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Simulated Comparison of Charles Schwab Recommended Retirement Portfolio Allocation and a Varying Running-Based Allocation Strategy

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ABSTRACT

Traditional retirement accounts have an investment strategy that holds fixed levels of asset allocation based on age. The rigidity causes the portfolio to lose out on potential gains. The investment strategy starts with an aggressive portfolio of largely stocks as a riskier asset and shifts to a smaller allocation toward retirement. This paper proposes a running-based strategy that varies the allocations and outperforms the traditional approach. The running-based strategy makes the risk proportional to the energy output during a running workout. This constitutes an inclusion of fluctuating intervals that function as a protection against overly aggressive portfolio risk during bearish market periods. The two strategies were compared through a simulation over the past 40 years. It was found that both strategies performed similarly while they maintained an aggressive stance. As the conventional strategy reduces risk, the proposed approach was able to capitalize on market gains while still adjusting for potential exposure.

INTRODUCTION

The Charles Schwab allocation model (SAM) is based on the Charles Schwab Retirement fund allocation recommendation that follows fixed allocations of stocks, bonds, and cash at constant rates of risk of a retirement portfolio over phases of its term. It begins with aggressive equity allocation to grow capital but then transitions to safer assets. This approach allows the portfolio time to quickly increase value and then let it grow until closer to retirement, where the allocation changes to minimize risk but also potential profit in stocks. The proposed allocation model based on running patterns (RAM) during a workout would allow for the portfolio to take full advantage of a bullish market and then pull back on the risk as a safety net, similar to the SAM approach. The varying allocations of RAM allow for safely building capital during the warmup and cooldown, and provides some variations during the workout phase for optimizing gains.

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The SAM maintains a highly aggressive strategy for the first 25 years, then switches to moderate, and then switches to a safe strategy for the last few years. This causes it to lose potential gains during the last 15 years. It is an overly conservative strategy that places too much capital into low margin assets in later years.

The purpose of this study is to test whether a varying allocation strategy provides measurable advantages over a traditional allocation model. The models will be compared and discussed.

LITERATURE REVIEW

Target-Date Funds (TDF) were first introduced by Donald Luskin and Larry Tint in 1994 (Barstein, 2024) as practical, low-interference retirement plans. TDFs give an approximate date of retirement for the portfolio owner by following the idea of a decreasing glidepath where risk decreases constantly with age. These were designed as simple retirement solutions to automatically adjust equity allocation downwards over time. They also prevented the population from introducing too much risk or too little risk into their portfolios.

Retirement Portfolio Allocation

The objective of a retirement account is to maximize the value of the account while minimizing risk and minimize the uncertainty of passive income near retirement. In addition, a retirement account should be simple to manage to avoid extra fees for financial management and prevent mistakes from the investor. TDFs fulfill the objectives of being simple, although they do not avoid extra fees for management, and minimizing uncertainty near retirement to secure passive income during retirement.

Campbell and Viceira (2002) concluded that a young household should invest aggressively because they have substantial human wealth, meaning they have strong future earnings, health, and education. It is not as dangerous to invest their financial wealth because they have their human wealth as a safety net. On the other hand, an older household does not have the same level of human wealth. They should invest their financial wealth more carefully. They add, however, that investor-specific factors such as attitudes on risk and timing have significant impacts on portfolio allocations.

This outcome supports the idea of TDFs where risk decreases over time. However, assumptions made about TDFs allow for more precise allocation methods to be even more efficient.

In 101 tests of 40 year periods, an increasing risk glidepath performed better than a standard decreasing glidepath (Arnott et al., 2013). This challenges the conventional idea of a decreasing glidepath, suggesting that there may be an optimal relationship between age and risk that is not monotonic. This cannot be a result of fortunate market timing because the differences of the distributions of the terminal values were significant. In fact, Arnott et al. (2013) argues that TDFs do not maximize profit or reduce uncertainty through multiple tests. Overall, savings are higher later in life so growth is stronger. A minimized risk later in life means an investor misses out on the largest profits. This is why an increasing glidepath might be better than a traditional TDF.

Less volatile equities might be a better solution to near retirement risk mitigation as they allow for a better upside without the minimal profit of low-yield bond (Arnott et al., 2013). If there exists a low volatility equity with dividends to the investor that allow for passive income then they will allow the portfolio to maintain allocation in stocks without increasing risk.

Studies have demonstrated that the standard glidepath of a TDF may not be the most efficient strategy for retirement accumulation. TDFs may forgo important growth from equities closer to retirement. New glidepaths and allocation strategies must be tested to ensure that retirement growth can be optimized.

Dynamic Asset Allocation

Depending on market performance, the glidepath of a portfolio should be increasing or decreasing. Mindlin (2015) suggests that an optimal portfolio begins with a "takeoff" - or a sharp increase in risk - at the start of its lifetime. This prevents the extremely harmful effects of large market crashes early in retirement investing that could impact the benefit of compounding capital in the future. Furthermore, it allows safe cash growth.

Cairns et al. (2006) establishes a stochastic asset allocation plan where allocation is determined by market returns, income, and interest rate risk. They found that this asset allocation strategy is superior to a deterministic strategy, building upon the idea that, while a TDF may be a working, simple asset allocation strategy, it can be improved by precise changes over time in the level of risk taken on by the portfolio.

Limitations of Existing Glidepath Research

Existing research supports increasing glidepaths (Arnott et al. 2013), dynamic allocation (Cairns et al, 2006), and early portfolio risk management (Mindlin, 2015). However, these approaches rely on changing glidepaths or stochastic optimization. There is little attention given to simple, predetermined periodic allocation strategies that alternate between high and low equity exposure while remaining easy for investors to implement themselves.

Performance Metrics

To determine the success of an allocation strategy, we must use technical metrics to measure their performance. Due to the nature of contributions in retirement accounts, it is not sufficient to calculate the average interest rate of strategy as a comparison. Performance must be compared in terms of growth excluding contributions, growth reliant on contributions, risk, and volatility.

Growth rate should be measured with the Internal Rate of Return (IRR) and the Time-Weighted Return (TWR). Both of these measures are required to see the growth of the portfolio wholly. The TWR isolates the strategy's growth from contributions, making it a strong metric for analyzing the performance of the strategy individually (Hasting, 2018). On the other hand, the IRR the realized experience for the investor which includes the benefits from cash flows into the portfolio (Hasting, 2018). These both can be used together to express the general monetary performance rate of a strategy.

