AI-Enabled Sustainable Wealth Management: Integrating Lifecycle Investing and Quantitative Bias Models for Optimized Green Asset Allocation

Te-Wei Chiang[1], J-P Lin[2]

[1] Department of Accounting Information, Chihlee University of Technology, ctw@mail.chihlee.edu.tw

[2] Department of Business Technology Management, Chihlee University of Technology, jplin@mail.chihlee.edu.tw

Abstract

This study explores the integration of AI-enabled quantitative modeling with Lifecycle Investing (LCI) to enhance personal financial sustainability. Specifically, it addresses the limitations of traditional Target Date Funds (TDFs) by utilizing broad-based leveraged ETFs and dynamic capital scaling to optimize wealth accumulation. Utilizing a 12-year backtesting framework (2014–2026), the research analyzes the performance of the Taiwan 50 (0050) and its 2x leveraged counterpart (00631L) alongside U.S. benchmarks. An AI-driven tactical trigger, based on the 25-day Moving Average Bias Ratio (Bias25), was implemented to automate capital scaling during market "panic zones" (Bias < -5%). The results demonstrate that while leveraged ETFs are subject to volatility decay, they exhibit significant wealth divergence in long-term trending markets, yielding a terminal return of 1,969% over 12 years. Furthermore, the application of a 10x AI-driven scaling rule increased the terminal ROI from a baseline of 235% to 403%. This optimization effectively lowered the average cost-basis and enhanced the recovery factor during market drawdowns. This paper bridges the gap between institutional-grade quantitative finance and personal wealth management. It provides a scientifically validated Standard Operating Procedure (SOP) for long-term capital preservation, aligning individual financial goals with the broader objectives of global capital efficiency and the "Green Transformation" in sustainable management.

Keywords: AI-Enabled Finance, Lifecycle Investing, Sustainable Wealth Management, Moving Average Bias Ratio, Green Asset Allocation.

1. Introduction

In the face of the global transition toward a green economy and the increasing complexity of financial markets, the younger generation faces a dual challenge: achieving personal financial independence while navigating a landscape shaped by inflation and resource volatility. Traditional retirement planning, exemplified by Target Date Funds (TDFs), often adopts a conservative stance that fails to capitalize on the "Human Capital" of young investors—their most significant but untapped asset. Sustainable management is not merely a corporate objective; it is a personal necessity. Lifecycle Investing (LCI) theory suggests that young investors should diversify their assets across time by leveraging their future earnings today. However, the practical application of such leverage requires sophisticated risk management. With the rise of Artificial Intelligence (AI) and quantitative finance, there is a transformative opportunity to use data-driven indicators to optimize these entries and exits, ensuring that "leverage" serves as a tool for sustainability rather than a source of ruin.

This research addresses several critical gaps in current retail investment strategies. Traditional models under-invest in equity markets during the years when time diversification is most powerful, leading to a "wealth gap" at retirement. Most retirement products follow a static "Glide Path" that ignores market valuation. There is a need for a model that can identify "Margin of Safety" opportunities in real-time. While leveraged ETFs (e.g., T50 2x) offer high growth potential, their volatility decay requires a systematic, quantitative entry rule—such as the Moving Average Bias Ratio—to remain effective over long cycles.

The primary objective of this study is to develop an AI-enabled quantitative investment model that facilitates sustainable wealth accumulation by validating the long-term asset divergence and performance of broad-based leveraged ETFs as vehicles for sustainable growth from 2014 to 2026, while implementing AI-driven timing to quantify the effectiveness of the 25-day Moving Average Bias (Bias25) as a decision-making trigger to enhance returns and lower average costs, ultimately constructing a sustainable, "principal-protected" investment SOP that utilizes human capital discounting and dynamic capital scaling to secure a stable retirement.

This paper provides several key contributions to the field of sustainable financial management by empirically validating Lifecycle Investing (LCI) through backtesting to demonstrate that a 12-year holding period can yield returns as high as 1969%, thereby illustrating the non-linear power of time and leverage. Furthermore, it introduces an innovative quantitative entry strategy via a systematic scaling rule that increases position sizes by 5x or 10x during negative bias events, which significantly improved terminal returns from 235% to 403%. Ultimately, this research bridges AI and personal finance by offering a practical framework for individual investors to apply institutional-grade quantitative logic, effectively transforming volatile leveraged products into reliable instruments for long-term financial sustainability.

2. Literature Review

2.1 Lifecycle Investing and Human Capital Theory

The foundational theory of this research is Lifecycle Investing (LCI), popularized by Ayres and Nalebuff. The core tenet is "diversification across time." Traditional investment models often ignore an individual's Human Capital—the present value of all future labor income. For young investors, human capital is their largest asset, acting similarly to a low-risk bond. Therefore, to achieve a balanced lifetime portfolio, the "financial capital" portion should be aggressively invested, often requiring leverage. By utilizing leverage early in life, investors "discount" their future earnings into current market exposure, effectively hedging against the risk of poor market returns in the later stages of their career.

