	0.007
EMA Condition.L2	-0.0005	0.003	-0.173	0.863	-0.007	0.006
EMA Condition.L3	-0.0075	0.003	-2.407	0.016	-0.014	-0.001
EMA Condition.L4	0.0003	0.003	0.100	0.920	-0.006	0.006
EMA Condition.L5	-0.0025	0.003	-0.823	0.411	-0.009	0.004
EMA Condition.L6	-0.0010	0.003	-0.335	0.738	-0.007	0.005

Close-EMA200 Price Diff.L0	0.0027	0.003	0.915	0.360	-0.003	0.008
Close-EMA200 Price Diff.L1	-0.0021	0.006	-0.377	0.706	-0.013	0.009
Close-EMA200 Price Diff.L2	-0.0015	0.005	-0.329	0.742	-0.011	0.008
Close-EMA200 Price Diff.L3	0.0046	0.003	1.558	0.119	-0.001	0.010
Close-EMA200 Price Diff.L4	-0.0039	0.004	-1.099	0.272	-0.011	0.003
Close-EMA200 Price Diff.L5	-0.0033	0.005	-0.705	0.481	-0.012	0.006
Close-EMA200 Price Diff.L6	0.0036	0.003	1.163	0.245	-0.002	0.010
BB Condition.L0	-0.0013	0.004	-0.347	0.728	-0.009	0.006
BB Condition.L1	0.0059	0.004	1.509	0.131	-0.002	0.014
BB Condition.L2	-0.0032	0.004	-0.808	0.419	-0.011	0.005
BB Condition.L3	0.0030	0.004	0.774	0.439	-0.005	0.011
BB Condition.L4	-0.0098	0.004	-2.500	0.013	-0.018	-0.002
BB Condition.L5	0.0039	0.004	0.990	0.322	-0.004	0.012
BB Condition.L6	0.0062	0.004	1.748	0.081	-0.001	0.013

	coef	std err	z	P>|z|	[0.025	0.975]
ATR.L0	0.0001	7.09e-05	1.496	0.135	-3.3e-05	0.000
ATR.L1	-0.0002	0.000	-1.992	0.047	-0.000	-3.52e-06
ATR.L2	0.0003	0.000	2.196	0.028	2.75e-05	0.000
ATR.L3	-0.0001	0.000	-0.969	0.333	-0.000	0.000
ATR.L4	0.0002	0.000	1.411	0.159	-6.55e-05	0.000
ATR.L5	-0.0002	0.000	-2.079	0.038	-0.000	-1.38e-05
ATR.L6	5.629e-05	7.1e-05	0.792	0.428	-8.3e-05	0.000
Trend.L0	-0.0040	0.004	-0.970	0.332	-0.012	0.004
Trend.L1	0.0059	0.005	1.220	0.223	-0.004	0.015
Trend.L2	0.0079	0.005	1.580	0.114	-0.002	0.018
Trend.L3	0.0068	0.005	1.352	0.177	-0.003	0.017
Trend.L4	-0.0132	0.005	-2.639	0.008	-0.023	-0.003
Trend.L5	-0.0013	0.005	-0.258	0.796	-0.011	0.008
Trend.L6	0.0019	0.004	0.449	0.654	-0.006	0.010

Forecasted.L0	0.0004	0.000	1.069	0.285	-0.000	0.001
Forecasted.L1	2.815e-05	0.001	0.044	0.965	-0.001	0.001
Forecasted.L2	-6.046e-05	0.001	-0.119	0.905	-0.001	0.001
Forecasted.L3	-0.0003	0.000	-0.862	0.389	-0.001	0.000
Forecasted.L4	-0.0003	0.000	-0.628	0.530	-0.001	0.001
Forecasted.L5	-0.0001	0.001	-0.207	0.836	-0.001	0.001
Forecasted.L6	0.0004	0.000	0.976	0.329	-0.000	0.001
Slope.L0	-0.0021	0.002	-0.917	0.359	-0.007	0.002
Slope.L1	-0.0007	0.004	-0.193	0.847	-0.008	0.007
Slope.L2	0.0011	0.003	0.376	0.707	-0.004	0.007
Slope.L3	0.0007	0.002	0.387	0.699	-0.003	0.005
Slope.L4	0.0019	0.003	0.750	0.454	-0.003	0.007
Slope.L5	0.0006	0.003	0.171	0.864	-0.006	0.007
Slope.L6	-0.0017	0.002	-0.865	0.387	-0.006	0.002

Acceleration.L0	0.0014	0.005	0.268	0.789	-0.009	0.011
Acceleration.L1	0.0028	0.011	0.260	0.795	-0.018	0.024
Acceleration.L2	-0.0111	0.010	-1.142	0.254	-0.030	0.008
Acceleration.L3	0.0109	0.007	1.485	0.138	-0.003	0.025
Acceleration.L4	0.0016	0.007	0.216	0.829	-0.013	0.016
Acceleration.L5	-0.0103	0.007	-1.528	0.127	-0.024	0.003
Acceleration.L6	0.0055	0.003	2.006	0.045	0.000	0.011

Model with Lag = 4

Dep. Variable:	future_price1 % P/L	**No. Observations:**	1834
Model:	ARDL(4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4)	**Log Likelihood**	3430.389
Method:	Conditional MLE	**S.D. of innovations**	0.037
Date:	Wed, 17 Nov 2021	**AIC**	-6718.777
Time:	12:22:17	**BIC**	-6327.420
Sample:	4	**HQIC**	-6574.433
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0358	0.012	-3.029	0.002	-0.059	-0.013
future_price1 % P/L.L1	-0.2732	0.069	-3.972	0.000	-0.408	-0.138
future_price1 % P/L.L2	-0.0446	0.070	-0.641	0.522	-0.181	0.092
future_price1 % P/L.L3	-0.0597	0.070	-0.856	0.392	-0.197	0.077
future_price1 % P/L.L4	-0.0758	0.070	-1.087	0.277	-0.212	0.061
Close.L0	-0.0008	0.002	-0.556	0.578	-0.004	0.002
Close.L1	0.0007	0.002	0.298	0.766	-0.004	0.006
Close.L2	0.0011	0.003	0.415	0.678	-0.004	0.006
Close.L3	-0.0030	0.003	-1.096	0.273	-0.009	0.002
Close.L4	0.0020	0.002	1.156	0.248	-0.001	0.005
Volume.L0	-4.8e-13	5.01e-13	-0.959	0.338	-1.46e-12	5.02e-13
Volume.L1	1.515e-12	5.83e-13	2.600	0.009	3.72e-13	2.66e-12
Volume.L2	-1.715e-12	5.71e-13	-3.004	0.003	-2.83e-12	-5.95e-13

Volume.L3	9.99e-13	5.87e-13	1.703	0.089	-1.52e-13	2.15e-12
Volume.L4	-4.745e-13	4.41e-13	-1.076	0.282	-1.34e-12	3.91e-13
RSI.L0	0.0015	0.000	3.134	0.002	0.001	0.002
RSI.L1	-0.0011	0.001	-1.726	0.085	-0.002	0.000
RSI.L2	-0.0002	0.001	-0.269	0.788	-0.001	0.001
RSI.L3	0.0009	0.001	1.512	0.131	-0.000	0.002
RSI.L4	-0.0004	0.000	-0.931	0.352	-0.001	0.000
RSI Condition.L0	0.0024	0.004	0.591	0.555	-0.006	0.010
RSI Condition.L1	-0.0029	0.004	-0.665	0.506	-0.011	0.006
RSI Condition.L2	-0.0049	0.004	-1.122	0.262	-0.014	0.004
RSI Condition.L3	0.0126	0.004	2.880	0.004	0.004	0.021
RSI Condition.L4	0.0006	0.004	0.151	0.880	-0.007	0.009
MACD Condition.L0	0.0274	0.004	7.163	0.000	0.020	0.035
MACD Condition.L1	0.0039	0.004	0.995	0.320	-0.004	0.012

MACD Condition.L2	0.0089	0.004	2.220	0.027	0.001	0.017
MACD Condition.L3	0.0006	0.004	0.153	0.879	-0.007	0.008
MACD Condition.L4	0.0101	0.004	2.645	0.008	0.003	0.018
EMA Condition.L0	-0.0010	0.003	-0.315	0.753	-0.007	0.005
EMA Condition.L1	0.0004	0.003	0.140	0.889	-0.006	0.007
EMA Condition.L2	-0.0001	0.003	-0.046	0.963	-0.006	0.006
EMA Condition.L3	-0.0079	0.003	-2.556	0.011	-0.014	-0.002
EMA Condition.L4	0.0003	0.003	0.089	0.929	-0.005	0.006
Close-EMA200 Price Diff.L0	0.0008	0.001	0.561	0.575	-0.002	0.004
Close-EMA200 Price Diff.L1	-0.0008	0.002	-0.309	0.757	-0.006	0.004
Close-EMA200 Price Diff.L2	-0.0011	0.003	-0.435	0.663	-0.006	0.004
Close-EMA200 Price Diff.L3	0.0031	0.003	1.112	0.266	-0.002	0.009
Close-EMA200 Price Diff.L4	-0.0020	0.002	-1.156	0.248	-0.005	0.001
BB Condition.L0	-0.0020	0.004	-0.549	0.583	-0.009	0.005

