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OPTIMIZATION OF PORTFOLIOS THROUGH MULTITEMPORAL SCREENING AND MOMENTUM STRATEGIES: AN ANALYSIS OF THE SEMICONDUCTOR SECTOR IN THE S&P 500 UNDER SIMULATION VALIDATION

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ABSTRACT

This study analyzes the effectiveness of asset selection methodologies (screening) based on multi-temporal returns and cross-sectional momentum within the S&P 500 index. The central problem lies in the manager's ability to capture alpha in sectors with high technological intensity and idiosyncratic volatility, such as the semiconductor industry. The methodology employed integrates quantitative filters that evaluate time windows ranging from one week to three years, allowing for the distinction between stochastic noise and structural trends. For empirical validation, the results of the simulation identified as "Madison," executed in the Investopedia Stock Simulator between January and June 2026, are analyzed. The findings reveal an exceptional portfolio performance, with an initial value of 1 million dollars reaching a value of $3,202,633.73, with an effective return of 112.64%. The tactical concentration in assets with persistent momentum such as Micron Technology (MU), Western Digital (WDC), and Applied Materials (AMAT)—with individual returns exceeding 75%—validates the hypothesis that multi-temporal screening optimizes the risk-return profile. However, the impact of the operational leverage used in the simulation and the sustainability of these results under the Adaptive Market Hypothesis are discussed. It is concluded that rigorous screening is a necessary condition for the generation of excess returns in high-beta environments.

Keywords: Financial Screening, Financial Simulation Momentum.

1.0 INTRODUCTION

In the current landscape of equity markets, characterized by minimal latency and saturated with asymmetric information, portfolio construction requires a methodological rigor that goes beyond static fundamental analysis. The ability of a manager to implement data-driven asset selection strategies has become a fundamental pillar for survival in highly volatile environments (Rösch, Subrahmanyam & Van Dijk, 2017).

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Screening has evolved from being a secondary filtering tool to becoming the algorithmic engine capable of identifying "Momentum" before its systemic exhaustion. The central challenge faced by institutional investors is capturing alpha in sectors experiencing exponential growth, specifically within the semiconductor industry, where technical obsolescence and market cycles can quickly erode capital. Transitioning from passive index management to a momentum strategy based on multitemporal screening transforms the risk-return profile, allowing exploitation of return persistence often underestimated by classical financial theory (Sukumalpongkul & Boonchoo, 2024; Joel, 2024). This study justifies its relevance by demonstrating that advanced financial literacy in the 21st century requires the validation of strategies in high-fidelity simulation environments before real capital exposure. To address this issue, it is imperative to establish clear research objectives.

2.0 GENERAL OBJECTIVE

To design and validate an investment portfolio creation methodology using multitemporal screening techniques and momentum analysis, aimed at maximizing returns on S&P 500 assets during technological growth cycles.

2.0 SPECIFIC OBJECTIVES

1. Synthesize the theoretical foundation that supports the persistence of returns and the market inefficiency exploitable thru momentum. Summarize the theoretical foundation that supports the persistence of returns and the market inefficiency exploitable thru momentum.
2. Develop a screening protocol based on multi-timeframe windows (1 month to 3 years) to rank assets according to their relative strength. Develop a screening protocol based on multi-temporal windows (1 month to 3 years) to rank assets according to their relative strength.
3. Validate the strategy using the "Madison" case study, analyzing metrics of annualized performance, leverage, and purchasing power. Validate the strategy using the "Madison" case study, analyzing metrics of annualized performance, leverage, and purchasing power.
4. Evaluate the impact of concentration in the semiconductor sector (MU, AMAT, STX, WDC) on the total portfolio variance. Evaluate the impact of concentration in the semiconductor sector (MU, AMAT, STX, WDC) on the total portfolio variance.

3.0 THEORETICAL FRAMEWORK

3.1 Ontological Foundation and Scientific Rigor in Investment

The sustainability of a high-level investment architecture does not reside in the mere contingent aggregation of financial assets, but in its ontological anchoring within an econometric construct

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capable of precisely discerning the genesis of return. This foundation constitutes the necessary technical bastion to transcend the intrinsic randomness of global markets, establishing investment not as a speculative practice, but as a rigorously replicable scientific discipline (Rosdiana & Sohilauw, 2024; Jaya & Lestari, 2024).