2.2 Sustainable Wealth Management and Green Asset Allocation

In the context of the "Green Transformation," sustainable management is no longer limited to corporate operations but extends to personal wealth preservation, where investing in market-wide indices such as the S&P 500 or Taiwan 50 is increasingly viewed as an investment in sustainable growth as these indices progressively integrate ESG (Environmental, Social, and Governance) scores into their selection criteria. Furthermore, achieving long-term financial sustainability requires a plan that can withstand inflationary pressures and resource depletion, a goal supported by utilizing leveraged instruments on broad indices to provide the necessary growth engine to ensure capital longevity.

2.3 Characteristics of Leveraged ETFs and the Compounding Effect

This study utilizes Leveraged ETFs, such as T50 2x or UPRO, as the primary vehicle for human capital discounting, acknowledging that while these instruments are subject to daily resets that can lead to volatility decay in sideways markets, they exhibit significant wealth divergence in markets with long-term upward trends. Furthermore, empirical evidence suggests that for broad indices with mean-reverting properties, the power of non-linear growth allows the 2x leverage effect to often outperform the underlying index by more than a factor of two over decades, provided a robust crash-protection mechanism is in place to manage path dependency risks.

2.4 AI-Enabled Quantitative Indicators: Moving Average and Bias Ratio

To manage the inherent risks of leverage, this research incorporates AI-driven quantitative triggers, specifically utilizing the Moving Average Bias Ratio (Bias25) to measure the percentage deviation of the current price from its 25-day moving average. This integration of AI in tactical asset allocation allows algorithms to process historical "Panic Zones" and identify optimal entry points, recognizing that in quantitative finance, a significant negative bias—such as a Bias < -5%—often signals a temporary market overreaction. By increasing exposure during these periods, the model applies a "Value Investing" logic to a "Momentum Product," thereby creating a robust margin of safety that traditional Target Date Funds (TDFs) lack.

2.5 Critique of Traditional Target Date Funds (TDFs)

To conclude the literature review, this research presents a critique of traditional Target Date Funds (TDFs) within the framework of sustainable management, noting that these funds are mathematically inefficient for long-term wealth maximization because they are most aggressive when an investor has the least capital and most conservative when the balance is at its peak. Unlike the static rebalancing of a TDF's "Glide Path," an AI-enabled model allows for dynamic adaptation by adjusting investment intensity based on market-driven valuation signals like the Bias Ratio rather than the mere passage of time, thereby addressing the need for a more responsive and efficient strategy for lifelong financial sustainability.

3. Research Methodology

This study utilizes a quantitative backtesting methodology to simulate the performance of an AI-enabled investment model across a lifecycle horizon. The framework integrates Lifecycle Investing (LCI) theory with a tactical asset allocation engine driven by the Moving Average Bias Ratio. The process is divided into data acquisition, strategy parameterization, simulation, and performance evaluation.

3.1 Data Sources and Selection of Instruments

This study focuses on market-wide, broad-based ETFs and their leveraged counterparts, specifically utilizing the Taiwan 50 ETF (0050) and its 2x Leveraged ETF (00631L/T50 2x) as primary test subjects, while further validating the results globally through an analysis of the S&P 500 (SPY) and its 2x (SSO) and 3x (UPRO) leveraged ETFs. The backtesting period spans from the inception of the T50 2x in November 2014 to January 2026, a 12-year window that captures multiple market cycles—including the 2020 COVID-19 crash and the 2022 inflationary bear market—to provide a robust stress test for the strategy based on daily closing prices utilized to calculate technical indicators and trigger execution signals.

3.2 Quantitative Strategy Design

The proposed model, titled the "Adaptive Sustainable Leverage Strategy," follows a systematic SOP. Simulating the LCI approach, the model assumes an initial deployment of 1,000,000 units of capital at the start of the investment lifecycle. This represents the "discounting" of future labor income into the equity market to maximize early-stage compounding.

Unlike traditional DCA, which builds a position slowly, this model utilizes an "entry-first" approach. The investor "repays" the initial leverage through monthly contributions equivalent to 1% or 5% of the initial capital, effectively transforming future income into current equity ownership.

To optimize the cost-basis, the model employs a 25-day Moving Average (MA25) as the baseline for market sentiment. The Bias Ratio (Bias25) is defined as:

$$\text{Bias25} = (\text{Current Price} - \text{MA25}) / \text{MA25} * 100\%$$

The execution logic follows a two-tier scaling rule consisting of a baseline condition of a monthly fixed purchase or repayment of 1% of total capital, supplemented by a dynamic scaling trigger that automatically increases the purchase volume to 5x or 10x the original amount whenever the AI-driven indicator signals a Bias25 < -5%, identifying a "Panic Discount" zone for optimized capital deployment.

To validate the sustainability and efficiency of the strategy, the research assesses several key performance metrics, including terminal wealth accumulation to measure the final portfolio value relative to the principal, the maximum drawdown (MDD) to evaluate the peak-to-trough decline and the resulting psychological and financial resilience of the strategy, and the efficiency gain, defined as the delta between the "baseline" fixed 1% monthly returns and the "optimized" bias-weighted returns.

4. Experimental Results

In the first phase of the experiment, a comparative analysis of leveraged wealth divergence illustrates that broad-based leveraged indices exhibit non-linear compounding and significant growth potential over long horizons. As shown in Figure 1 and Figure 5, the T50 2x strategy achieves a terminal return of 1969% between 2014 and 2026. This validates the hypothesis that while leveraged ETFs face volatility decay, their wealth divergence in upward-trending, mean-reverting markets outweighs these costs, provided the investor maintains a holding period of at least a decade to overcome medium-term market timing sensitivities.