BB Condition.L1	0.0066	0.004	1.703	0.089	-0.001	0.014
BB Condition.L2	-0.0042	0.004	-1.065	0.287	-0.012	0.003
BB Condition.L3	0.0041	0.004	1.052	0.293	-0.004	0.012
BB Condition.L4	-0.0065	0.004	-1.835	0.067	-0.013	0.000
ATR.L0	0.0001	7e-05	1.673	0.094	-2.02e-05	0.000
ATR.L1	-0.0003	0.000	-2.239	0.025	-0.000	-3.14e-05
ATR.L2	0.0003	0.000	2.248	0.025	3.32e-05	0.000
ATR.L3	-5.636e-05	0.000	-0.490	0.624	-0.000	0.000
ATR.L4	-6.226e-05	6.93e-05	-0.898	0.369	-0.000	7.37e-05
Trend.L0	-0.0037	0.004	-0.889	0.374	-0.012	0.004
Trend.L1	0.0064	0.005	1.308	0.191	-0.003	0.016
Trend.L2	0.0083	0.005	1.668	0.095	-0.001	0.018
Trend.L3	0.0031	0.005	0.645	0.519	-0.006	0.013
Trend.L4	-0.0111	0.004	-2.698	0.007	-0.019	-0.003

Forecasted.L0	7.919e-05	0.000	0.356	0.722	-0.000	0.001
Forecasted.L1	7.475e-05	0.000	0.241	0.809	-0.001	0.001
Forecasted.L2	0.0001	0.000	0.393	0.695	-0.001	0.001
Forecasted.L3	-0.0004	0.000	-1.117	0.264	-0.001	0.000
Forecasted.L4	0.0001	0.000	0.675	0.500	-0.000	0.001
Slope.L0	-0.0003	0.001	-0.211	0.833	-0.003	0.002
Slope.L1	-0.0009	0.002	-0.516	0.606	-0.004	0.002
Slope.L2	0.0001	0.002	0.064	0.949	-0.003	0.004
Slope.L3	0.0013	0.002	0.730	0.465	-0.002	0.005
Slope.L4	-0.0006	0.001	-0.580	0.562	-0.003	0.001
Acceleration.L0	-0.0003	0.003	-0.110	0.913	-0.006	0.005
Acceleration.L1	0.0035	0.006	0.582	0.561	-0.008	0.015
Acceleration.L2	-0.0086	0.007	-1.290	0.197	-0.022	0.004
Acceleration.L3	0.0072	0.006	1.177	0.240	-0.005	0.019

Acceleration.L4	-0.0018	0.003	-0.703	0.482	-0.007	0.003

Model with Lag = 2

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2)	Log Likelihood	3400.721
Method:	Conditional MLE	S.D. of innovations	0.038
Date:	Wed, 17 Nov 2021	AIC	-6715.441
Time:	12:22:39	BIC	-6478.375
Sample:	2	HQIC	-6628.009
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0201	0.010	-1.962	0.050	-0.040	-6.43e-06
future_price1 % P/L.L1	-0.3004	0.069	-4.365	0.000	-0.435	-0.165
future_price1 % P/L.L2	-0.0452	0.070	-0.649	0.516	-0.182	0.091
Close.L0	-0.0006	0.001	-0.405	0.685	-0.004	0.002
Close.L1	0.0014	0.002	0.593	0.553	-0.003	0.006
Close.L2	-0.0008	0.002	-0.538	0.591	-0.004	0.002
Volume.L0	-4.797e-13	4.46e-13	-1.076	0.282	-1.35e-12	3.95e-13

Volume.L1	8.115e-13	5.51e-13	1.473	0.141	-2.69e-13	1.89e-12
Volume.L2	-3.887e-13	4.12e-13	-0.943	0.346	-1.2e-12	4.19e-13
RSI.L0	0.0017	0.000	3.567	0.000	0.001	0.003
RSI.L1	-0.0010	0.001	-1.714	0.087	-0.002	0.000
RSI.L2	-0.0002	0.000	-0.428	0.668	-0.001	0.001
RSI Condition.L0	0.0041	0.004	0.993	0.321	-0.004	0.012
RSI Condition.L1	-0.0014	0.004	-0.331	0.741	-0.010	0.007
RSI Condition.L2	-0.0012	0.004	-0.292	0.770	-0.009	0.007
MACD Condition.L0	0.0265	0.004	6.979	0.000	0.019	0.034
MACD Condition.L1	0.0026	0.004	0.659	0.510	-0.005	0.010
MACD Condition.L2	0.0083	0.004	2.154	0.031	0.001	0.016
EMA Condition.L0	-0.0011	0.003	-0.347	0.729	-0.007	0.005
EMA Condition.L1	-0.0005	0.003	-0.151	0.880	-0.007	0.006
EMA Condition.L2	-0.0016	0.003	-0.546	0.585	-0.007	0.004

Close-EMA200 Price Diff.L0	0.0006	0.001	0.406	0.685	-0.002	0.004
Close-EMA200 Price Diff.L1	-0.0014	0.002	-0.602	0.547	-0.006	0.003
Close-EMA200 Price Diff.L2	0.0008	0.002	0.535	0.593	-0.002	0.004
BB Condition.L0	-0.0032	0.004	-0.866	0.387	-0.010	0.004
BB Condition.L1	0.0073	0.004	1.901	0.058	-0.000	0.015
BB Condition.L2	-0.0045	0.004	-1.287	0.198	-0.011	0.002
ATR.L0	0.0001	6.73e-05	1.929	0.054	-2.19e-06	0.000
ATR.L1	-0.0002	0.000	-1.738	0.082	-0.000	2.49e-05
ATR.L2	7.659e-05	6.64e-05	1.153	0.249	-5.37e-05	0.000
Trend.L0	-0.0033	0.004	-0.814	0.416	-0.011	0.005
Trend.L1	0.0041	0.005	0.861	0.389	-0.005	0.013
Trend.L2	0.0016	0.004	0.386	0.699	-0.006	0.010
Forecasted.L0	0.0001	0.000	0.466	0.642	-0.000	0.001
Forecasted.L1	-0.0001	0.000	-0.398	0.691	-0.001	0.000

Forecasted.L2	3.522e-05	0.000	0.180	0.857	-0.000	0.000
Slope.L0	-0.0003	0.001	-0.282	0.778	-0.003	0.002
Slope.L1	0.0005	0.002	0.293	0.769	-0.003	0.004
Slope.L2	-0.0002	0.001	-0.171	0.864	-0.002	0.002
Acceleration.L0	-0.0014	0.003	-0.475	0.635	-0.007	0.004
Acceleration.L1	0.0018	0.005	0.365	0.715	-0.008	0.012
Acceleration.L2	-0.0008	0.002	-0.322	0.748	-0.005	0.004

Model with Lag = 1

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)	Log Likelihood	3397.861
Method:	Conditional MLE	S.D. of innovations	0.038
Date:	Wed, 17 Nov 2021	AIC	-6737.721
Time:	12:23:07	BIC	-6577.824
Sample:	1	HQIC	-6678.751
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0191	0.009	-2.056	0.040	-0.037	-0.001
future_price1 % P/L.L1	-0.3048	0.068	-4.473	0.000	-0.438	-0.171
Close.L0	-0.0009	0.001	-0.691	0.489	-0.004	0.002
Close.L1	0.0009	0.001	0.681	0.496	-0.002	0.003
Volume.L0	-4.047e-13	4.1e-13	-0.988	0.324	-1.21e-12	3.99e-13
Volume.L1	3.133e-13	3.99e-13	0.786	0.432	-4.68e-13	1.1e-12
RSI.L0	0.0017	0.000	3.666	0.000	0.001	0.003

RSI.L1	-0.0013	0.000	-2.931	0.003	-0.002	-0.000
RSI Condition.L0	0.0038	0.004	0.947	0.344	-0.004	0.012
RSI Condition.L1	-0.0026	0.004	-0.659	0.510	-0.010	0.005
MACD Condition.L0	0.0259	0.004	6.922	0.000	0.019	0.033
MACD Condition.L1	0.0012	0.004	0.307	0.759	-0.006	0.009
EMA Condition.L0	-0.0008	0.003	-0.260	0.795	-0.007	0.005
EMA Condition.L1	-6.605e-05	0.003	-0.024	0.981	-0.006	0.005
Close-EMA200 Price Diff.L0	0.0009	0.001	0.692	0.489	-0.002	0.004
Close-EMA200 Price Diff.L1	-0.0009	0.001	-0.693	0.488	-0.003	0.002
BB Condition.L0	-0.0033	0.004	-0.911	0.362	-0.010	0.004
BB Condition.L1	0.0060	0.003	1.712	0.087	-0.001	0.013
ATR.L0	0.0001	5.97e-05	1.830	0.067	-7.86e-06	0.000
ATR.L1	-9.795e-05	5.97e-05	-1.640	0.101	-0.000	1.92e-05
Trend.L0	-0.0029	0.004	-0.757	0.449	-0.011	0.005

