Quantifying Ideal Time Frames for Leveraged ETF Strategies via Optimized RSI Parameters and Position Sizing with Genetic Optimization

Principal Investigator: Ethan Kuo | Contact: emk6025@psu.edu

Faculty Mentor(s): Shahid Hussain, Naseem Ibrahim, Wen-Li Wang, School of Engineering | Faculty Contact: shussain@psu.edu, nii1@psu.edu, wxw18@psu.edu

Abstract

Context: Retail trading is at an all-time high, yet challenges like risk assessment, psychological biases, and the pursuit of maximized returns remain. **Problem:** With this new generation of investors, their desire for financial success combined with higher risk tolerance makes the potential benefits of leveraged trading strategies extremely attractive. The mainstream consensus is that leveraged products like margin trading, options, and leveraged exchange-traded funds (LETFs) are beneficial for "short-term" trades but suboptimal for "long-term" investments due to increased risk. However, the ambiguity of these time frames, particularly for risk assessments regarding LETFs, has not been properly addressed in academic research. **Method:** This study will use optimized RSI indicator signals and position sizing, adjusted through genetic optimization (GO) to avoid human biases, to identify the ideal time frame for using LETFs by maximizing risk-adjusted returns in a RSI-based swing trading strategy. **Result:** The results of this study will quantify the performance difference, if any, between the optimal use of LETFs in a “long-term” versus “short-term” context, along with identifying the ideal time frame itself. **Conclusion:** This study aims to quantify the optimal time frame for leveraged ETF strategies using RSI-based indicators and position sizing. By analyzing the relationship between time frame and risk-adjusted performance, the findings may challenge conventional views on the use of LETFs for long-term investing. The results could demonstrate that, when optimized, LETFs may be underutilized in long-term strategies, with no significant downsides compared to short-term trading after accounting for active management costs and tax implications.

Introduction:

Background: The Relative Strength Index (RSI) is a common indicator for identifying overbought (≥ 70) and oversold (≤ 30) conditions. However, studies indicate that the standard RSI parameters yield no profits when used as a trading strategy and may even result in small losses. However, RSI indicators can still be an effective tool for generating profits relative to the underlying asset if the parameter thresholds are altered to align with the actual trading strategy being implemented [1], [2]. The most common forms of leverage used in financial markets—margins trading, options, and futures—have well documented downsides in long-term investing. However, their use still persists due to the lack of alternatives for risk-seeking investors, often leading to increased volatility in the underlying asset [3], [4], [5], [2]. LETFs are designed to amplify the daily returns of the underlying asset. While they can experience tracking deviations caused by volatility drag and higher expense ratios, research suggests that these tracking errors are often insignificant, even in the long term. In some cases, the compounding effects of amplified daily returns may even make them favorable for long-term investors [6]. Despite this, the majority of past research on LETFs has been on measuring the cause and magnitude of tracking errors for various ETFs, with little on quantifying the additional risk of holding LETFs for time frames over a week [7], [8]. **Problem Statement:** Lack of insight on a topic contributes to the use of over-generalized terminology and vague explanations [9], which is especially true regarding the unstandardized use of “short” and “long” when describing the optimal time frames for strategies involving various financial derivatives, indicators, and products [10], [11], [12]. As a relatively new financial product, there exists much less research on LETFs, which both worsens the lack of general understanding regarding the topic while also presenting a unique opportunity for additional analysis that can identify insight regarding their optimal use case. **Personal Motivation:** As a young investor with a long investment horizon, I am less concerned with the short-term volatility of LETFs and more focused on their potential for amplified compound growth. Since I can continue investing during market downturns, volatility becomes less significant over time. Still, I would prefer not to rely on intuition alone, and instead seek a rigorous, data-driven approach that validates my trading philosophy with quantitative evidence rather than blind assumptions. **Objectives:** The main objectives of this proposed work is to identify the ideal time frame for an RSI-based LETFs strategy through analyzing its optimal parameters, along with quantifying the relationship between risk-adjusted performance and time frame for a LETFs strategy. To achieve the research objective, we have formulated the following research questions (RQs).

RQ-1: How different RSI timeframes impact key performance metrics (e.g.,Annualized Returns, Maximum Drawdown, Calmar Ratio, and Sharpe Ratio) of an LETF strategy.

RQ-2: To what extent do optimized RSI parameters improve the performance of LETF investment strategies compared to standard RSI thresholds.

RQ-3: Whether there is a statistically significant advantage to using LETFs in a short-term investment strategy when accounting for active management costs and tax implications.

Methods and Processes

In this study, “short-term” and “long-term” trading patterns will be defined by their tax-considerations, specifically the type of capital gains taxes, over or under 1 year, that they fall under [1]. Position sizing in this study follows a structured block-based approach: a base investment (Block-0) allocated to the ETF and is reset only after each RSI cycle, which completes when the RSI returns back to overbought levels after reaching oversold at least once. Additional capital will be deployed in incremental blocks each time RSI reaches distinct, non-overlapping oversold levels: Block-1 is invested when RSI reaches the specified oversold level for the first time during the current RSI cycle, Block-2 for the second, and so on and so forth. The abstract level layout of the proposed framework is shown below:

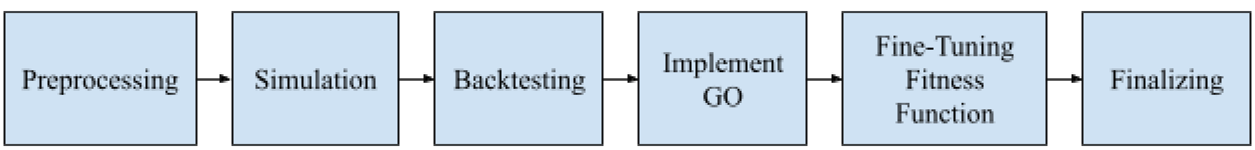

Figure 1: Layout of proposed Research Design

We will extract historical SPX data from 1957 to 2024 and preprocess RSI values for time frames from 2 to 20 days. Since the first LETF only became available in 2006, the performance of 2x, 3x, and 4x leveraged SPX ETFs will be simulated using historical data, factoring in daily compounding, volatility drag, and expense ratios similar to current LETFs [6], [7]. To prevent overfitting, the backtesting program will use minimal inputs, with only static RSI parameters and position sizing. Genetic Optimization (GO) will be used for parameter optimization due to discrete parameters, local optima risk, and non-deterministic nature of this problem, with the stopping criteria being when the fitness improvement of the population reaches <1%. The fitness function will incorporate standardized risk management and performance metrics, evaluated using Annualized Returns, Maximum Drawdown, Calmar Ratio, and Sharpe Ratio [13]. Weights will be fine-tuned according to backtesting insights before presenting the finalized results.

Faculty Contribution

Professor Hussain and other faculty mentor(s) will provide feedback and review on the technical implementation of machine learning algorithms and data analytics, specifically on data preprocessing and retrieval methodology as well as verifying my approach to navigating the high-dimensional search spaces inherent to genetic optimization.

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