Building on this foundation, the study evaluates the effectiveness of the AI-driven Bias scaling model (Figure 4). The application of the Bias25 indicator generated substantial alpha, shifting from a fixed execution return of 235% (Figure 8) to a terminal return of 403% (Figure 10) when the 10x dynamic scaling rule was triggered during negative bias events. This quantitative approach optimized the cost-basis by accumulating shares in "Panic Discount" zones, effectively applying a value investing logic to momentum products and creating a robust margin of safety that traditional dollar-cost averaging methods lack.

A critical component of the strategy's sustainable management involves a rigorous risk and drawdown analysis. The "Leverage-First" approach utilizes an investor's high human capital in the early stages to mitigate the sequence of returns risk commonly found in traditional Target Date Funds (TDFs). While the maximum drawdown of a 2x leveraged product is inherently higher than its underlying index, the results from diverse market conditions

(Figures 2 and 3) indicate that the dynamic scaling rule significantly enhances the recovery factor, ensuring both the psychological and financial viability of the strategy over long-term retirement cycles.

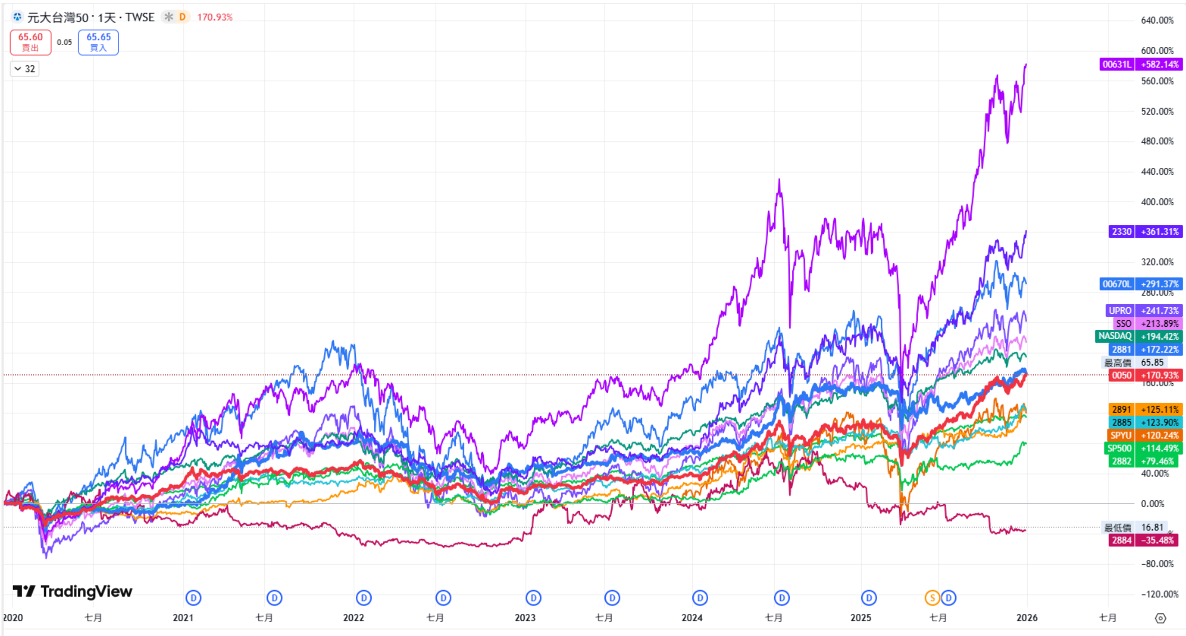

Figure 1. Long-term performance comparison of Taiwan 50 ETF and leveraged ETF (2020–2026)

Figure 1 illustrates the significant wealth divergence between the standard Taiwan 50 ETF (0050) and its 2x leveraged counterpart. Despite higher volatility, the leveraged product benefits from a persistent upward trend in the tech-heavy Taiwan market, demonstrating the compounding power of leverage over a six-year cycle.