To understand the risk exposure of a strategy we look at 3 metrics: Maximum Drawdown (MDD), Sharpe ratio, and Sortino ratio.

The MDD indicates the largest drop or trough from a peak that the performance of a portfolio sustains. These are very important to be minimized for two reasons: first, significant drops in capital will influence investors to act recklessly or emotionally, causing them to withdraw or lose out on additional money to that which they already lost (Mendes & Lavrado, 2017); second, it is significantly more difficult to recover from a large drop due to a lack of capital. For example, if a portfolio drops 50%, it will take a 100% growth to bring the portfolio back to its original state. However, just looking at one MDD can be misleading. Taken as one point, the MDD could be an outlier from the performance of the portfolio. But an average of the three largest MDD gives a much stronger view of the downside performance of a strategy.

The Sharpe and Sortino ratios are risk-adjusted metrics that focus on comparing returns to the amount of risk taken to obtain that gain. The Sharpe ratio focuses on measuring the risk taken on risky assets relative to the volatility of the portfolio (Brinza et al., 2024). A risk-free portfolio would have a Sharpe ratio of 0 with a larger value signifying a more efficient returns-for-risk strategy. This metric is used to determine the stability of the portfolio and whether they benefit accordingly to risk.

The Sortino ratio is similar to the Sharpe ratio but only compares returns to downside risk - or volatility of returns less than the risk-free rate. The Sortino ratio can give less biased insight measuring the performance of a portfolio due to its inclusion of only poorly performing periods (Chaudhry & Johnson, 2008). The Sharpe ratio includes positive and negative spikes into its measure of performance, while the Sortino ratio only recognizes the negative spikes.

Motivation for a Periodic Running-Based Allocation Strategy

An ideal retirement allocation plan should be simple and introduce minimal risk while maximizing capital by retirement.

Formation of the ideal asset allocation strategy first focuses on minimizing risk. The "takeoff" strategy (Mindlin, 2015) is useful for minimizing critical risk at the beginning of a retirement plan's lifetime.

When financial wealth is low, an increasing glidepath may allow safely growing capital without risking significant portions of savings, especially because income is expected to rise.

Closer to retirement, risk must be minimized to reduce uncertainty and critical losses of capital leading into retirement. Therefore, the strategy implements a decreasing glidepath near retirement - or a “touchdown.”

We must determine ideal asset allocation for the time following the “takeoff” and before the “touchdown.” A dynamic allocation plan performs better than a traditional TDF (Cairns et al., 2006), so this period should be made of some sort of uncomplicated dynamic strategy that minimizes risk while maintaining assets in equities for profit.

The “takeoff” and “touchdown” intervals can be repeated as subintervals of rising and falling equity allocation during the lifetime of the portfolio. Following the initial “takeoff” there will be a periodic switch between a smaller “touchdown” and “takeoff.” This allows the account to enjoy the same benefits of these methods, but on a smaller scale. These smaller periods provide the advantage of building capital safely and then having equity exposure rather than continuous high-risk to low-risk asset exposure.

The simplicity of this strategy comes from its repeating structure. Because the market cannot be reliably predicted, predetermined periods of risk and safety have no inherent advantage over different timings of these periods. Therefore, a singular allocation path can work for any end date. The investor has no more work to do than they would in a simple TDF. Additionally, it is clear at any time where their money is allocated. The investor may contribute money at any time without worrying about their market timing.

A periodic asset allocation strategy is a simple strategy that allows for minimal risk and safe capital growth while maintaining high equity allocations at some times. There are risky periods and safer periods. The cycle between risk and safety allows for equity exposure with sufficient backup for the risk.

METHODS

The purpose of this section is to describe the SAM approach as well as the RAM approach, including assumptions and factors considered.

Risk Calculation

The risk allocation is derived from the time-based allocation levels of the SAM. A range of risk levels is determined using curves of best fit of the SAM, rather than specific values. These values can be used as inputs to determine allocation percentages for each asset. These curves of best fit are computed by compiling the known points for asset allocation level in terms of risk. By performing logarithmic regression on these points to create lines that naturally fit the given points. Basically, building curves defined by logarithms that follow the trend of the given points from the SAM.

Risk, r, describes the aggression of the model.

$$r \in [0, 1]$$

For the three levels of risk in the SAM, when r=1, it is aggressive; when r=0.5, it is moderate; and when r=0, it is conservative. Intermediate percentage values of asset allocations are mapped using the previously described logarithmic regression curves that fit the data of the SAM.

$$S(r) = 6.45681\log(0.441289r + 1.43911) - 0.820773$$
$$C(r) = -0.0112084\log(1.13r + 3.9896810 \cdot 10^{-23}) + 0.0489193$$
$$B(r) = 0.639229\log(2.04539 - 1.70765r) + 0.301344$$

Where, at risk level r, C(r) is the cash allocation, S(r) is the stock allocation, and B(r) is the bond allocation. Due to truncation, these formulas will not always add up to 1. In this case, the bond allocation is modified accordingly. We use these formulas to determine the allocation percentages of the RAM.

For simplicity, cash assets were assumed to earn a constant annual return of 2%. This value was also used as the risk-free rate when calculating Sharpe and Sortino ratios. While historical short-term interest rates varied during the study period, a constant rate was chosen to isolate differences between allocation strategies rather than interest-rate environments.

For bond assets, they will be assessed yearly as U.S. issued 1-year T-bills, with historical data from 1986-2025 (Federal Reserve Bank of St. Louis, 2026). In our simulation, T-bills are simply assets that grow at a fixed, safe rate in the duration of their lifetime. They grow faster than cash and slower than stocks, but they are significantly safer than stocks. T-bills are government backed assets that work as loans to the government. They are paid back in full at maturity in addition to the interest rate.

For stock assets, the ^GSPC ticker was used with historical data provided by Yahoo Finance. The ^GSPC ticker does not include dividends, which are payments from a company to an investor that are a portion of the company's profits, serving as a reward or incentive for investing. The dividends are considered negligible because it will be evident that the strategy with the most allocation of stock creates the best returns - even without dividends.