Trend.L1	0.0044	0.004	1.139	0.255	-0.003	0.012
Forecasted.L0	0.0002	0.000	0.698	0.485	-0.000	0.001
Forecasted.L1	-0.0001	0.000	-0.667	0.505	-0.000	0.000
Slope.L0	-0.0007	0.001	-0.563	0.574	-0.003	0.002
Slope.L1	0.0005	0.001	0.559	0.576	-0.001	0.002
Acceleration.L0	-0.0004	0.001	-0.713	0.476	-0.001	0.001
Acceleration.L1	0.0002	0.001	0.359	0.720	-0.001	0.001

Annex A – Main ADL Models

AR(1)-BH(1), Trend = Constant Trend, Causal = True

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)	Log Likelihood	3358.975
Method:	Conditional MLE	S.D. of innovations	0.039
Date:	Fri, 12 Nov 2021	AIC	-6685.951
Time:	23:59:24	BIC	-6597.732
Sample:	1	HQIC	-6653.416
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0044	0.008	-0.529	0.597	-0.021	0.012
future_price1 % P/L.L1	-0.0305	0.024	-1.280	0.201	-0.077	0.016
Close.L1	-5.289e-07	3.08e-06	-0.171	0.864	-6.58e-06	5.52e-06
Volume.L1	-3.38e-15	1.25e-13	-0.027	0.978	-2.48e-13	2.41e-13
RSI.L1	0.0002	0.000	0.975	0.330	-0.000	0.000
RSI Condition.L1	-0.0006	0.004	-0.181	0.857	-0.008	0.006
MACD Condition.L1	-0.0007	0.004	-0.176	0.860	-0.008	0.007
EMA Condition.L1	0.0018	0.003	0.666	0.506	-0.003	0.007
Close-EMA200 Price Diff.L1	-1.655e-06	1.11e-06	-1.498	0.134	-3.82e-06	5.13e-07
BB Condition.L1	0.0039	0.003	1.227	0.220	-0.002	0.010
ATR.L1	1.153e-05	7.09e-06	1.625	0.104	-2.38e-06	2.54e-05
Trend.L1	0.0007	0.002	0.442	0.658	-0.002	0.004
Forecasted.L1	-3.745e-07	3.12e-06	-0.120	0.904	-6.48e-06	5.74e-06
Slope.L1	3.41e-05	2.49e-05	1.371	0.170	-1.47e-05	8.29e-05
Acceleration.L1	-0.0002	0.000	-1.353	0.176	-0.000	8.28e-05

AR(1)-BH(1), Trend = Constant Trend, Causal = False

	coef	std err	z	P>|z|	[0.025	0.975]
Dep. Variable:	future_price1 % P/L			**No. Observations:**		1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)			**Log Likelihood**		3397.861
Method:	Conditional MLE			**S.D. of innovations**		0.038
Date:	Fri, 12 Nov 2021			**AIC**		-6737.721
Time:	19:00:08			**BIC**		-6577.824
Sample:	1			**HQIC**		-6678.751
	1834					

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0191	0.009	-2.056	0.040	-0.037	-0.001
future_price1 % P/L.L1	-0.3048	0.068	-4.473	0.000	-0.438	-0.171
Close.L0	-0.0009	0.001	-0.691	0.489	-0.004	0.002
Close.L1	0.0009	0.001	0.681	0.496	-0.002	0.003
Volume.L0	-4.047e-13	4.1e-13	-0.988	0.324	-1.21e-12	3.99e-13
Volume.L1	3.133e-13	3.99e-13	0.786	0.432	-4.68e-13	1.1e-12
RSI.L0	0.0017	0.000	3.666	0.000	0.001	0.003
RSI.L1	-0.0013	0.000	-2.931	0.003	-0.002	-0.000
RSI Condition.L0	0.0038	0.004	0.947	0.344	-0.004	0.012
RSI Condition.L1	-0.0026	0.004	-0.659	0.510	-0.010	0.005
MACD Condition.L0	0.0259	0.004	6.922	0.000	0.019	0.033
MACD Condition.L1	0.0012	0.004	0.307	0.759	-0.006	0.009
EMA Condition.L0	-0.0008	0.003	-0.260	0.795	-0.007	0.005
EMA Condition.L1	-6.605e-05	0.003	-0.024	0.981	-0.006	0.005
Close-EMA200 Price Diff.L0	0.0009	0.001	0.692	0.489	-0.002	0.004
Close-EMA200 Price Diff.L1	-0.0009	0.001	-0.693	0.488	-0.003	0.002
BB Condition.L0	-0.0033	0.004	-0.911	0.362	-0.010	0.004
BB Condition.L1	0.0060	0.003	1.712	0.087	-0.001	0.013
ATR.L0	0.0001	5.97e-05	1.830	0.067	-7.86e-06	0.000
ATR.L1	-9.795e-05	5.97e-05	-1.640	0.101	-0.000	1.92e-05
Trend.L0	-0.0029	0.004	-0.757	0.449	-0.011	0.005
Trend.L1	0.0044	0.004	1.139	0.255	-0.003	0.012
Forecasted.L0	0.0002	0.000	0.696	0.485	-0.000	0.001
Forecasted.L1	-0.0001	0.000	-0.667	0.505	-0.000	0.000
Slope.L0	-0.0007	0.001	-0.563	0.574	-0.003	0.002
Slope.L1	0.0005	0.001	0.559	0.576	-0.001	0.002
Acceleration.L0	-0.0004	0.001	-0.713	0.476	-0.001	0.001
Acceleration.L1	0.0002	0.001	0.359	0.720	-0.001	0.001

AR(1)-BH(1), Trend = No Trend, Causal = False

*This is the base model selected after Section 3.1

Dep. Variable:		future_price1 % P/L	No. Observations:		1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)		Log Likelihood		3395.717
Method:		Conditional MLE	S.D. of innovations		0.038
Date:		Fri, 12 Nov 2021		AIC	-6735.434
Time:		21:10:58		BIC	-6581.050
Sample:		1		HQIC	-6678.497
		1834			

	coef	std err	z	P>|z|	[0.025	0.975]
future_price1 % P/L.L1	-0.2855	0.068	-4.226	0.000	-0.418	-0.153
Close.L0	-0.0009	0.001	-0.710	0.478	-0.004	0.002
Close.L1	0.0009	0.001	0.700	0.484	-0.002	0.004
Volume.L0	-3.766e-13	4.1e-13	-0.919	0.358	-1.18e-12	4.27e-13
Volume.L1	3.116e-13	3.99e-13	0.781	0.435	-4.71e-13	1.09e-12
RSI.L0	0.0014	0.000	3.149	0.002	0.001	0.002
RSI.L1	-0.0013	0.000	-3.001	0.003	-0.002	-0.000
RSI Condition.L0	0.0012	0.004	0.327	0.743	-0.006	0.009
RSI Condition.L1	-0.0050	0.004	-1.315	0.189	-0.013	0.002
MACD Condition.L0	0.0252	0.004	6.757	0.000	0.018	0.032
MACD Condition.L1	0.0005	0.004	0.123	0.902	-0.007	0.008
EMA Condition.L0	0.0012	0.003	0.422	0.673	-0.004	0.007
EMA Condition.L1	0.0019	0.003	0.708	0.479	-0.003	0.007
Close-EMA200 Price Diff.L0	0.0009	0.001	0.711	0.477	-0.002	0.004
Close-EMA200 Price Diff.L1	-0.0009	0.001	-0.713	0.476	-0.004	0.002
BB Condition.L0	-0.0045	0.004	-1.251	0.211	-0.011	0.003
BB Condition.L1	0.0049	0.003	1.419	0.156	-0.002	0.012
ATR.L0	0.0001	5.97e-05	1.741	0.082	-1.31e-05	0.000
ATR.L1	-9.329e-05	5.97e-05	-1.562	0.119	-0.000	2.39e-05
Trend.L0	-0.0031	0.004	-0.790	0.430	-0.011	0.005
Trend.L1	0.0038	0.004	0.981	0.327	-0.004	0.011
Forecasted.L0	0.0001	0.000	0.664	0.507	-0.000	0.001
Forecasted.L1	-0.0001	0.000	-0.633	0.527	-0.000	0.000
Slope.L0	-0.0006	0.001	-0.531	0.595	-0.003	0.002
Slope.L1	0.0005	0.001	0.541	0.589	-0.001	0.002
Acceleration.L0	-0.0004	0.001	-0.821	0.411	-0.001	0.001
Acceleration.L1	0.0002	0.001	0.376	0.707	-0.001	0.001