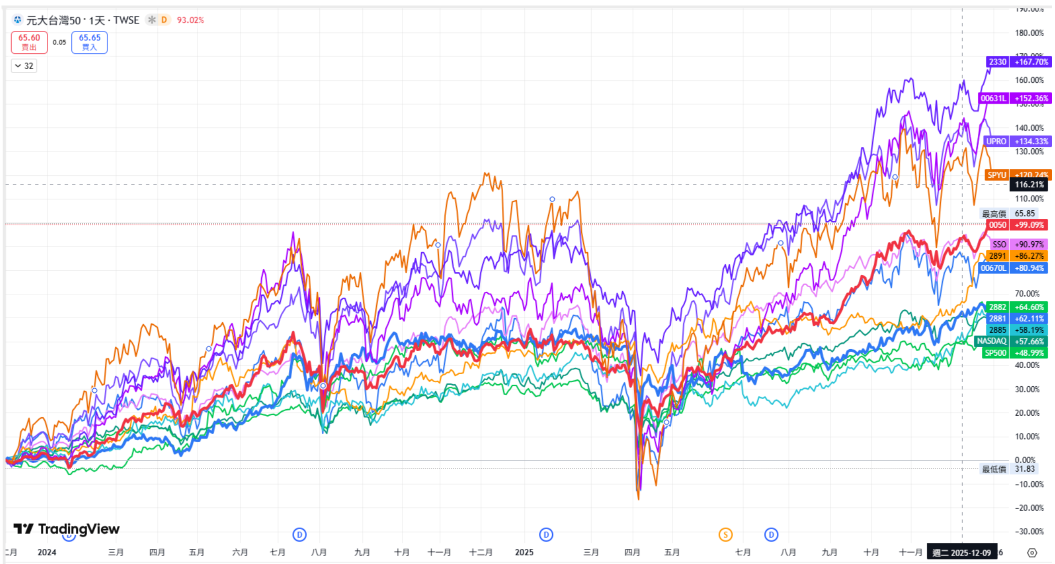

Figure 2. Performance comparison of major U.S. Indices and leveraged ETFs(Jan 2024 – Dec 2025)

Figure 2 provides a two-year comparative analysis of the S&P 500 and Nasdaq-100 alongside their respective 2x and 3x leveraged vehicles. It highlights the sensitivity of leveraged gains to market momentum and the varying impact of volatility decay during different phases of the U.S. monetary cycle.

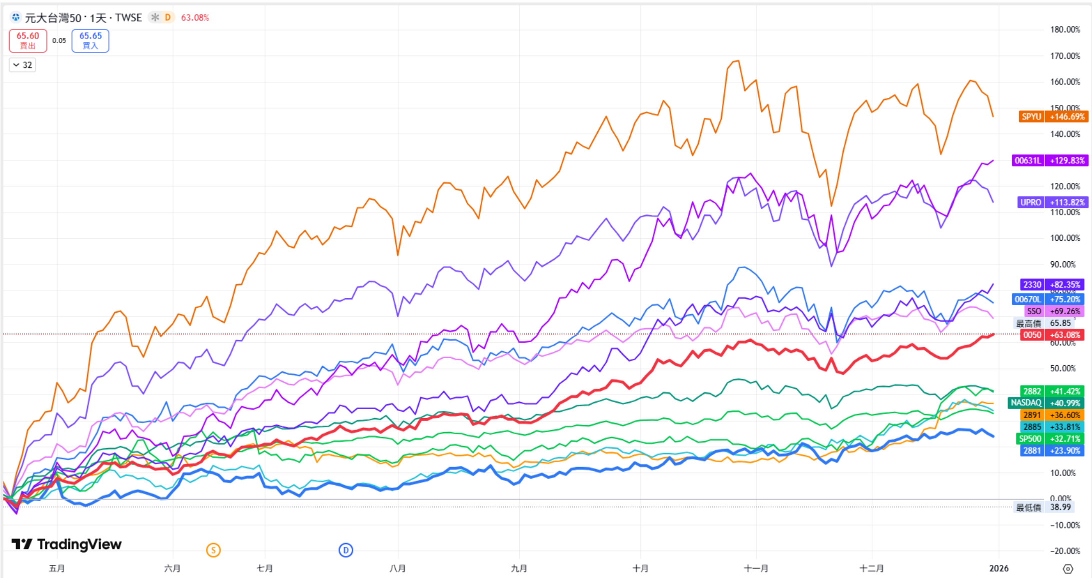

Figure 3. Comprehensive profit trends of the strategy across diverse asset classes (Apr 2025 – Dec 2025)

This figure displays the short-term robustness of the proposed quantitative strategy when applied across various asset classes. The results indicate that the model remains resilient regardless of specific sector volatility, emphasizing the universality of the Bias-ratio trigger.