Charles Schwab Allocation Model (SAM)

The SAM is based on the Charles Schwab Allocation by age recommendations for retirement accounts. The recommendation is split into three parts; aggressive, moderate, and conservative as shown in Table 1 (Schwab Center for Financial Research, 2026).

Aggressive	Moderate	Conservative
>15 years until retirement	~10 years until retirement	3-5 years until retirement
95% Stock, 5% Cash, 0% Bonds	65% Stock, 5% Cash, 30% Bonds	20% Stock, 30% Cash, 50% Bonds

Table 1: Charles Schwab Allocation by age recommendations for retirement accounts

Let n be the number of years until retirement.

$$C(r(n)) = \begin{cases} 0.05 & n \le 25 \\ 0.3 & 25 < n \le 40 \end{cases}$$

$$S(r(n)) = \begin{cases} 0.95 & n \le 25 \\ 0.65 & 25 < n \le 35 \\ 0.2 & 35 < n \le 40 \end{cases}$$

$$B(r(n)) = \begin{cases} 0 & n \le 25 \\ 0.35 & 25 < n \le 35 \\ 0.5 & 35 < n \le 40 \end{cases}$$

$$r(n) = \begin{cases} 1 & n \le 25 \\ 0.5 & 25 < n \le 35 \\ 0 & 35 < n \le 40 \end{cases}$$

The algorithm representing the SAM switches to a risk level of 0 at n=33 because there is some ambiguity with how Charles Schwab presents their recommendation in Table 1, the resolved recommendation is in Figure 1.

This allocation plan allows for aggressive growth over the majority of the account's lifetime and begins to taper off and favor safer investments, such as bonds and cash, during later years.

This model is popular due to its simplicity and opportunity for growth. However, despite its widespread use, it is unable to take advantage of bullish markets due to its fixed allocation and takes a shortsighted view of how long these funds must last upon retirement.

The formulas in this model are based on time rather than risk level. The idea of a risk level is sourced from the SAM's allocation levels, and those risk levels are also used in the RAM.

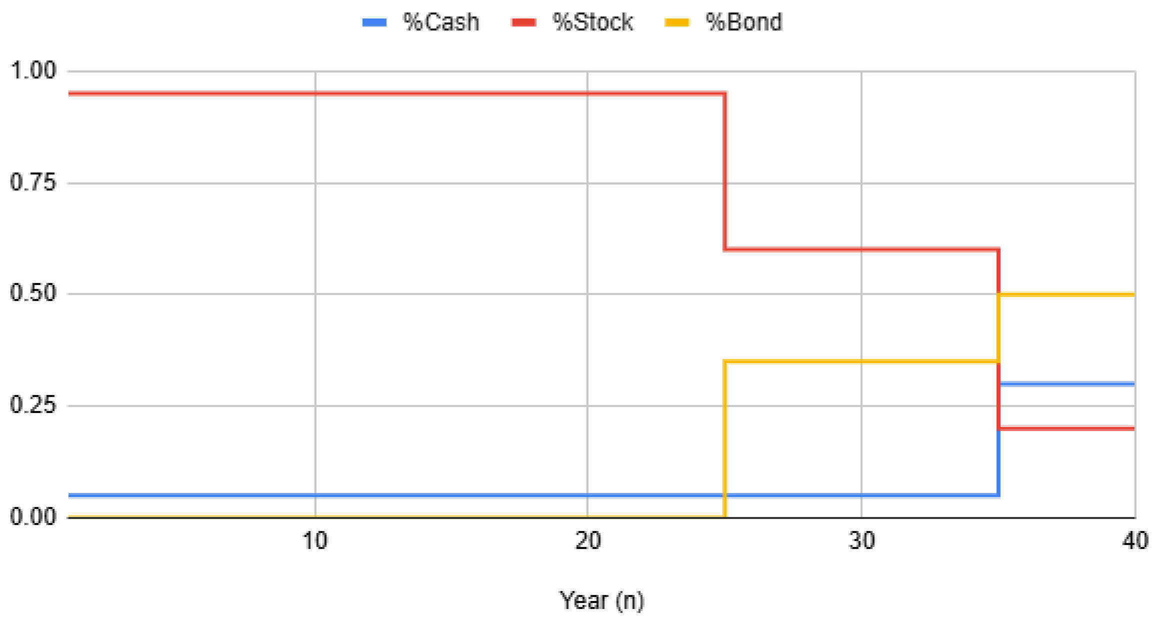

Figure 1: Asset Allocation vs. Time

Running-Based Allocation Model (RAM)

The RAM portfolio risk follows a curve analogous to a running workout consisting of a warm-up, high intensity intervals, recovery periods, and a cooldown as shown in Figure 2.

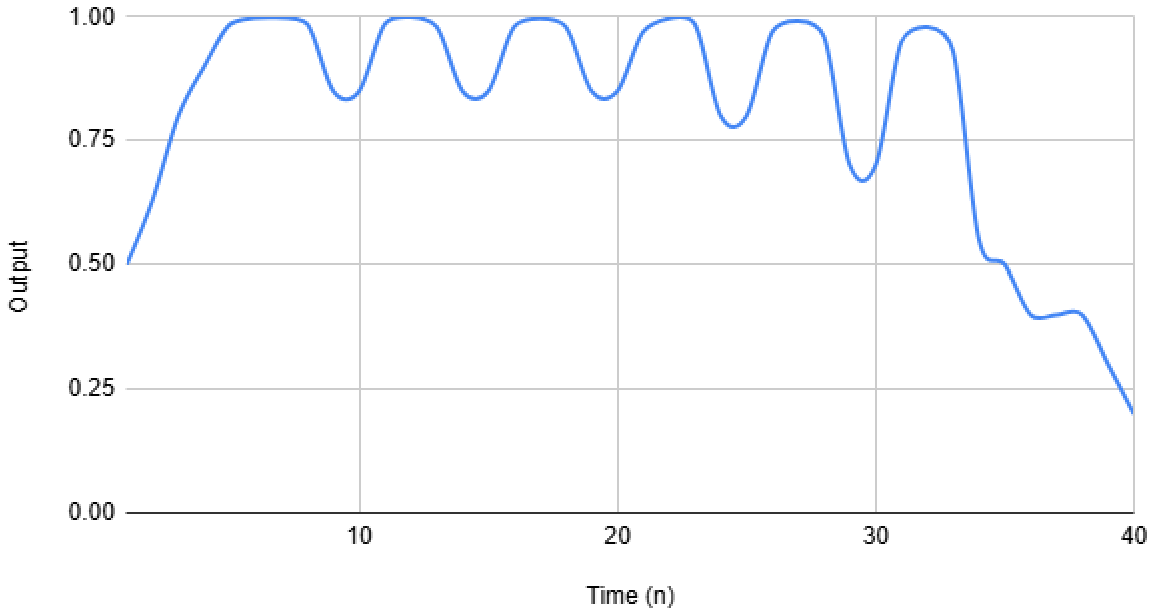

Figure 2: Running Output vs. Time (n)