Following Eugene Fama's theses on market efficiency, any approach lacking a solid technical structure condemns its results to be interpreted as mere statistical artifacts or products of fleeting fortune. By proposing verifiable financial laws, the strategist redefines success as a systematic process where the portfolio architecture becomes a deliberate response to market inefficiencies. This scientific rigor, which synthesizes the stochastic nature of assets, finds its first operational phase in the purification of the investment universe thru algorithmic filtering (Weller, 2018; Cooper Currie, Seddon & Van Vliet, 2023).

3.2 Epistemology of Algorithmic Filtering and Information Theory

The asset selection process should be approached as a superior epistemological exercise, whose aim is the purification of the investment universe to mitigate structural uncertainty. This stage is not merely a superficial discard, but rather the application of a Bayesian filter that, by integrating the axioms of information theory, allows for the isolation of real value from the prevailing algorithmic noise (Summers, 2025; Ibanez, 2026).

Such normalization is essential to neutralize the risk of spurious correlations that threaten the mathematical integrity of Markowitz's efficient frontier. By ensuring the quality of the input data, the model preserves its internal coherence, preventing statistical distortions from compromising the long-term stability of the portfolio. This information cleansing constitutes the indispensable prerequisite for integrating strategic market visions thru modern and balanced quantitative management (Härdle, Klochkov, Petukhina & Zhivotovskiy, 2022; Botero, Mazo, & Arboleda, 2024).

3.3 Quantitative filtering reduces bias in the design of institutional portfolios.

In the architecture of institutional portfolios, it is imperative to balance market capital with the manager's visions thru quantitative methods that eliminate human bias. The creation of investment portfolios requires a technical combination that optimizes asset distribution while incorporating subjective perspectives under strict mathematical control. The implementation of automated screening in this framework acts as a mechanism to neutralize cognitive biases that frequently cloud professional judgment. This shift in the decision axis toward constant empirical validation forces the prioritization of statistical probability over intuition. However, in a data-saturated environment (Senescall & Low, 2024; Ioannidis, Sarikeisoglou & Angelidis, 2023).

3.4 Validation in Simulation Environments and Algorithm Resilience

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Conventional backtesting has proven insufficient in the face of the sophistication of current markets and the prevalence of p-hacking, a problematic practice in statistics and scientific research where data or analysis is manipulated to obtain "statistically significant" results, typically to achieve a p-value < 0.05. Addressing the warnings about inadvertent data manipulation, methodological validation must evolve toward real-time simulation environments that function as controlled testing and psychological simulation environments and resilience laboratories (Arakelian et al., 2024; Li & Ling, 2026). These environments allow the algorithm and operational discipline to be subjected to authentic volatility, certifying the robustness of the system without compromising institutional capital. An overfitted model may exhibit impeccable historical optimization, but it will lack predictive capacity in the face of structural changes; therefore, resilience under dynamic conditions is the only valid certification criterion. Once the robustness of the method is validated, the analysis should focus on identifying momentum as the main driver of excess return or Alpha (Hossain, Yuan & Sultan, 2025; Sun, 2026).

3.5 The Momentum Anomaly as an Endogenous Market Distortion

The momentum factor should not be interpreted as a superficial graphical trend, but as an endogenous distortion in the price discovery mechanism that subverts the axiom of the "random walk." By challenging the weak form of the Efficient Market Hypothesis, the inertial persistence of identified winning assets suggests an asynchronous incorporation of information by economic agents (Han, 2025; Bipasha, 2022). This phenomenon, known as the momentum effect, is considered an additional factor to explain the performance of financial assets. Various studies have shown that it appears in many markets around the world: assets that have had a good recent performance tend to continue performing better than average for some time. A practical way to identify this effect is thru relative strength, which measures how well an asset performs compared to its benchmark index. In simple terms, it allows you to detect assets that are showing a stronger upward trend than the market. However, for this advantage to be more consistent, it is not enough to select assets based on their recent performance. It is also necessary to consider the quality of the companies and analyze their behavior over different time horizons, avoiding reliance solely on results observed in a specific period (Sehgal, Pandey & Sen, 2025; Karki & Bikram Khadka, 2024).