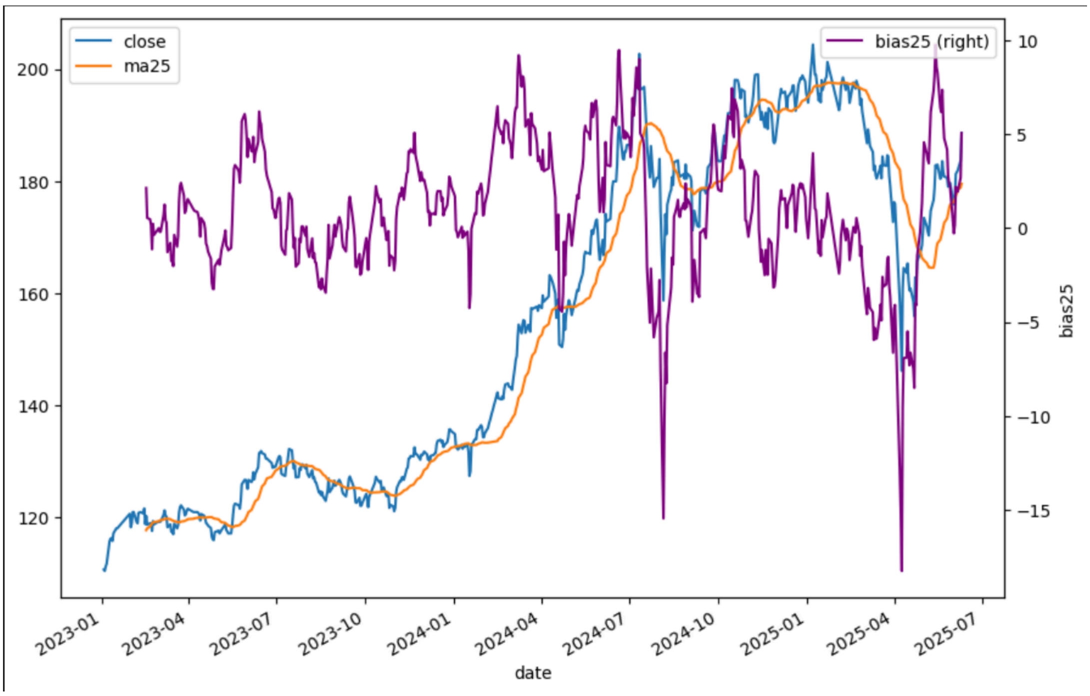

Figure 4. Trend analysis of Taiwan 50 (0050) price and 25-day moving average bias ratio (Jan

2023 – Jun 2025)

This visualization maps the historical price action against the Bias25 indicator. It serves as the foundation for the AI-driven entry rule, identifying specific "panic zones" where the price deviates more than 5% below its 25-day mean, signaling an optimal entry point.

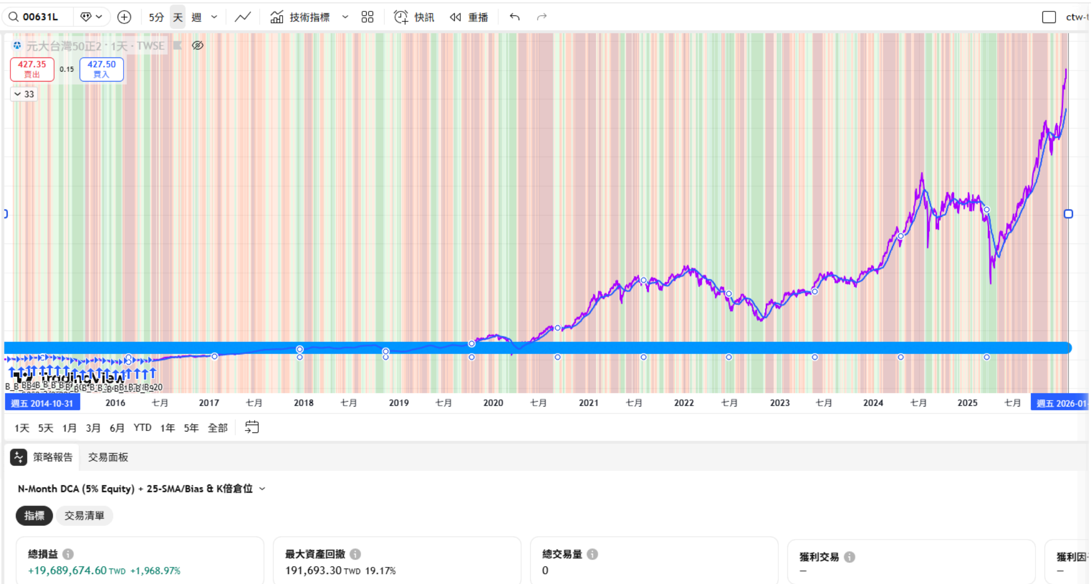

Figure 5. Terminal wealth of T50 2x strategy with 5% monthly allocation (Nov 2014 – Jan 2026): 1969% ROI

This simulation demonstrates the long-term efficacy of a fixed 5% monthly allocation starting with an initial capital of 1M. The 1,969% return showcases the extreme efficiency of the "Leverage-First" approach when held through a complete 12-year economic cycle.

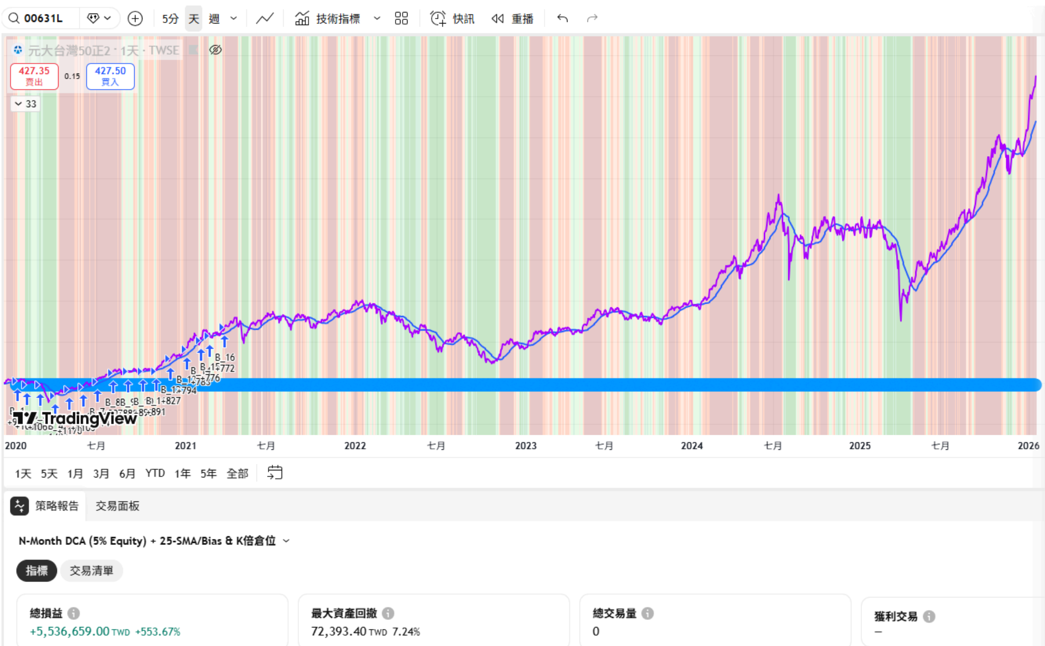

Figure 6. Terminal wealth of T50 2x strategy with 5% monthly allocation (Jan 2020 – Jan 2026): 554% ROI