AR(1)-BH(1), Trend = Time Trend, Causal = False

Dep. Variable:		future_price1 % P/L	No. Observations:	1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)		Log Likelihood	3399.590
Method:		Conditional MLE	S.D. of innovations	0.038
Date:		Fri, 12 Nov 2021	AIC	-6741.180
Time:		21:58:18	BIC	-6581.282
Sample:		1	HQIC	-6682.209
		1834		

|	coef	std err	z	P>|z|	[0.025	0.975]
trend	1.276e-05	4.62e-06	2.765	0.006	3.71e-06	2.18e-05
future_price1 % P/L.L1	-0.2826	0.067	-4.190	0.000	-0.415	-0.150
Close.L0	-0.0009	0.001	-0.652	0.514	-0.003	0.002
Close.L1	0.0008	0.001	0.641	0.522	-0.002	0.003
Volume.L0	-4.51e-13	4.1e-13	-1.100	0.272	-1.26e-12	3.53e-13
Volume.L1	2.031e-13	4e-13	0.508	0.612	-5.82e-13	9.88e-13
RSI.L0	0.0013	0.000	2.987	0.003	0.000	0.002
RSI.L1	-0.0013	0.000	-3.037	0.002	-0.002	-0.000
RSI Condition.L0	0.0007	0.004	0.172	0.863	-0.007	0.008
RSI Condition.L1	-0.0056	0.004	-1.457	0.145	-0.013	0.002
MACD Condition.L0	0.0248	0.004	6.666	0.000	0.018	0.032
MACD Condition.L1	0.0002	0.004	0.064	0.949	-0.007	0.008
EMA Condition.L0	0.0014	0.003	0.504	0.614	-0.004	0.007
EMA Condition.L1	0.0021	0.003	0.811	0.417	-0.003	0.007
Close-EMA200 Price Diff.L0	0.0009	0.001	0.653	0.514	-0.002	0.003
Close-EMA200 Price Diff.L1	-0.0009	0.001	-0.653	0.514	-0.003	0.002
BB Condition.L0	-0.0047	0.004	-1.305	0.192	-0.012	0.002
BB Condition.L1	0.0047	0.003	1.364	0.173	-0.002	0.011
ATR.L0	0.0001	5.96e-05	1.798	0.072	-9.72e-06	0.000
ATR.L1	-8.953e-05	5.96e-05	-1.501	0.134	-0.000	2.75e-05
Trend.L0	-0.0035	0.004	-0.896	0.370	-0.011	0.004
Trend.L1	0.0033	0.004	0.857	0.391	-0.004	0.011
Forecasted.L0	0.0001	0.000	0.627	0.531	-0.000	0.001
Forecasted.L1	-0.0001	0.000	-0.596	0.551	-0.000	0.000
Slope.L0	-0.0006	0.001	-0.491	0.624	-0.003	0.002
Slope.L1	0.0005	0.001	0.504	0.614	-0.001	0.002
Acceleration.L0	-0.0004	0.001	-0.881	0.379	-0.001	0.001
Acceleration.L1	0.0002	0.001	0.435	0.664	-0.001	0.001

AR(1)-BH(1), Trend = Constant and Time Trend, Causal = False

		coef	std err	z	P>|z|	[0.025	0.975]
Dep. Variable:		future_price1 % P/L		No. Observations:			1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)			Log Likelihood			3402.257
Method:		Conditional MLE		S.D. of innovations			0.038
Date:		Fri, 12 Nov 2021		AIC			-6744.514
Time:		23:06:59		BIC			-6579.103
Sample:		1		HQIC			-6683.510
		1834					

|	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0214	0.009	-2.293	0.022	-0.040	-0.003
trend	1.362e-05	4.63e-06	2.945	0.003	4.55e-06	2.27e-05
future_price1 % P/L.L1	-0.3039	0.068	-4.470	0.000	-0.437	-0.171
Close.L0	-0.0008	0.001	-0.627	0.531	-0.003	0.002
Close.L1	0.0008	0.001	0.615	0.538	-0.002	0.003
Volume.L0	-4.874e-13	4.1e-13	-1.189	0.235	-1.29e-12	3.17e-13
Volume.L1	1.976e-13	4e-13	0.494	0.621	-5.86e-13	9.81e-13
RSI.L0	0.0017	0.000	3.592	0.000	0.001	0.003
RSI.L1	-0.0013	0.000	-2.961	0.003	-0.002	-0.000
RSI Condition.L0	0.0035	0.004	0.865	0.387	-0.004	0.011
RSI Condition.L1	-0.0029	0.004	-0.734	0.463	-0.011	0.005
MACD Condition.L0	0.0256	0.004	6.850	0.000	0.018	0.033
MACD Condition.L1	0.0010	0.004	0.266	0.790	-0.006	0.008
EMA Condition.L0	-0.0008	0.003	-0.255	0.799	-0.007	0.005
EMA Condition.L1	-4.077e-06	0.003	-0.001	0.999	-0.005	0.005
Close-EMA200 Price Diff.L0	0.0008	0.001	0.628	0.530	-0.002	0.003
Close-EMA200 Price Diff.L1	-0.0008	0.001	-0.628	0.530	-0.003	0.002
BB Condition.L0	-0.0034	0.004	-0.929	0.353	-0.010	0.004
BB Condition.L1	0.0059	0.003	1.690	0.091	-0.001	0.013
ATR.L0	0.0001	5.96e-05	1.901	0.057	-3.58e-06	0.000
ATR.L1	-9.448e-05	5.96e-05	-1.585	0.113	-0.000	2.24e-05
Trend.L0	-0.0034	0.004	-0.867	0.386	-0.011	0.004
Trend.L1	0.0040	0.004	1.027	0.305	-0.004	0.012
Forecasted.L0	0.0001	0.000	0.662	0.508	-0.000	0.001
Forecasted.L1	-0.0001	0.000	-0.633	0.527	-0.000	0.000
Slope.L0	-0.0006	0.001	-0.524	0.601	-0.003	0.002
Slope.L1	0.0005	0.001	0.522	0.601	-0.001	0.002
Acceleration.L0	-0.0004	0.001	-0.763	0.445	-0.001	0.001
Acceleration.L1	0.0002	0.001	0.420	0.675	-0.001	0.001