3.6 Strategic Design: Sectoral Concentration and Capture of Risk Premiums

There is an important debate between two ways of investing. On one hand, traditional diversification holds that spreading investments across many assets helps reduce risk. On the other hand, active management argues that excessive diversification can reduce the potential to achieve market-beating returns, as the best opportunities become diluted within an overly broad portfolio (Sorensen, 2025; Anjaneyulu & Manasa, 2025). It is essential to analyze the behavior of assets over different periods of time. This allows for differentiation between companies whose value is steadily growing and those that only experience temporary

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recoveries driven by short-term factors. From this perspective, a strategy may consist of concentrating investments in key sectors for the digital economy, such as manufacturers of lithography equipment for semiconductors and leading companies in memory and data storage. These companies play a fundamental role in the global technological infrastructure and, therefore, can offer greater profitability opportunities (Jin, Wu & Xie, 2025). However, these assets are also often more volatile and sensitive to market movements. Although this volatility can create opportunities for momentum-based strategies, it also increases the risks. Therefore, a concentrated portfolio requires rigorous risk control, especially in aspects such as liquidity and the level of debt or leverage of the selected companies (Nafiu, Balogun, Oko-Odion, & Odumuwagun, 2025).

3.7 Critical Management of Risks, Liquidity, and Reversal Phenomena

The momentum strategy can work well under normal conditions, but it is vulnerable to sharp market declines, known as momentum crashes. That's why it requires very careful risk management. The use of debt or leverage can increase profits when the trend is positive, but it also amplifies losses when the market suddenly reverses. For this reason, it is important to manage risk by considering not only the general market volatility but also the specific behavior of each asset (Sukma & Namahoot, 2025). In this context, liquidity should not be seen merely as unused available money, but as a strategic tool. Having liquidity allows one to take advantage of market downturns to adjust or improve investment positions. It is suggested that there is a relationship between market liquidity and expected returns: when liquidity is lower, assets may offer higher returns as compensation for that risk. Overall, maintaining liquidity and using it strategically allows the investor to better react to market changes and turn volatility into opportunities rather than risks (Deng & Zhou, 2023).

3.8 Operational Efficiency and the Adaptive Market Hypothesis

The success of an investment strategy depends not only on choosing good assets but also on being able to execute it efficiently and adapt to market changes. The costs of operating in the market (such as commissions, spreads, and execution errors) can significantly reduce the profits of active strategies. Therefore, it is important to minimize the difference between the price at which an asset is bought or sold and its real value (Teall, 2022). To achieve this, automated selection and analysis systems are used to make faster and more efficient decisions, reducing frictions and improving the consistency of results over time (Jukl & Lansky, 2025). On the other hand, according to the Adaptive Market Hypothesis, markets are neither completely efficient nor static, but rather change over time. In this environment, successful investors are those who continuously adapt, as happens in an evolutionary process where the most effective strategies survive (Lo, & Zhang, 2024). Together, the use of quantitative methods, automation in asset selection, and good risk management allow for the construction of portfolios that not only seek good opportunities in the present but also adapt and remain solid over time in a changing financial environment (Olanrewaju et al., 2025).

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4.0 METHODOLOGY

Methodological rigor is what separates professional investment from gambling. The applied methodology is divided into a four-phase process designed to mitigate selection risk and maximize trend capture.

Quantitative Screening Protocol: The Investing.com screener was used to filter the S&P 500 universe under two criteria: YTD Return > 100% and 1-Year Return > 200%. This multi-temporal filter ensures that the selected assets possess structural momentum and not merely cyclical.

Execution in Simulation Environment: The strategy was tested using Investopedia's stock simulator, which allowed for practicing order execution in real time. This type of environment is useful for evaluating how the investor reacts to daily market volatility and for training decision-making under pressure. However, it is important to note a limitation: this simulator does not include actual transaction costs or price slippage, that is, the difference between the expected price and the actual execution price. This may make the results appear slightly better than they would be in a real market.

Image 1. Performance of Stocks by Time Horizon, S&P 500

North & South American Stock Markets

Americas | S&P 500

Price | Performance | Technical | Fundamental | Charts | Normal

Name	Daily	1 Week	1 Month	YTD	1 Year	3 Years
Micron	-1.43%	+3.41%	+35.46%	+243.93%	+719.10%	0.00%
Seagate	+7.25%	+6.19%	+17.04%	+238.08%	+610.50%	0.00%
Intel	+6.51%	+12.97%	+14.53%	+237.59%	+500.63%	+242.51%
Western Digital	+6.35%	+6.83%	+16.78%	+226.77%	+880.53%	0.00%
Dell Tech	+1.05%	-1.30%	+63.47%	+214.24%	+247.78%	+696.40%
AMD	+4.73%	+4.33%	+20.62%	+138.87%	+304.76%	+326.02%
Applied Materials	+2.64%	+15.25%	+29.92%	+120.73%	+221.30%	+308.30%
ON Semiconductor	+0.72%	-3.40%	+3.25%	+115.68%	+116.76%	+29.55%
Lam Research	+1.18%	+13.06%	+28.83%	+114.28%	+292.69%	+498.73%
KLA Corp	+5.55%	+20.75%	+41.07%	+109.48%	+185.24%	+447.53%
Teradyne	+5.72%	+7.61%	+19.33%	+108.31%	+359.85%	+263.05%
Corning	+1.50%	-4.45%	-6.57%	+104.66%	+252.89%	+399.86%

Source: Investing.com (2026)

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Relative Strength and Beta Filter: Technological sector assets with Betas above 1.2 were prioritized, aiming to maximize sensitivity to bullish movements of the index.