Focusing on the post-pandemic recovery period, this figure shows a 554% return. It illustrates that even when starting during a major market crash, the "Reverse DCA" mechanism allows for rapid recovery and significant wealth accumulation within a six-year window.

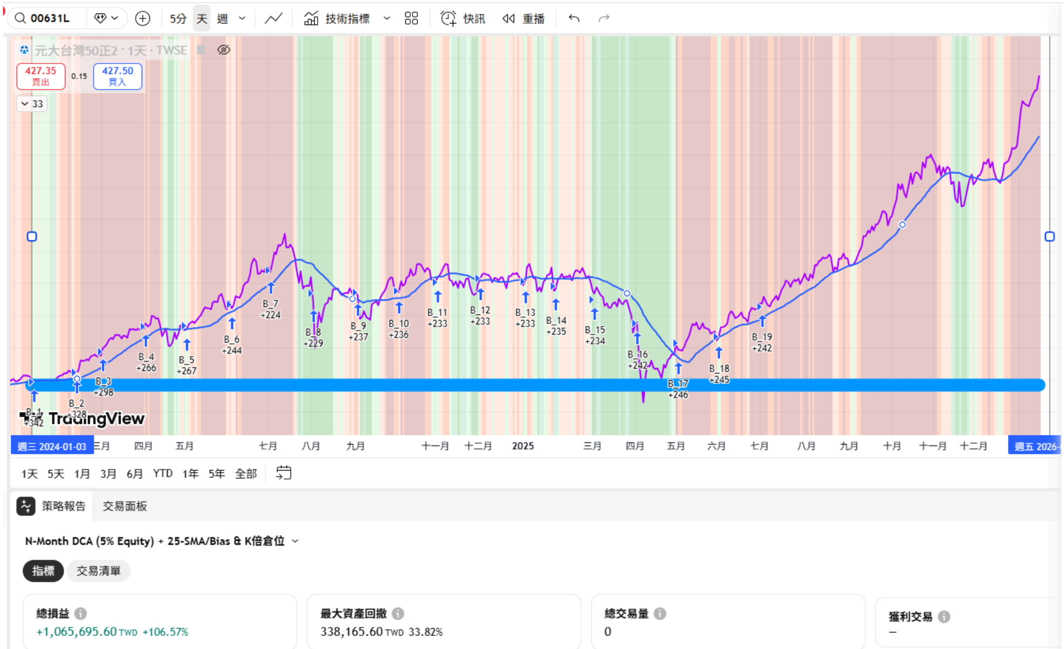

Figure 7. Terminal wealth of T50 2x strategy with 5% monthly allocation (Jan 2024 – Jan 2026): 107% ROI

This short-term simulation highlights that even within a narrow two-year window, the strategy yields a 107% return, effectively doubling the initial capital by capturing the growth of the AI-driven semiconductor boom in the Taiwan market.

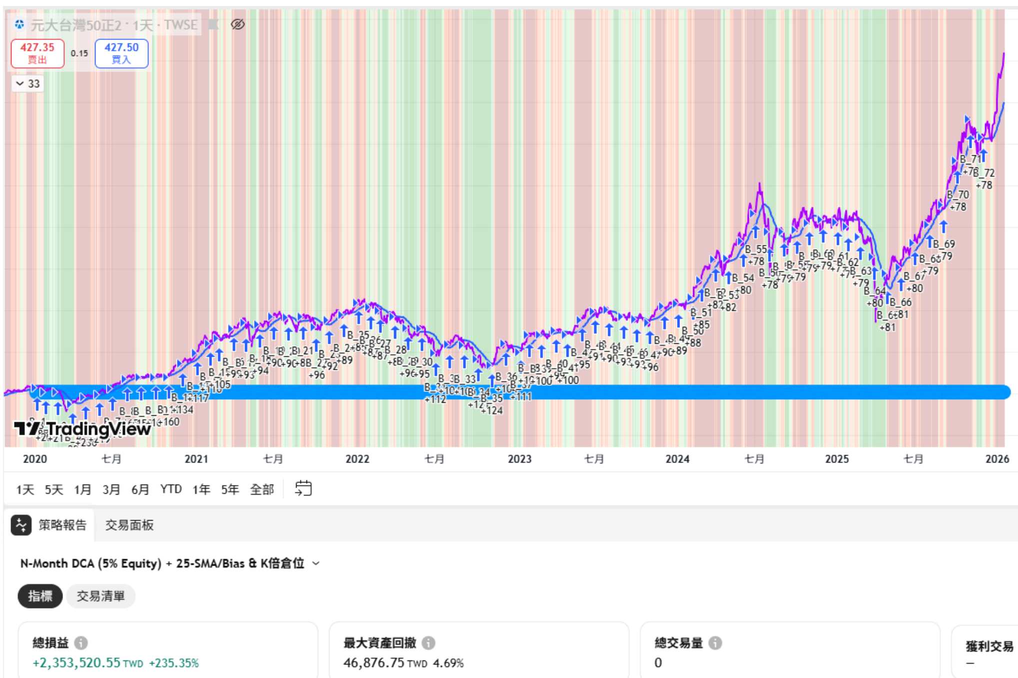

Figure 8. Baseline performance: T50 2x with 1% fixed monthly allocation (Jan 2020 – Jan