Annex – Holding Times

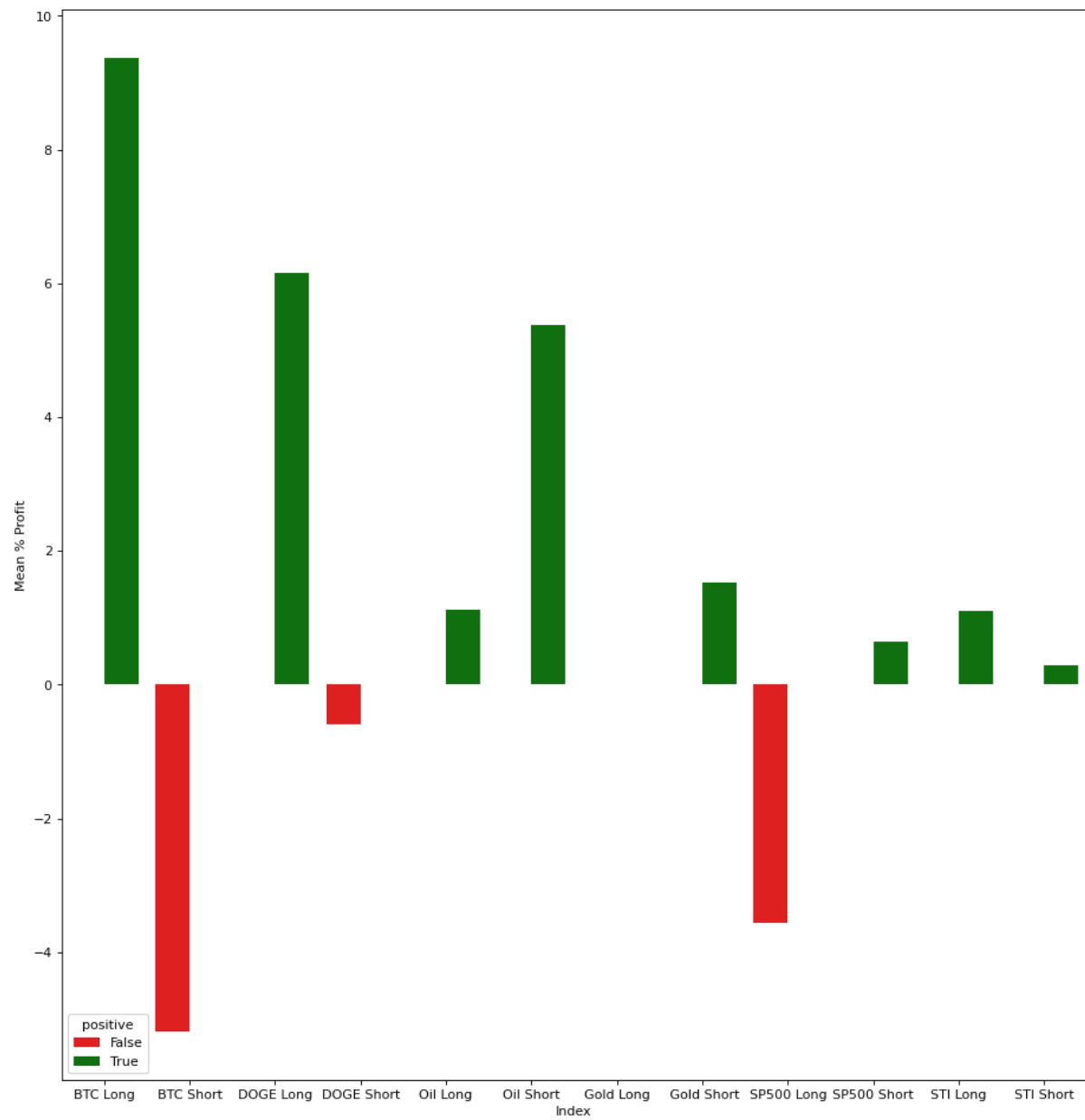**Holding Time = 1 Day**
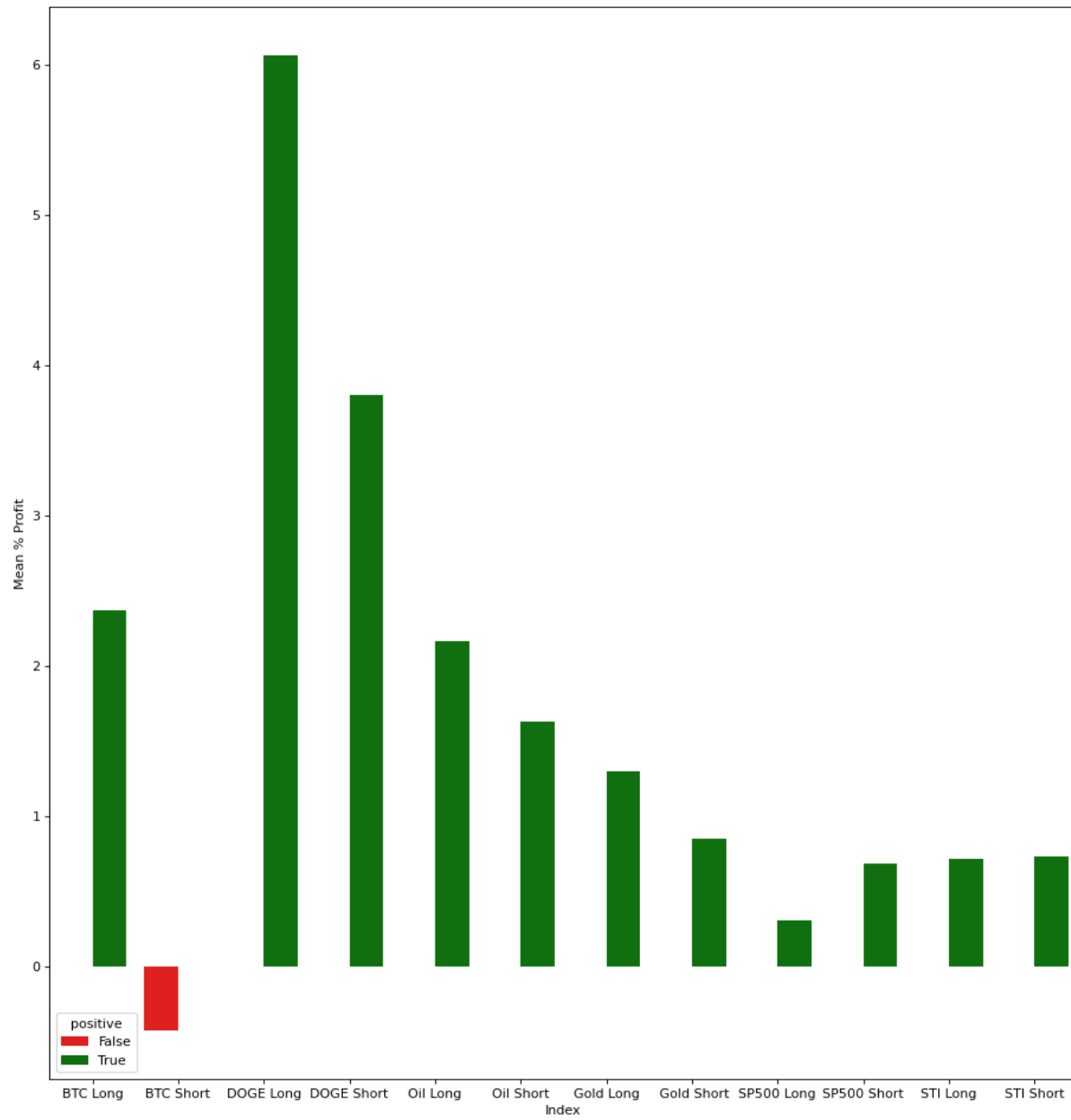
Holding Time = 3 Days
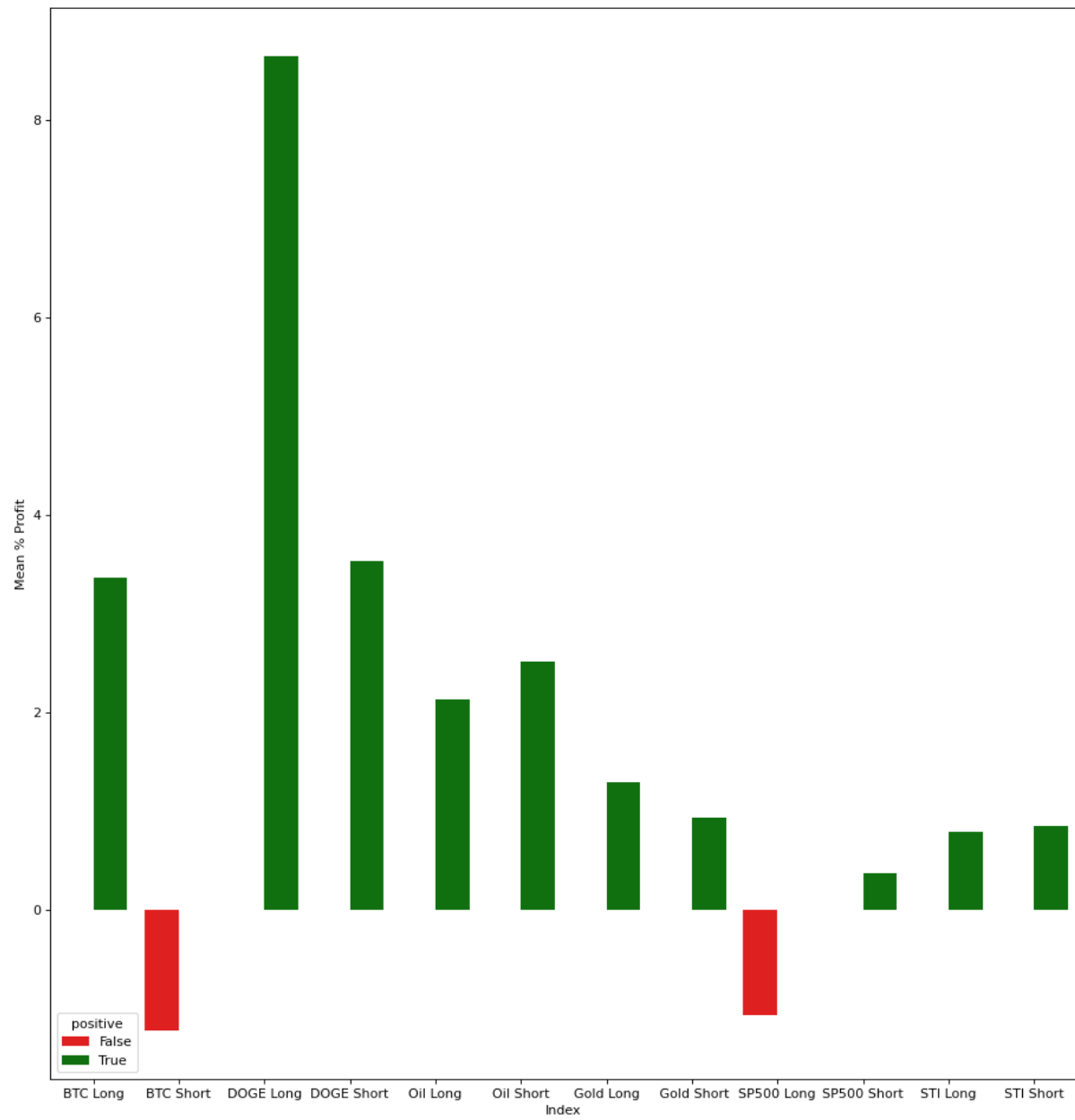