Monitoring and Rebalancing: The simulation case was named "Madison" as it was the pseudonym of the participant in the context of the simulator, and it covered the period from January to June 2026, evaluating not only the gross return but also the management of liquidity (Buying Power) and the strategic use of margin.

5.0 RESULTS

The presented results demonstrate the consistency of the multitemporal screening approach as a mechanism for identifying assets with persistent momentum across different investment horizons. The simultaneous observation of positive returns in short, medium, and long-term windows suggests the existence of structural trends beyond random market fluctuations. In particular, the concentration of extreme returns in the semiconductor and storage technology sector reinforces the hypothesis that the combination of cross-sectional momentum and multi-horizon analysis allows capturing prolonged phases of expansion in high-beta assets. Under this framework, the relative performance of the selected assets is not a product of chance, but rather the statistical persistence of trends identifiable thru systematic quantitative filters.

Table 1: Performance of Stocks by Time Horizon, S&P 500

Name	Daily	1 Week	1 Month	YTD	1 Year	3 Years
Micron (MU)	-1.43%	+3.41%	+35.46%	+243.93%	+719.10%	0.00%
Seagate (STX)	+7.25%	+6.19%	+17.04%	+238.08%	+610.50%	0.00%
Intel (INTC)	+6.51%	+12.97%	+14.53%	+237.59%	+500.63%	+242.51%
Western Digital (WDC)	+6.35%	+6.83%	+16.78%	+226.77%	+880.53%	0.00%
Dell Tech	+1.05%	-1.30%	+63.47%	+214.24%	+247.78%	+696.40%
AMD	+4.73%	+4.33%	+20.62%	+138.87%	+304.76%	+326.02%
Applied Materials (AMAT)	+2.64%	+15.25%	+29.92%	+120.73%	+221.30%	+308.30%

Source: Investing.com (2026)

Image 2 presents the performance of the simulated portfolio in the Investopedia Stock Simulator during the period from January to June 2026. The results show a significant expansion of the initial capital, reaching a total value of $3,202,633.73 and an accumulated profit of ,696,470.27, equivalent to a return of 112.64%. A strong concentration of performance is observed in technology and semiconductor assets, particularly Micron Technology (MU), Seagate Technology (STX), and Western Digital Corporation (WDC), which contribute the majority of the total gains. This behavior suggests an adequate capture of persistent momentum within the portfolio.