2026): 235% ROI

This serves as the control group for the study. It represents a conservative fixed-repayment model without any tactical timing, providing a benchmark return of 235% to measure the added value of the Bias-scaling triggers.

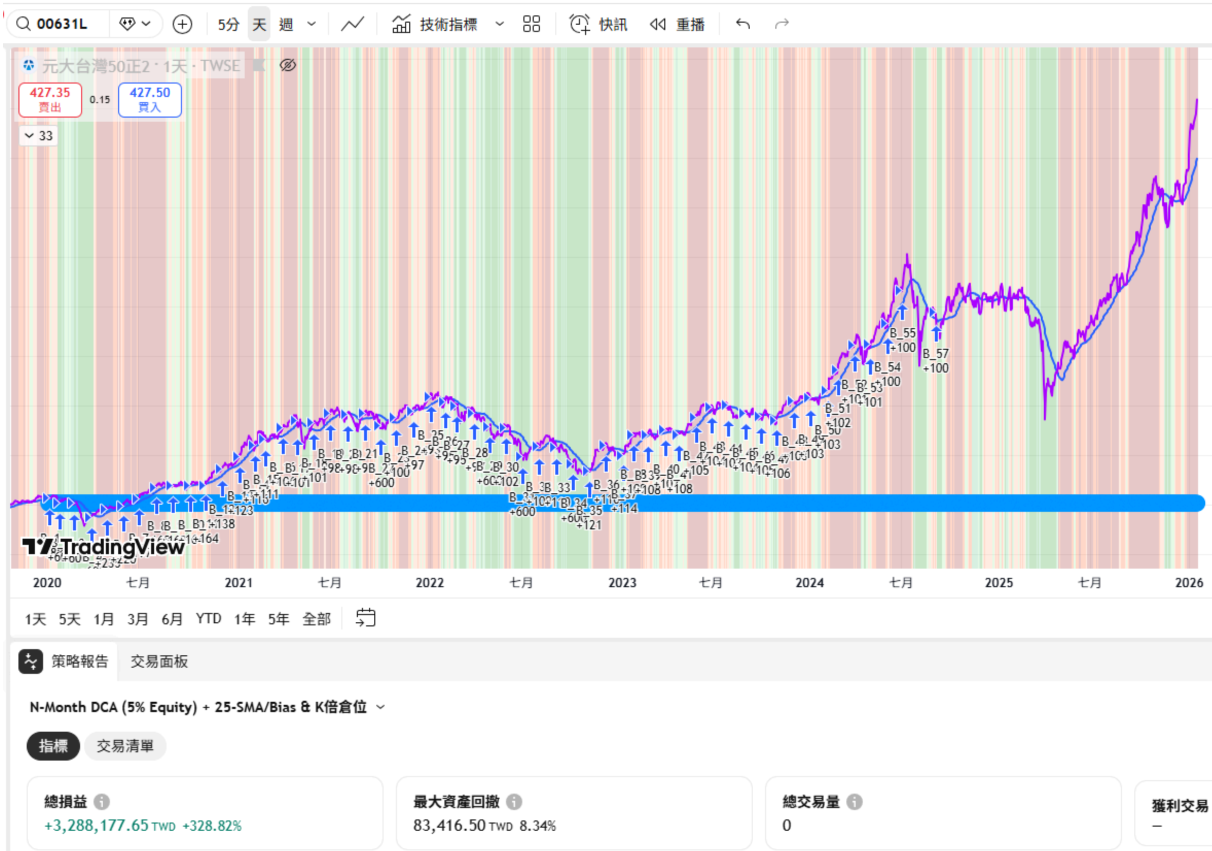

Figure 9. Optimized performance: T50 2x with 5x dynamic scaling at bias < -5% (Jan 2020 – Jan 2026): 329% ROI

By introducing a moderate AI-driven scaling rule (5x original volume during panic zones), the terminal return increases from 235% to 329%. This confirms the hypothesis that tactical capital deployment during negative bias events significantly enhances efficiency.