The RAM utilizes varying risk levels based off of this running workout: a warmup, where it becomes riskier over the years; workout intervals, where it stays at high risk where risk is directly correlated to output; rest intervals, where the risk falls to a more conservative allocation; and a cooldown, where the risk gradually declines. These levels are visualized in Figure 3. The risk levels make the strategy dynamic and risk-cycling.

The RAM is different from the SAM because of its varying allocation levels - shown in Figure 4 - that allow it to minimize the amount of time that the model is at the highest risk while still maintaining aggressive periods.

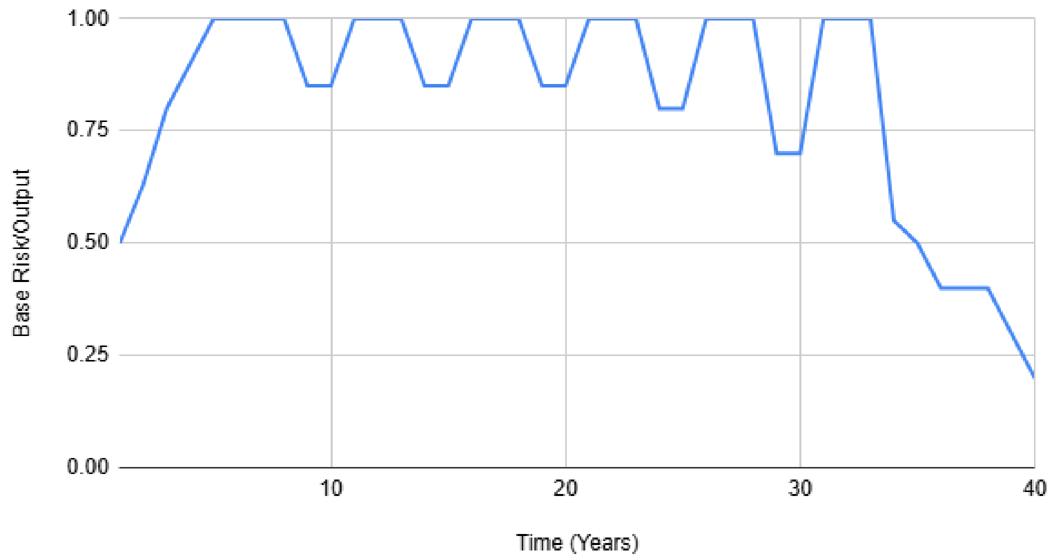

Figure 3: Base Risk/Output vs. Time (Years)

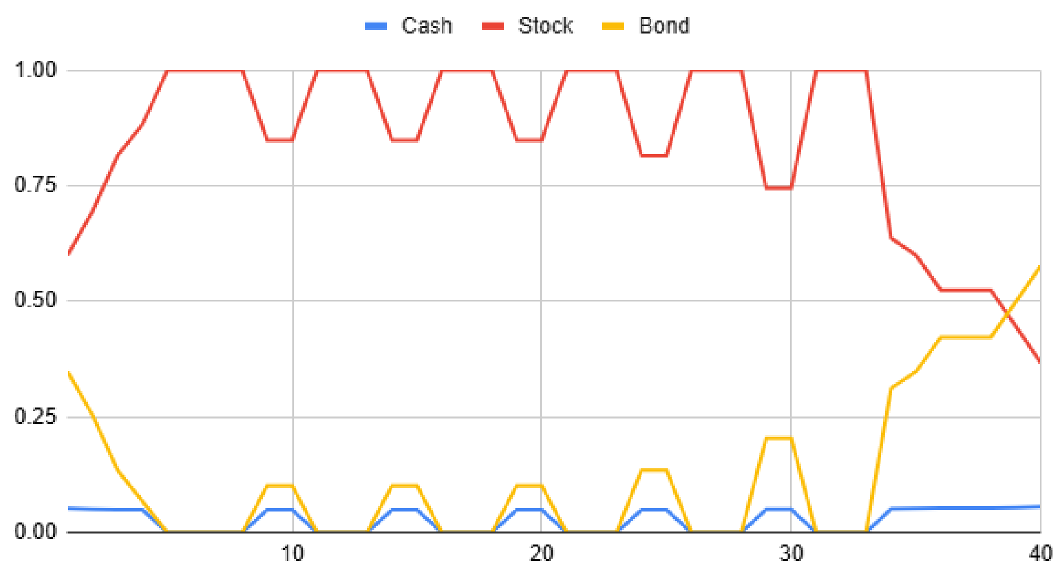

Figure 4: Asset Allocation vs. Time (years)

Each rest interval lasts 2 years while each "Running" interval lasts for 3 years except for the first "Running" interval because more time was spent on the first interval in the original workout from Figure 2. Additionally, the warmup ends in year 5 and the cooldown starts in year 34.

Aggressiveness on Decline

An additional rule is used to increase exposure to gains from high potential assets following negative performance. If the portfolio increased in value in the past year, then no allocation changes occur. If the portfolio underperforms, then the stock allocation increases by an amount no greater than 50% for the following year. The bond allocation decreases accordingly so that the total allocation is 100%. In one example, when the stock allocation is 60% and the bond allocation is 40%, the stock allocation will be adjusted to 100% and the bond allocation will be adjusted to 0%. In another example, when the stock allocation is 40% and the bond allocation is 60%, the stock allocation will be adjusted to 90% and the bond allocation will be adjusted to 10%.