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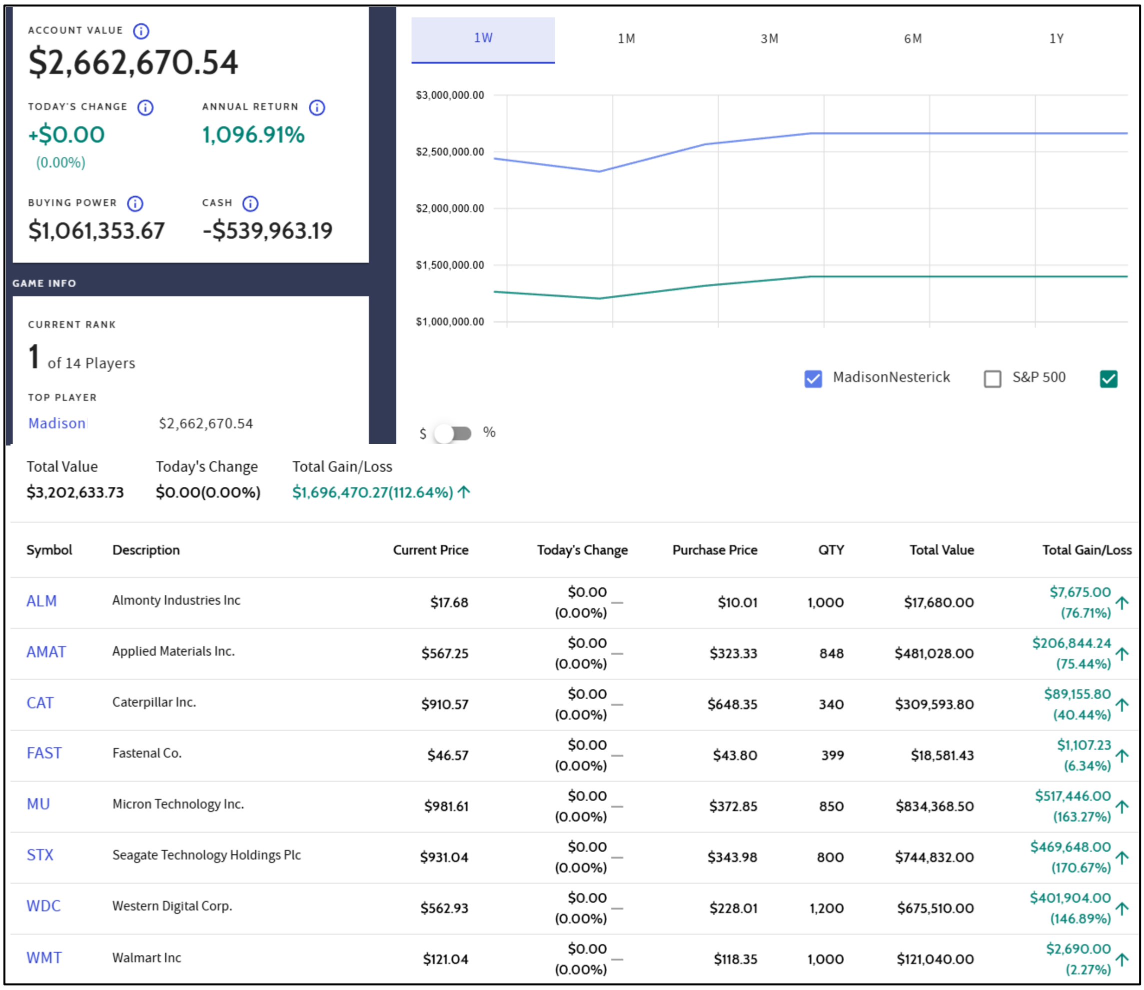
Image 2. Investment Portfolio Performance, using Investopedia Stock Simulator: From January to June 2026



Symbol	Description	Current Price	Today's Change	Purchase Price	QTY	Total Value	Total Gain/Loss
ALM	Almonty Industries Inc	$17.68	$0.00 (0.00%)	$10.01	1,000	$17,680.00	$7,675.00 (76.71%)
AMAT	Applied Materials Inc.	$567.25	$0.00 (0.00%)	$323.33	848	$481,028.00	$206,844.24 (75.44%)
CAT	Caterpillar Inc.	$910.57	$0.00 (0.00%)	$648.35	340	$309,593.80	$89,155.80 (40.44%)
FAST	Fastenal Co.	$46.57	$0.00 (0.00%)	$43.80	399	$18,581.43	$1,107.23 (6.34%)
MU	Micron Technology Inc.	$981.61	$0.00 (0.00%)	$372.85	850	$834,368.50	$517,446.00 (163.27%)
STX	Seagate Technology Holdings Plc	$931.04	$0.00 (0.00%)	$343.98	800	$744,832.00	$469,648.00 (170.67%)
WDC	Western Digital Corp.	$562.93	$0.00 (0.00%)	$228.01	1,200	$675,510.00	$401,904.00 (146.89%)
WMT	Walmart Inc	$121.04	$0.00 (0.00%)	$118.35	1,000	$121,040.00	$2,690.00 (2.27%)

Source: Investopedia Stock Simulator (2026)

Table 2 presents the performance of the portfolio corresponding to the "Madison" Case within the Investopedia simulation environment. This portfolio reflects an investment strategy based on the systematic selection of assets with momentum and relative strength characteristics within the U.S. market. The portfolio structure is primarily oriented toward technology and semiconductor sectors, where the highest growth trends are concentrated. The results illustrate the ability of the applied approach to identify assets with persistent upward behavior, highlighting the effectiveness of the multitemporal screening model in constructing portfolios biased toward superior returns in high volatility environments.