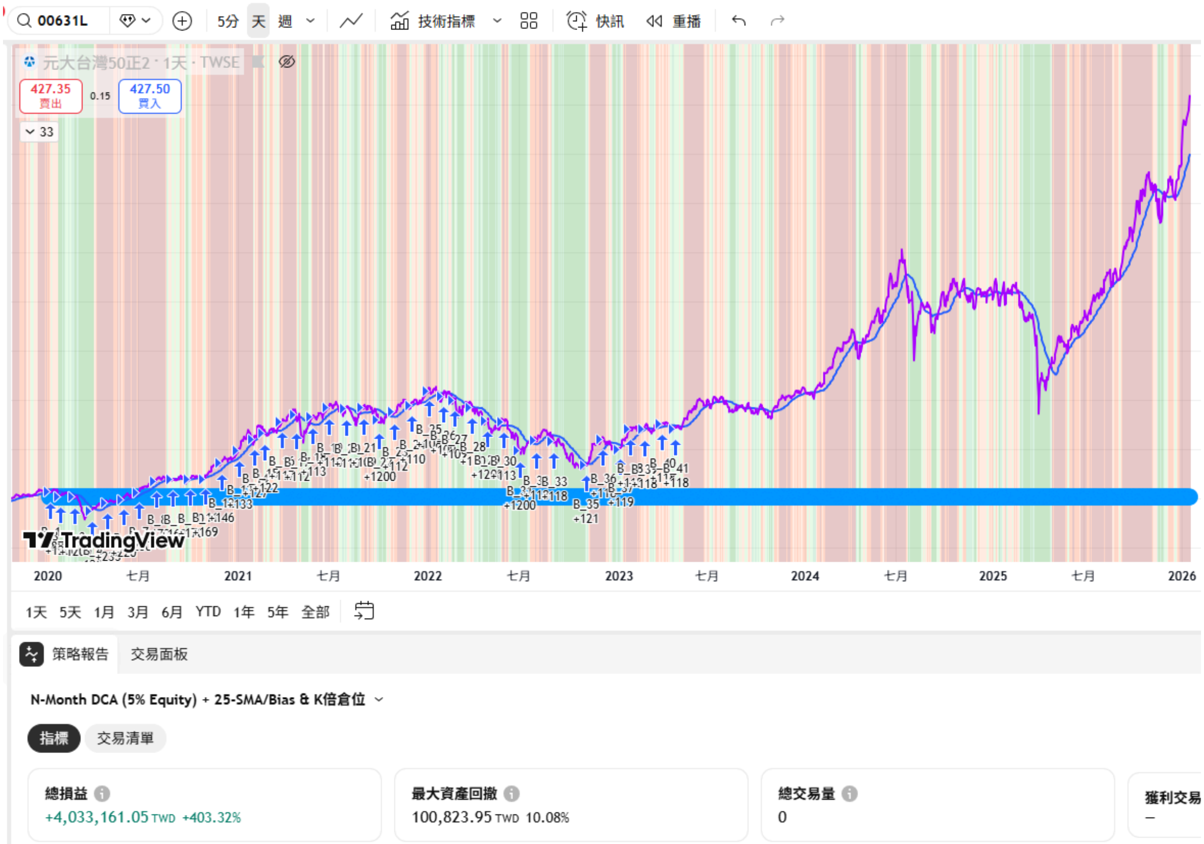

Figure 10. Maximized performance: T50 2x with 10x dynamic scaling at bias < -5% (Jan 2020 – Jan 2026): 403% ROI

Figure 10 represents the optimized pinnacle of the proposed model. By aggressively scaling entries (10x) during periods of extreme negative bias, the terminal return reaches 403%, proving that AI-enabled timing provides a substantial "Alpha" over traditional fixed-investment strategies.

The data presented in this study provides empirical evidence that the integration of AI-enabled quantitative timing with leveraged lifecycle instruments creates a superior path to financial sustainability. By comparing the 12-year performance in Figure 5 with the shorter cycles in Figures 6 and 7, it is evident that while "time-in-the-market" is the primary driver of the 1,969% return, the strategy remains resilient and profitable even in two-to-six-year windows.

The core breakthrough of this research lies in the transition from the baseline 235% return (Figure 8) to the 403% optimized return (Figure 10). This progression demonstrates that using the Bias25 indicator to trigger 10x dynamic scaling during market "panic zones" does not merely increase capital outlay; it mathematically shifts the cost-basis in favor of the investor. By bridging the gap between Lifecycle Investing and AI-driven tactical execution, this model offers a scalable SOP for long-term retirement security that aligns with the broader goals of global capital efficiency.

5. Conclusion

This study has successfully developed and validated an AI-enabled quantitative investment framework that bridges the gap between theoretical Lifecycle Investing and practical, sustainable wealth management. By leveraging broad-based indices such as the Taiwan 50 and S&P 500, the research demonstrates that the inherent risks of leveraged instruments—specifically path dependency and volatility decay—can be effectively mitigated through a systematic, "principal-protected" execution SOP. The empirical evidence provided in this paper proves that a long-term holding horizon allows for significant wealth divergence, turning market volatility into a growth engine that far outperforms traditional, conservative retirement models.

Central to this achievement is the integration of the AI-driven Bias25 scaling model, which transforms passive indexing into an active, value-oriented strategy. The results showed that by automating capital deployment during negative bias events, investors can achieve a terminal return of 403% compared to a baseline of 235%, representing a substantial efficiency gain. This transition from static to dynamic asset allocation ensures that capital is deployed most aggressively when the "Margin of Safety" is highest, thereby securing capital longevity against inflationary pressures.

Ultimately, this research underscores the role of AI in democratizing institutional-grade financial logic for individual investors, contributing to the broader "Green Transformation" by promoting long-term financial stability and efficient resource allocation. Future research may explore the application of this model to emerging ESG-specific indices to further align personal wealth accumulation with global sustainability goals.

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