Following this strategy, the adjusted allocation levels can be seen in Figure 5.

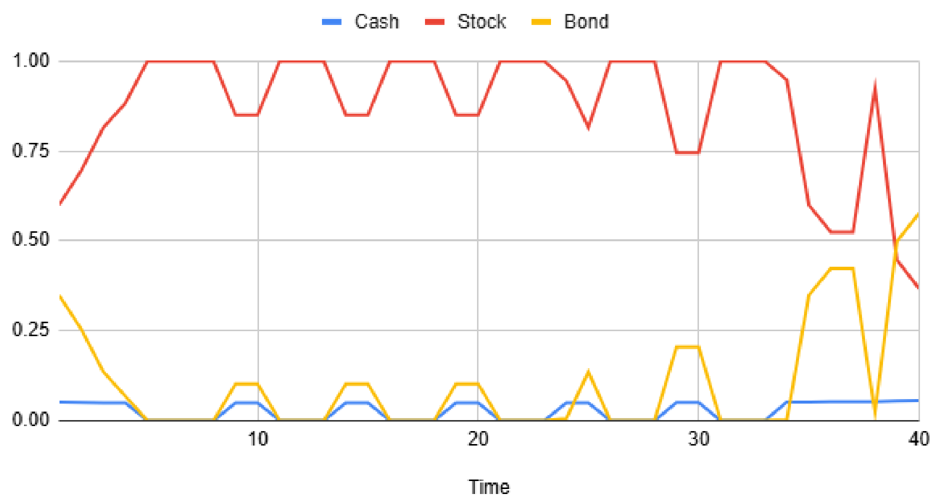

Figure 5: Adjusted Asset Allocation vs. Time (years)

Let x_n be the value of the portfolio at year n:

$$\alpha = max\left\{ i \in \{1, 2, \ldots, 50\} : B(r) - \frac{i}{100} \geq 0 \right\}$$

$$\frac{x_n}{x_{n-1}} < 1 \Rightarrow \begin{cases} S(r) \leftarrow S(r) + \frac{\alpha}{100} \\ B(r) \leftarrow B(r) - \frac{\alpha}{100} \end{cases}$$

This strategy introduces a degree of freedom for the benefit of the RAM, meaning that a new variable is introduced that may only be beneficial to a certain data set. If it is only beneficial to a singular data set, then it would be misleading within the comparison of the two models, however, if the variable proves to be significant over multiple data sets, then it can be considered a reasonable variable that does not give an unfair advantage to one model. This degree of freedom will be accounted for in the Monte Carlo simulation section as it will be shown that this strategy is not only beneficial in the true historical data case but also in many data sets.

Implementation Details

The code for this implementation was written in Python using standard data structures and mathematical operations. Python worked well for keeping data analysis efficient. Both models were tested during the same historical periods with the same data. The models were run simultaneously and completed without error.

Historical input data was obtained from Yahoo! finance while risk levels were determined through Excel calculations. Each model was tested over the same 40 years from the beginning of 1986 to the beginning of 2026 with allocation adjustments only occurring the first day of each year. Each year was considered a tick, and after each tick, the portfolios would reallocate.

Plotting and data management libraries were used to stay organized and make visualizations of the data.

RESULTS

Backtesting Results

A 40-year historical simulation was run from 1986-2026 with identical data to test the two models. The RAM was able to take advantage of strong market years much better than the SAM towards the end of their lifetimes. However, during early years, the RAM managed to stay very close in value to the SAM in all market conditions.

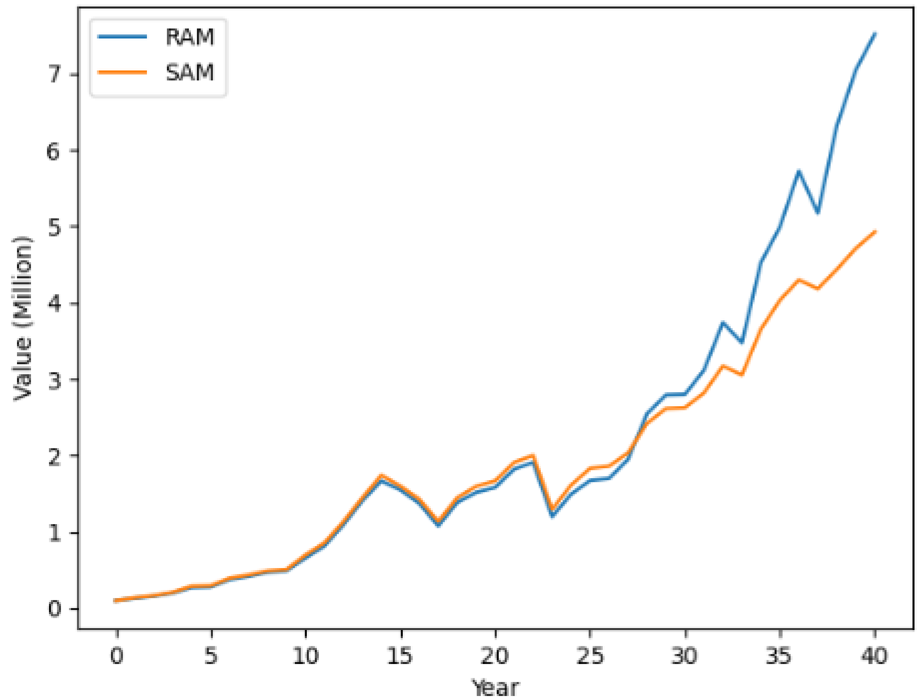

Figure 6: 40-year backtest of the SAM and RAM

As shown in Figure 6, both models perform similarly until year 28 when the market performs favorably. Even before the SAM started to ramp down the risk level, because the RAM has a greater stock allocation, the RAM is better positioned to take advantage of the bull market. In bearish markets, before the SAM switches to its more conservative risk strategy, both models have identical returns. Once the SAM becomes more conservative, its losses are much smaller than those of the RAM.