Table 2: Investment Portfolio Performance (Madison Case)

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Symbol	Purchase price	Current price	Quantity	Total value	Total gain/loss	Total gain/loss (%)
ALM	$10.01	$17.68	1,000	$17,680.00	$7,675.00	76.71%
AMAT	$323.33	$567.25	848	$481,028.00	$206,844.24	75.44%
CAT	$648.35	$910.57	340	$309,593.80	$89,155.80	40.44%
FAST	$43.80	$46.57	399	$18,581.43	$1,107.23	6.34%
MU	$372.85	$981.61	850	$834,368.50	$517,446.00	163.27%
STX	$343.98	$931.04	800	$744,832.00	$469,648.00	170.67%
WDC	$228.01	$562.93	1,200	$675,510.00	$401,904.00	146.89%
WMT	$118.35	$121.04	1,000	$121,040.00	$2,690.00	2.27%
TOTAL	---	---	---	**$3,202,633.73**	**$1,696,470.27**	**112.64%**

Source: Investopedia Stock Simulator (2026)

5.1 Cross-Sectional Analysis

The success of the portfolio is attributed to the identification of assets with massive trend persistence. Micron Technology (MU) and Seagate Technology (STX) not only led the screening (Table 1) with 1-year returns exceeding 600%, but their integration into the portfolio generated individual gains of $517k and $469k respectively. Another key differentiator in the simulation was the inclusion of Applied Materials (AMAT) and Almonty Industries (ALM), which contributed a combined return of over 75%, shielding the portfolio from the lower volatility of assets like Walmart (WMT). The use of windows from 1 month to 3 years allowed the manager participating in the simulation to ignore daily noise and position themselves in the acceleration of the value curve.

6.0 CONCLUSION AND DISCUSSION

The multitemporal screening methodology proved capable of capturing returns that exceed, among others, the S&P 500 benchmark. According to the Adaptive Market Hypothesis, high levels of Alpha or extra return over a desired benchmark level tend to be quickly arbitraged by institutional algorithms in real markets. The negative cash position in the context of the simulation (-$539,963.19) reveals an aggressive margin strategy. While this boosted gains in a bull cycle, a 10% corrective move in the tech sector would have triggered significant margin calls, highlighting the risk in momentum strategies. For institutional investors, multitemporal screening represents a primary filter, but it must be accompanied by tail risk management.

Financial education has evolved from passive lecturing and static analysis to dynamic experimentation. The use of high-fidelity tools, such as the Investopedia Stock Simulator, allows academic training to bridge the gap with professional practice, transforming portfolio theory into an executable operational experience. Portfolio simulation is now a necessary condition for 21st-century financial literacy. The case of the simulation participant identified as "Madison" represents a practical example that allows students, by actively participating in financial simulation exercises, to develop skills in terms of the ability to maintain discipline in the face of volatility and manage liquidity without risking real institutional capital. This active learning approach ensures that the technique does not remain theoretical but becomes a resilient competency. The following is Table 3, which compares the main differences between the active teaching methodology based on financial simulation and the traditional theoretical learning approach. The analysis highlights how the use of tools like the Investopedia Stock Simulator transforms training into a practical experience, allowing direct interaction with real market conditions. Unlike the traditional model, which focuses on theory and static analysis, the active methodology incorporates decision-making under uncertainty, liquidity management, and the development of operational discipline. This strengthens applied skills and reduces the gap between academic knowledge and effective professional practice.

Table 3. Advantages of Active Methodology over Traditional Teaching

Characteristic	Active Methodology (Simulation)	Traditional Teaching (Static)
Data Validation	Real-time backtesting with dynamic data.	Historical analysis of passive, closed datasets.
Liquidity Management	Critical monitoring of margin requirements and buying power.	Theoretical calculation of ratios without capital constraints.
Psychological Factor	Stress management and discipline in response to market conditions.	Purely cognitive and mathematical approach.
Adaptability	Response to structural changes in the market.	Validation based on optimization of historical data.

Source: Elaboración propia en base a la experiencia de aplicar la simulación financiera en el aula de clase

This pedagogical convergence ensures that technical competence is validated by constant empirical practice, preparing future financial leaders for high-uncertainty markets. This research confirms that the multitemporal screening protocol is a robust tool for generating excess returns, achieving an effective return of 112.64% in the case of the simulation applied from January to June 2026, referred to as the "Madison" case. The results validate that professional investment is not a speculative practice, but a scientific discipline where the portfolio architecture responds to identifiable and replicable market inefficiencies. Validation in simulation environments is an indispensable prerequisite for the certification of investment models, acting as the necessary resilience laboratory in the face of the sophistication of the global ecosystem. Ultimately, superiority in asset management emanates from the convergence between mathematical rigor and the capacity for evolutionary adaptation in a market that, by nature, never remains static.

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