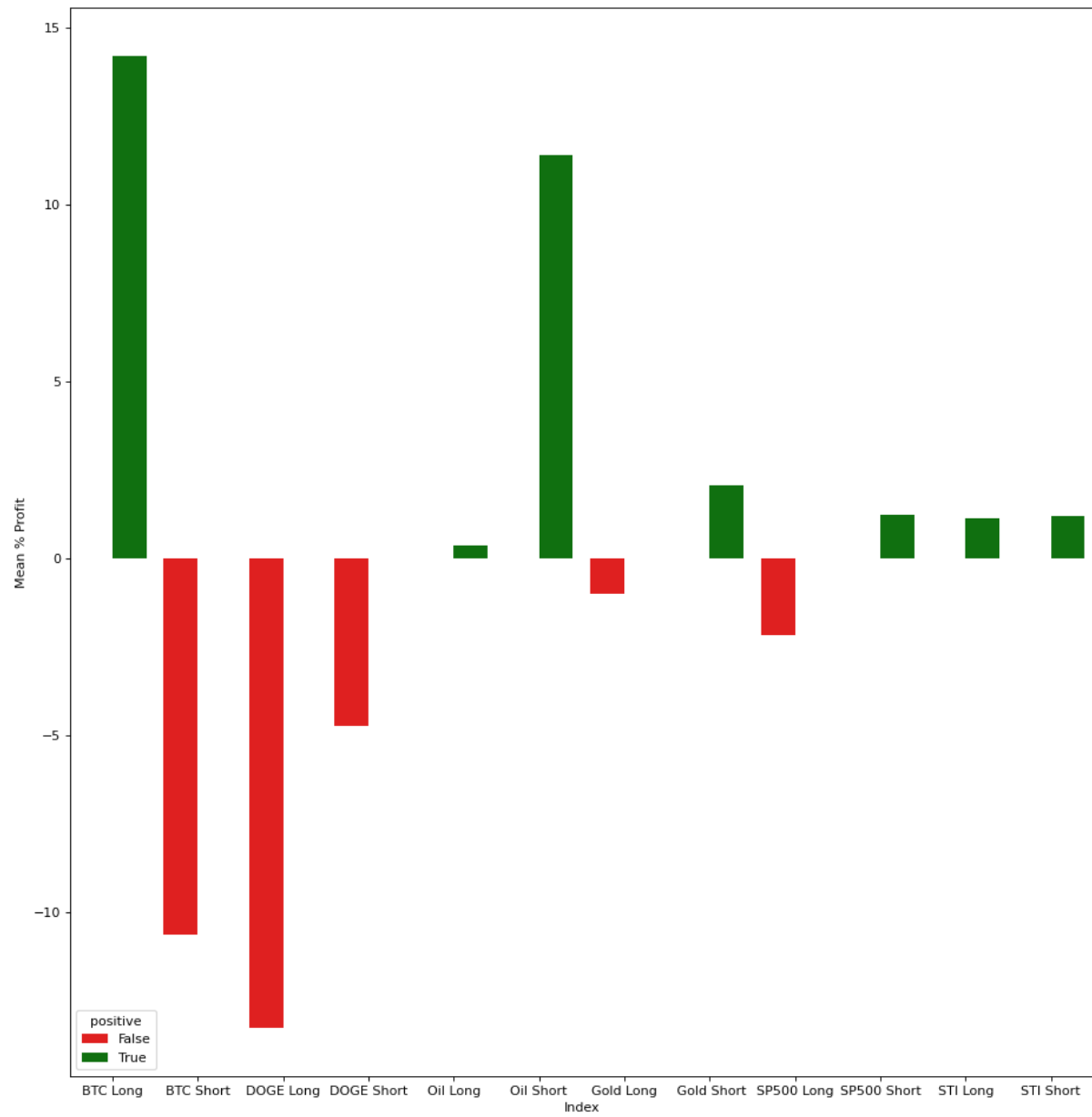**Holding Time = 5 Days**
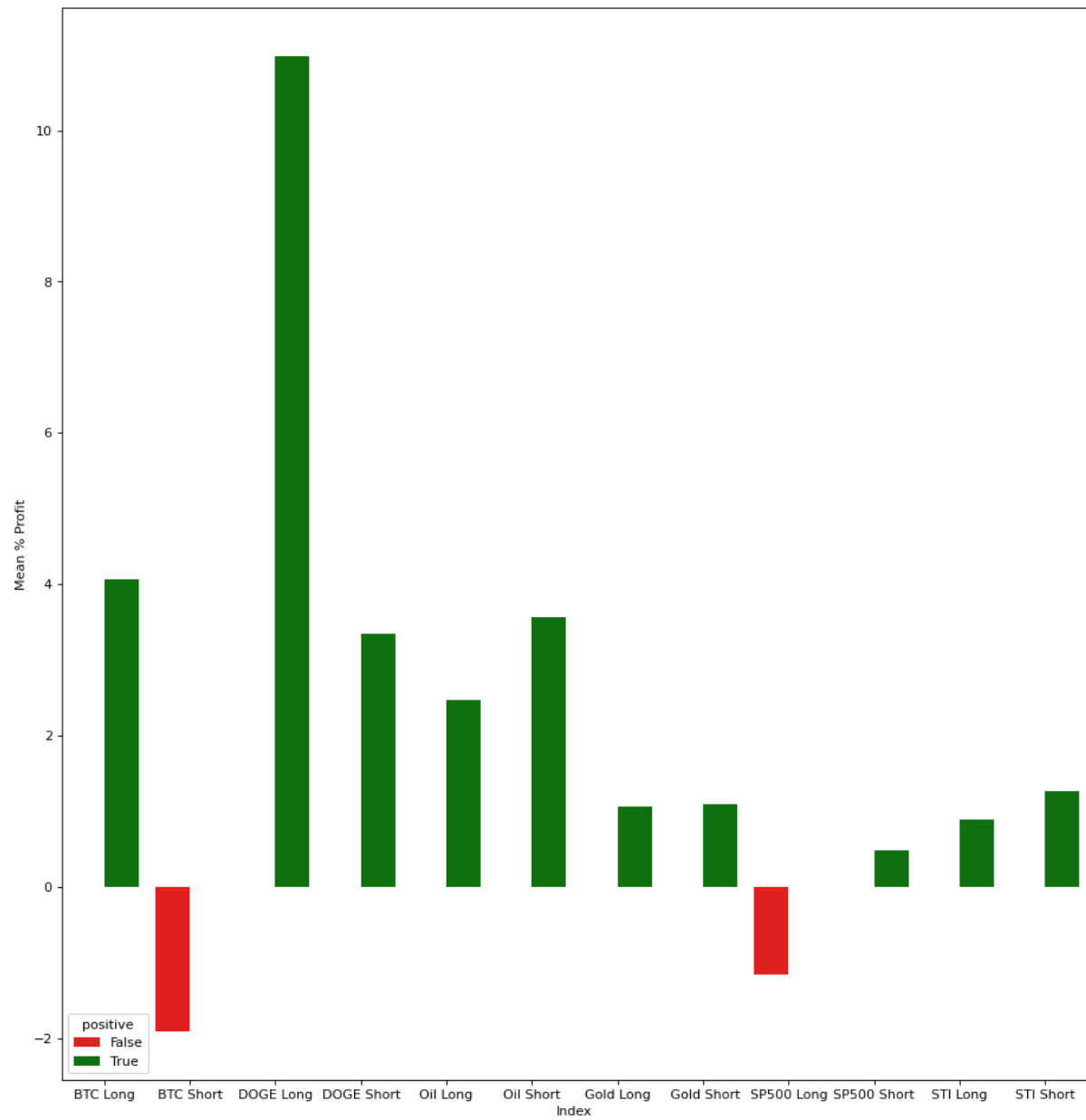
Holding Time = 10 Days
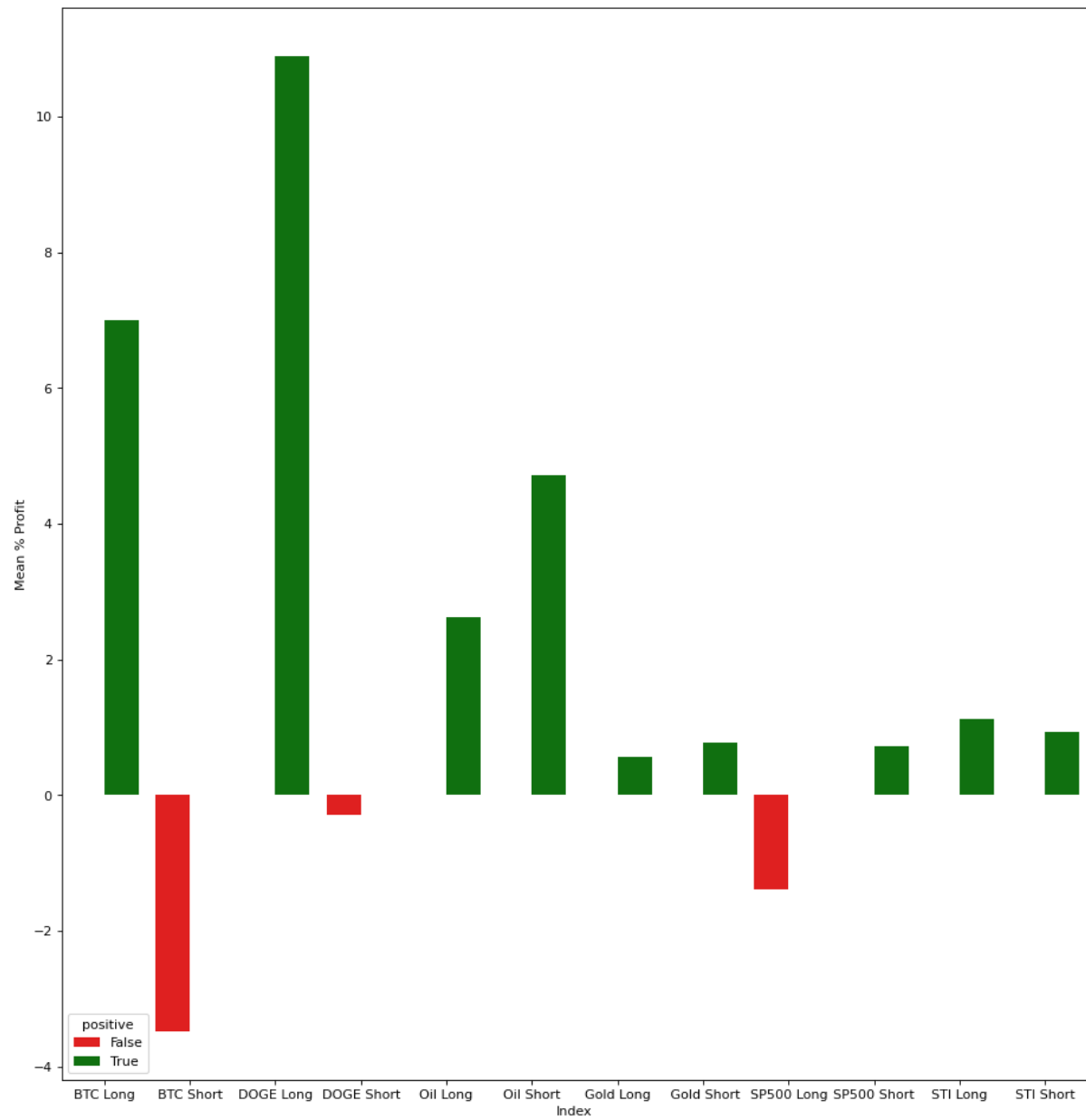
Holding Time = 15 Days