The RAM's aggressiveness on decline strategy was called six times over 40 years. It is first called in three consecutive years: 15, 16, and 17. In these years, the allocation level was already 100% stock so no changes were made. These years represent the period of 2000-2002, which is known for a recession due to terrorist attacks and the dot-com bubble burst where unemployment rose to 6.3% (Hagan, 2022). Next, in year 23, which is around 2008-2009, the Great Recession and financial crisis of 2008 occurred. These were marked by significant drops in stock values. The strategy is also called at year 33, or 2019, when the COVID-19 pandemic struck, causing panic, uncertainty, and isolation. Finally, in year 37, or 2023, there was both turmoil within banks and questions about the U.S. debt ceiling that was reached at the beginning of that year. It is important to note that if the strategy was only called six times, then the model only had negative annual returns 6 out of 40 years, or 15% of the time.

Monte Carlo Simulation

In addition to testing the models on historical data, Monte Carlo simulations were performed on random combinations of the 40 years of historical returns provided in the backtest; this was done to simulate combinations of years that have actually occurred.

A Monte Carlo simulation is a repeated random sampling with respect to a variable. These simulations allow us to test a hypothesis under multiple conditions to attain a general result rather than a specific result tied to a fixed variable or dataset.

This simulation helps predict the probability of an event occurring. This paper evaluates the likelihood of the RAM outperforming the SAM, as well as determining additional data confirming the superiority of one model. The Monte Carlo simulations help to understand how much one model outperforms the other.

The changing variable is the dataset of price changes year after year for stocks. The selection of this particular variable can show that the RAM not only performs better based on historical data, but also on random sequences of stock price returns from the original dataset. This ensures that each period given by the random sequences has realistic returns.

A total of 100,000 independent simulations were performed. To have a simulation of every sequence of 40 years of returns, 40! sequences would be needed, which is unrealistic. 100,000 simulations is considered to be significant to show the trend of the comparison of the models. Each simulation represented a 40 year period where the SAM and RAM were applied to identical sequences of returns to ensure a fair comparison.

Each simulation began with $100,000 and deposited $24,500 a year into the account and was performed identically to how the backtest was performed.

For every simulation, terminal wealth was recorded for both strategies. Additional statistics calculated included average terminal wealth, median terminal wealth, terminal wealth distributions, cumulative distribution functions (CDFs), kernel density estimates (KDEs), excess terminal wealth distributions, and the proportion of simulations in which RAM produced greater terminal wealth than SAM. These metrics were used to evaluate both the magnitude and consistency of any performance differences between the two allocation approaches.

Monte Carlo Simulation Results

This section outlines the results of the Monte Carlo simulation on the RAM and the SAM.

Strategy	Mean	Median	Minimum	Maximum	5th Percentile	25th Percentile	75th Percentile	95th Percentile
RAM	$9,079,383	$8,772,619	$4,052,825	$24,228,703	$6,146,572	$7,522,272	$10,307,487	$13,068,564
SAM	$6,643,976	$6,424,399	$3,345,845	$16,156,579	$4,613,070	$5,564,275	$7,511,162	$9,395,373

Table 2: Metrics and distributions determined by the Monte Carlo Simulation

Terminal Wealth Comparison

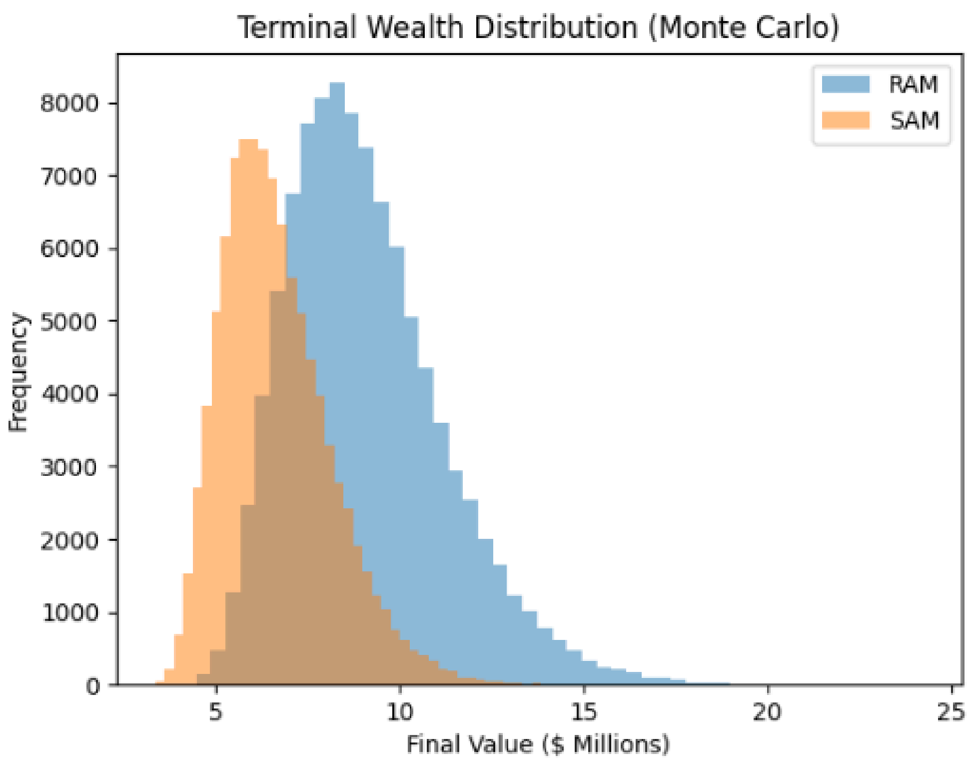

Figure 7: Terminal Wealth Comparison of the SAM and RAM

The Terminal Wealth Comparison shows how many simulations each final value was reached for each model. The rightward shift of the RAM over the SAM in Figure 7 indicates that higher terminal wealth outcomes were consistently more likely under RAM across the simulated market environments.

Terminal Wealth Distribution

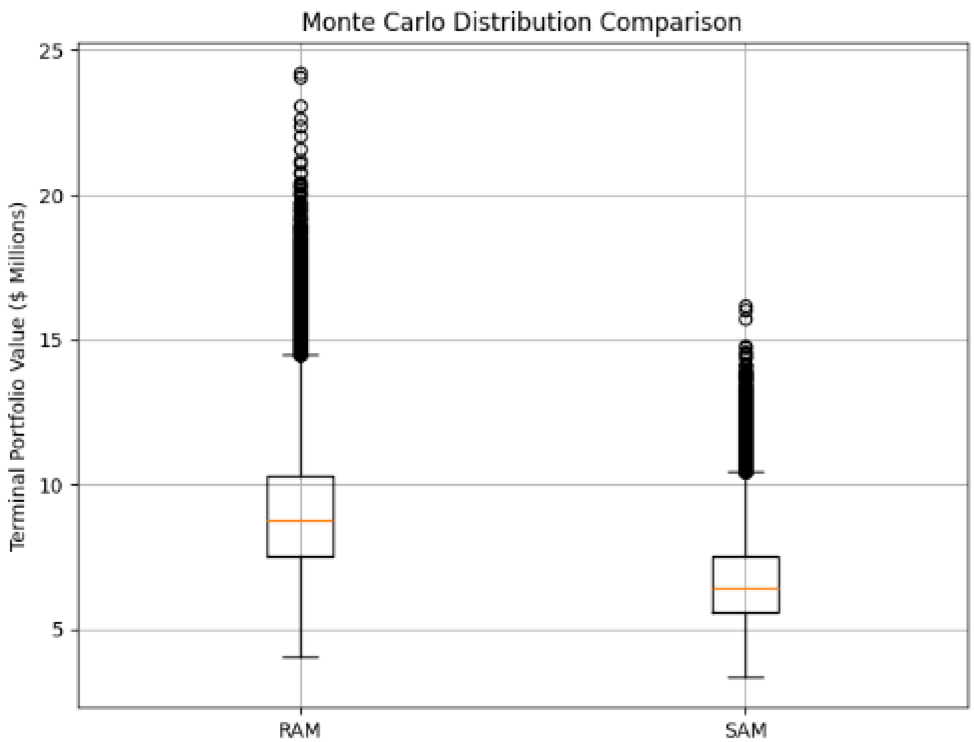

Figure 8: Terminal Wealth Distribution of the SAM and RAM

The Terminal Wealth Distribution shows the distributions of the two models across the simulation including the median, the quartiles, and the extremes. The upward shift of the plot of the RAM over the SAM, as seen in Figure 8, suggests that the RAM significantly outperformed the SAM. It is clear that the RAM outperforms the SAM in every percentile. Additionally, the RAM has greater upside potential as some of the simulations reach $22,500,000.

Kernel Density Estimate

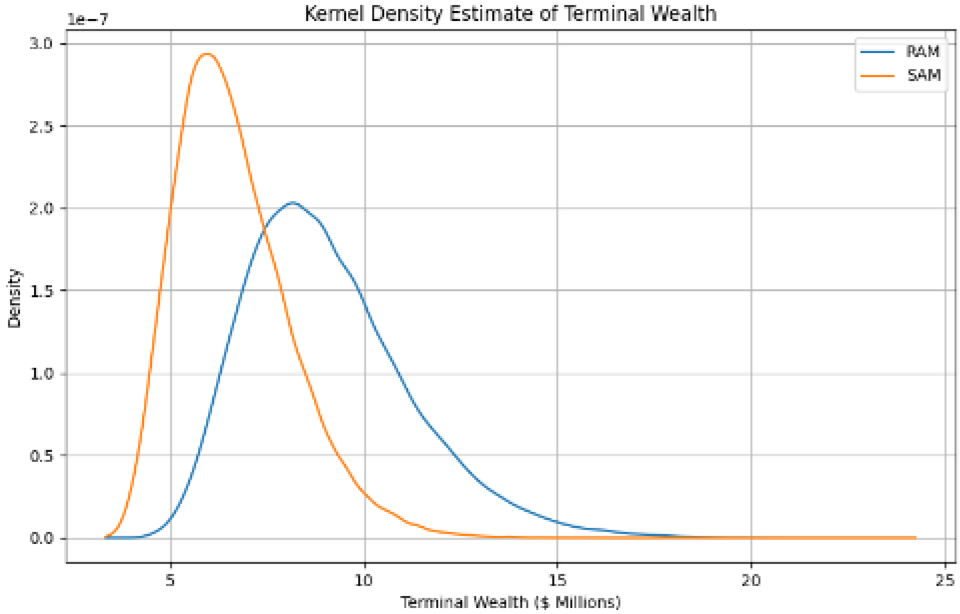

Figure 9: Kernel Density Estimate of Terminal Wealth of the SAM and RAM

The Kernel Density Estimate is similar to the distributions of the two models but instead of describing the distributions as a boxplot, it is a graph comparing the density of the points in the distribution to their final values. In Figure 9, the RAM is shifted right and wider spread than the SAM. This means that the RAM has a higher terminal wealth on average and that there is a higher variance of results between simulations of the RAM. Additionally, it has a right tail that shows the occasional high upside outcome.

The SAM is much less widespread and concentrated further left than the RAM. This means it has lower expected terminal wealth and lower variance. Its right tail is also much weaker than the RAM so it has less opportunity for upside outcomes.

The SAM dominates in stability while the RAM dominates in expected outcomes. However, the RAM's worst performances are similar to lower percentile performances of the SAM.