Holding Time = 30 Days

Annex B – Main ADL Models (Modified Terms)

Model before modification of terms

	coef	std err	z	P>|z|	[0.025	0.975]
Dep. Variable: future_price1 % P/L				No. Observations:		1834
Model: ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)				Log Likelihood		3395.717
Method: Conditional MLE				S.D. of innovations		0.038
Date: Fri, 12 Nov 2021				AIC		-6735.434
Time: 21:10:58				BIC		-6581.050
Sample: 1				HQIC		-6678.497
1834						

	coef	std err	z	P>|z|	[0.025	0.975]
future_price1 % P/L.L1	-0.2855	0.068	-4.226	0.000	-0.418	-0.153
Close.L0	-0.0009	0.001	-0.710	0.478	-0.004	0.002
Close.L1	0.0009	0.001	0.700	0.484	-0.002	0.004
Volume.L0	-3.766e-13	4.1e-13	-0.919	0.358	-1.18e-12	4.27e-13
Volume.L1	3.116e-13	3.99e-13	0.781	0.435	-4.71e-13	1.09e-12
RSI.L0	0.0014	0.000	3.149	0.002	0.001	0.002
RSI.L1	-0.0013	0.000	-3.001	0.003	-0.002	-0.000
RSI Condition.L0	0.0012	0.004	0.327	0.743	-0.006	0.009
RSI Condition.L1	-0.0050	0.004	-1.315	0.189	-0.013	0.002
MACD Condition.L0	0.0252	0.004	6.757	0.000	0.018	0.032
MACD Condition.L1	0.0005	0.004	0.123	0.902	-0.007	0.008
EMA Condition.L0	0.0012	0.003	0.422	0.673	-0.004	0.007
EMA Condition.L1	0.0019	0.003	0.708	0.479	-0.003	0.007
Close-EMA200 Price Diff.L0	0.0009	0.001	0.711	0.477	-0.002	0.004
Close-EMA200 Price Diff.L1	-0.0009	0.001	-0.713	0.476	-0.004	0.002
BB Condition.L0	-0.0045	0.004	-1.251	0.211	-0.011	0.003
BB Condition.L1	0.0049	0.003	1.419	0.156	-0.002	0.012
ATR.L0	0.0001	5.97e-05	1.741	0.082	-1.31e-05	0.000
ATR.L1	-9.329e-05	5.97e-05	-1.562	0.119	-0.000	2.39e-05
Trend.L0	-0.0031	0.004	-0.790	0.430	-0.011	0.005
Trend.L1	0.0038	0.004	0.981	0.327	-0.004	0.011
Forecasted.L0	0.0001	0.000	0.664	0.507	-0.000	0.001
Forecasted.L1	-0.0001	0.000	-0.633	0.527	-0.000	0.000
Slope.L0	-0.0006	0.001	-0.531	0.595	-0.003	0.002
Slope.L1	0.0005	0.001	0.541	0.589	-0.001	0.002
Acceleration.L0	-0.0004	0.001	-0.821	0.411	-0.001	0.001
Acceleration.L1	0.0002	0.001	0.376	0.707	-0.001	0.001

Model after modification of terms

ARDL Model Results

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)	Log Likelihood	3404.549
Method:	Conditional MLE	S.D. of innovations	0.038
Date:	Sun, 14 Nov 2021	AIC	-6753.098
Time:	00:35:53	BIC	-6598.715
Sample:	1	HQIC	-6696.162
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
future_price1 % P/L.L1	-0.0884	0.102	-0.864	0.388	-0.289	0.112
Close.L0	6.243e-06	6.24e-06	1.001	0.317	-5.99e-06	1.85e-05
Close.L1	-7.205e-06	6.25e-06	-1.153	0.249	-1.95e-05	5.05e-06
Price Relative Volume.L0	-1.592e-10	2.8e-09	-0.057	0.955	-5.64e-09	5.32e-09
Price Relative Volume.L1	8.221e-10	2.75e-09	0.299	0.765	-4.58e-09	6.22e-09
RSI.L0	0.0012	0.000	2.786	0.005	0.000	0.002
RSI.L1	-0.0012	0.000	-2.775	0.006	-0.002	-0.000
RSI Condition.L0	-0.0002	0.004	-0.060	0.952	-0.008	0.007
RSI Condition.L1	-0.0039	0.004	-1.008	0.314	-0.011	0.004
MACD Condition.L0	0.0250	0.004	6.703	0.000	0.018	0.032
MACD Condition.L1	0.0003	0.004	0.086	0.931	-0.007	0.008
EMA Condition.L0	0.0021	0.003	0.751	0.453	-0.003	0.008
EMA Condition.L1	0.0027	0.003	0.989	0.323	-0.003	0.008
Price Relative Close-EMA200 Price Diff.L0	-0.2212	0.064	-3.438	0.001	-0.347	-0.095
Price Relative Close-EMA200 Price Diff.L1	0.2141	0.064	3.351	0.001	0.089	0.339
BB Condition.L0	-0.0047	0.004	-1.304	0.192	-0.012	0.002
BB Condition.L1	0.0036	0.004	1.023	0.306	-0.003	0.010
Price Relative ATR.L0	0.0051	0.004	1.355	0.176	-0.002	0.012
Price Relative ATR.L1	-0.0039	0.004	-1.047	0.295	-0.011	0.003
Trend.L0	-0.0029	0.004	-0.730	0.466	-0.011	0.005
Trend.L1	0.0023	0.004	0.592	0.554	-0.005	0.010
Forecasted % Profit.L0	-0.0575	0.104	-0.554	0.579	-0.261	0.146
Forecasted % Profit.L1	0.0845	0.091	0.928	0.354	-0.094	0.263
Slope.L0	0.0002	0.000	1.452	0.147	-5.49e-05	0.000
Slope.L1	-0.0001	0.000	-1.056	0.291	-0.000	9.64e-05
Acceleration.L0	-0.0005	0.001	-1.030	0.303	-0.001	0.000
Acceleration.L1	0.0003	0.000	0.563	0.573	-0.001	0.001

Main ADL Models (Non-Linear Terms)

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)	Log Likelihood	3399.599
Method:	Conditional MLE	S.D. of Innovations	0.038
Date:	Sun, 14 Nov 2021	AIC	-6743.199
Time:	13:50:31	BIC	-6588.815
Sample:	1	HQIC	-6686.262
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
future_price1 % P/L.L1	-0.1951	0.100	-1.958	0.050	-0.391	0.000
Close.L0	8.176e-06	6.08e-06	1.344	0.179	-3.76e-06	2.01e-05
Close.L1	-8.659e-06	6.09e-06	-1.423	0.155	-2.06e-05	3.28e-06
Log(Price Relative Volume).L0	0.0025	0.003	0.704	0.482	-0.004	0.009
Log(Price Relative Volume).L1	-0.0032	0.003	-0.926	0.355	-0.010	0.004
RSI.L0	0.0013	0.000	2.719	0.007	0.000	0.002
RSI.L1	-0.0011	0.000	-2.467	0.014	-0.002	-0.000
RSI Condition.L0	0.0009	0.004	0.237	0.812	-0.007	0.009
RSI Condition.L1	-0.0036	0.004	-0.908	0.364	-0.011	0.004
MACD Condition.L0	0.0258	0.004	6.871	0.000	0.018	0.033
MACD Condition.L1	0.0007	0.004	0.179	0.858	-0.007	0.008
EMA Condition.L0	0.0015	0.003	0.506	0.613	-0.004	0.007
EMA Condition.L1	0.0016	0.003	0.564	0.573	-0.004	0.007
Log(Price Relative Close-EMA200 Price Diff).L0	-0.3833	0.147	-2.599	0.009	-0.673	-0.094
Log(Price Relative Close-EMA200 Price Diff).L1	0.3539	0.146	2.425	0.015	0.068	0.640
BB Condition.L0	-0.0036	0.004	-0.985	0.325	-0.011	0.004
BB Condition.L1	0.0040	0.004	1.126	0.260	-0.003	0.011
Log(Price Relative ATR).L0	0.0174	0.018	0.958	0.338	-0.018	0.053
Log(Price Relative ATR).L1	-0.0132	0.018	-0.728	0.467	-0.049	0.022
Trend.L0	-0.0061	0.004	-1.528	0.127	-0.014	0.002
Trend.L1	0.0055	0.004	1.390	0.165	-0.002	0.013
Forecasted % Profit.L0	-0.0348	0.103	-0.339	0.735	-0.237	0.167
Forecasted % Profit.L1	0.0668	0.090	0.741	0.459	-0.110	0.244
Slope.L0	0.0001	0.000	1.145	0.252	-8.76e-05	0.000
Slope.L1	-9.499e-05	0.000	-0.896	0.370	-0.000	0.000
Acceleration.L0	-0.0004	0.001	-0.797	0.425	-0.001	0.001
Acceleration.L1	0.0002	0.000	0.443	0.658	-0.001	0.001

Dep. Variable:	future_price1 % P/L	No. Observations:	1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)	Log Likelihood	3405.157
Method:	Conditional MLE	S.D. of Innovations	0.038
Date:	Sun, 14 Nov 2021	AIC	-6754.315
Time:	12:59:46	BIC	-6599.931
Sample:	1	HQIC	-6697.378
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
future_price1 % P/L.L1	-0.1104	0.102	-1.077	0.281	-0.311	0.091
Close.L0	6.157e-06	6.26e-06	0.984	0.325	-6.11e-06	1.84e-05
Close.L1	-6.751e-06	6.26e-06	-1.078	0.281	-1.9e-05	5.53e-06
Log(Price Relative Volume).L0	0.0020	0.003	0.602	0.547	-0.005	0.009
Log(Price Relative Volume).L1	-0.0029	0.003	-0.857	0.392	-0.009	0.004
RSI.L0	0.0014	0.000	2.976	0.003	0.000	0.002
RSI.L1	-0.0012	0.000	-2.628	0.009	-0.002	-0.000
RSI Condition.L0	0.0008	0.004	0.193	0.847	-0.007	0.008
RSI Condition.L1	-0.0030	0.004	-0.770	0.442	-0.011	0.005
MACD Condition.L0	0.0254	0.004	6.795	0.000	0.018	0.033
MACD Condition.L1	0.0006	0.004	0.155	0.877	-0.007	0.008
EMA Condition.L0	0.0015	0.003	0.512	0.609	-0.004	0.007
EMA Condition.L1	0.0018	0.003	0.632	0.527	-0.004	0.007
Price Relative Close-EMA200 Price Diff.L0	-0.2273	0.065	-3.523	0.000	-0.354	-0.101
Price Relative Close-EMA200 Price Diff.L1	0.2157	0.064	3.379	0.001	0.091	0.341
BB Condition.L0	-0.0041	0.004	-1.131	0.258	-0.011	0.003
BB Condition.L1	0.0041	0.004	1.154	0.249	-0.003	0.011
Price Relative ATR.L0	0.0045	0.004	1.190	0.234	-0.003	0.012
Price Relative ATR.L1	-0.0032	0.004	-0.852	0.394	-0.011	0.004
Trend.L0	-0.0027	0.004	-0.692	0.489	-0.010	0.005
Trend.L1	0.0029	0.004	0.731	0.465	-0.005	0.011
Forecasted % Profit.L0	-0.0813	0.105	-0.777	0.437	-0.286	0.124
Forecasted % Profit.L1	0.1034	0.091	1.134	0.257	-0.075	0.282
Slope.L0	0.0002	0.000	1.493	0.136	-5.06e-05	0.000
Slope.L1	-0.0001	0.000	-1.141	0.254	-0.000	8.73e-05
Acceleration.L0	-0.0005	0.001	-0.904	0.366	-0.001	0.001
Acceleration.L1	0.0002	0.000	0.490	0.624	-0.001	0.001

Main ADL Models (Interaction Terms)

Dep. Variable:	future_price1 % P/L	**No. Observations:**	1834
Model:	ARDL(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)	**Log Likelihood**	3409.735
Method:	Conditional MLE	**S.D. of innovations**	0.038
Date:	Sun, 14 Nov 2021	**AIC**	-6735.47
Time:	13:46:34	**BIC**	-6503.89
Sample:	1	**HQIC**	-6650.06
	1834		

	coef	std err	z	P>|z|	[0.025	0.975]
future_price1 % P/L.L1	-0.189	0.135	-1.399	0.16	-0.454	0.076
Close.L0	5.81E-06	6.42E-06	0.906	0.37	-6.77E-06	1.84E-05
Close.L1	-6.55E-06	6.42E-06	-1.02	0.31	-1.91E-05	6.05E-06
Price Relative Volume.L0	-6.66E-10	2.99E-09	-0.223	0.82	-6.54E-09	5.20E-09
Price Relative Volume.L1	1.72E-09	2.96E-09	0.579	0.56	-4.09E-09	7.52E-09
Log(Price Relative Volume).L0	0.0023	0.004	0.635	0.53	-0.005	0.009
Log(Price Relative Volume).L1	-0.0035	0.004	-0.97	0.33	-0.011	0.004
RSI.L0	0.0012	0.001	2.434	0.02	0	0.002
RSI.L1	-0.0009	0	-1.961	0.05	-0.002	-3.84E-09
RSI Condition.L0	0.0024	0.004	0.543	0.59	-0.006	0.011
RSI Condition.L1	-0.0004	0.004	-0.102	0.92	-0.009	0.008
MACD Condition.L0	0.0254	0.004	6.548	0	0.018	0.033
MACD Condition.L1	0.0006	0.004	0.141	0.89	-0.007	0.008
EMA Condition.L0	0.0008	0.003	0.271	0.79	-0.005	0.007
EMA Condition.L1	0.001	0.003	0.334	0.74	-0.005	0.007
Price Relative Close-EMA200 Price Diff.L0	-0.1575	0.101	-1.559	0.12	-0.356	0.041
Price Relative Close-EMA200 Price Diff.L1	0.1625	0.104	1.562	0.12	-0.042	0.367
BB Condition.L0	-0.0038	0.004	-1.032	0.3	-0.011	0.003

	coef	std err	z	P>|z|	[0.025	0.975]
BB Condition.L1	0.0041	0.004	1.148	0.25	-0.003	0.011
Price Relative ATR.L0	0.0051	0.004	1.22	0.22	-0.003	0.013
Price Relative ATR.L1	-0.0037	0.004	-0.883	0.38	-0.012	0.004
Trend.L0	0.0101	0.014	0.743	0.46	-0.017	0.037
Trend.L1	-0.0043	0.014	-0.32	0.75	-0.031	0.022
Forecasted % Profit.L0	-0.0503	0.11	-0.458	0.65	-0.266	0.165
Forecasted % Profit.L1	0.071	0.095	0.748	0.45	-0.115	0.257
Slope.L0	0.0001	0	1.33	0.18	-6.91E-05	0
Slope.L1	-0.0001	0	-0.948	0.34	0	0
Acceleration.L0	-0.0004	0.001	-0.856	0.39	-0.001	0.001
Acceleration.L1	0.0002	0.001	0.415	0.68	-0.001	0.001
RSI x Trend.L0	-0.0003	0	-0.97	0.33	-0.001	0
RSI x Trend.L1	0.0001	0	0.548	0.58	0	0.001
RSI x Price Relative Close-EMA200 Price Diff.L0	0.0015	0.002	0.971	0.33	-0.001	0.004
RSI x Price Relative Close-EMA200 Price Diff.L1	-0.0017	0.001	-1.218	0.22	-0.005	0.001
RSI Condition x Trend.L0	-0.0002	0.007	-0.035	0.97	-0.014	0.013
RSI Condition x Trend.L1	-0.0062	0.007	-0.898	0.37	-0.02	0.007
RSI Condition x Price Relative Close-EMA200 Price Diff.L0	-0.0099	0.021	-0.472	0.64	-0.051	0.031
RSI Condition x Price Relative Close-EMA200 Price Diff.L1	0.002	0.021	0.094	0.93	-0.039	0.043
MACD Condition x Trend.L0	-0.0016	0.006	-0.249	0.8	-0.014	0.011
MACD Condition x Trend.L1	0.0031	0.006	0.479	0.63	-0.01	0.016
MACD Condition x Price Relative Close-EMA200 Price Diff.L0	0.0156	0.022	0.698	0.49	-0.028	0.059
MACD Condition x Price Relative Close-EMA200 Price Diff.L1	-0.0086	0.022	-0.386	0.7	-0.052	0.035