Cumulative Distribution Function

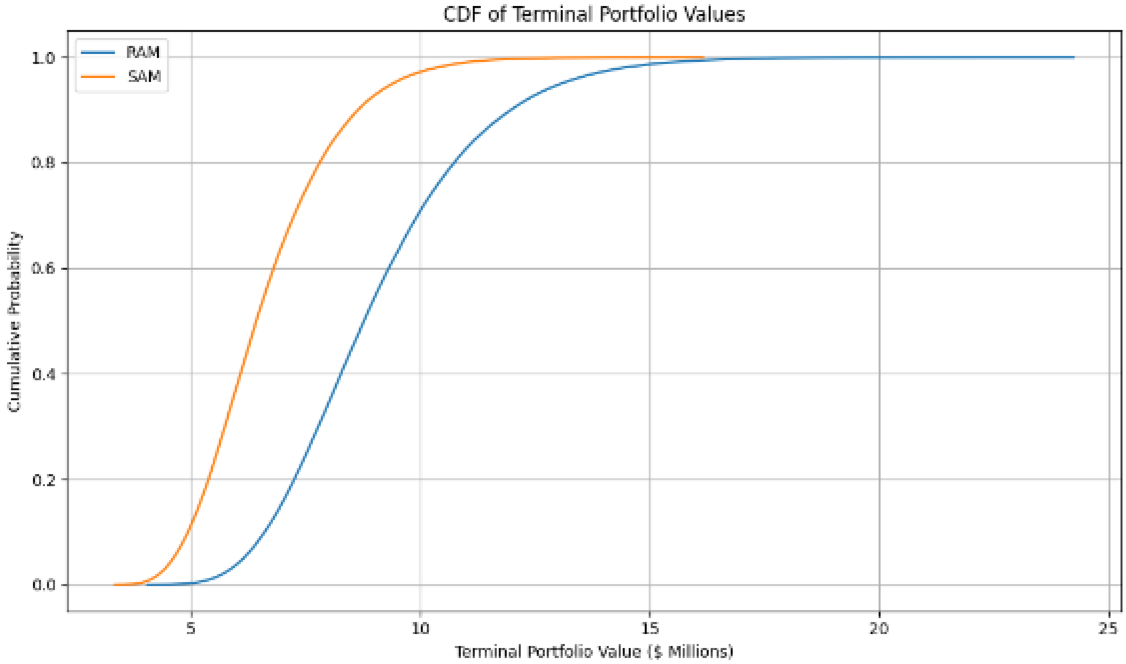

Figure 10: Cumulative Distribution Function of the SAM and RAM

The Cumulative Distribution Function finds, that for any final value, an expected percentage of the simulations where the model had less than or equal to that terminal value. The RAM outperforms the SAM at every point in Figure 10. This means that the RAM is consistently expected to achieve a higher terminal wealth. For any probability, the RAM will have a higher value.

Excess Terminal Wealth

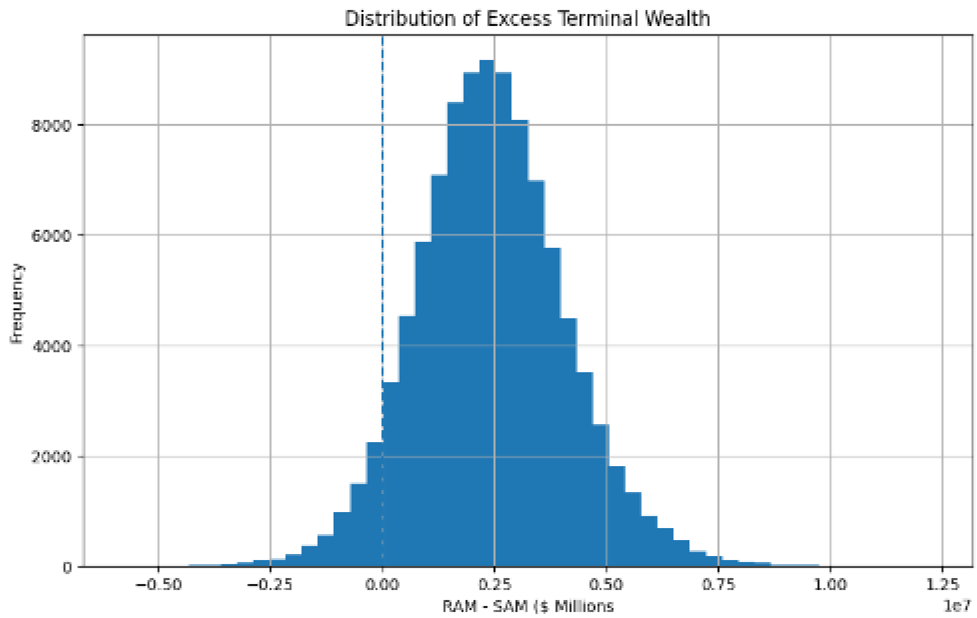

Figure 11: Distribution of Excess Terminal Wealth of the SAM and RAM

The Distribution of Excess Terminal Wealth shows the number of simulations where the difference between the terminal values of the two models is a given number. Figure 11 shows the distribution of the difference between the RAM and the SAM. The dotted line represents where the two models are equal. The majority of the graph is located to the right of the dotted line, meaning that the RAM tends to outperform the SAM - usually by about $2,500,000.

The part of the graph that is to the left of the dotted line also remains relatively close to a difference of 0 compared to the right side. This means that even when the SAM beats the RAM, it is not by a large difference.

Probability of Outperformance

Through the 100,000 Monte Carlo simulations it was found that the RAM outperforms the SAM 93.744% of the time with $t = 463$ and $p < 0.001$. This is significant and follows the analysis of the previous evidence.

TECHNICAL ANALYSIS

This section analyzes the mechanical drivers behind the performance gap observed between the RAM and SAM, specifically focusing on risk-curve volatility and the conditional rebalancing logic.

Risk Curve Divergence

The primary difference between the two models is static vs. dynamic risk. The SAM operates on an interval basis, maintaining a risk level of 1 for 25 years before dropping sharply to 0.5. This creates an event where the portfolio is forced into conservative assets regardless of market expectations.

In contrast, the RAM utilizes an oscillating risk model based on “Running” intervals. By incorporating "rest intervals" ($r<1$) even during aggressive phases, the RAM effectively harvests gains and reallocates capital, preventing the portfolio from becoming over-extended during peak market conditions.

Performance Metrics

This section reviews important metrics pertaining to the performance of the models.

Annual returns were calculated using an end-of-period cash flow assumption. To prevent the artificial dilution of return percentages, contributions were excluded from the denominator, as these funds were not exposed to market risk during the growth interval. This ensures the standard deviation reflects the true volatility of the invested capital.

Final Portfolio Value

The final value of the SAM was $4,926,509, while the final value of the RAM was $7,517,118. The difference of the two values is $2,590,609.

Money-Weighted Return

The Internal Rate of Return (IRR) of the models given their final and initial values and annual contribution is 6.07% and 7.57% for the SAM and RAM, respectively.

Let v_t be the value of a portfolio at time t, with t being time in years:

$$0 = -100000 + \frac{v_{40} + 24500}{(1+r)^{40}} - \sum_{t=1}^{39} - \frac{24500}{(1+r)^{t}}$$

Annualized Time-Weighted Return

The Annualized Time-Weighted Return (TWR) is utilized here to measure the growth of the allocation strategies. By eliminating the distorting effects of contributions, the TWR reveals the pure geometric mean return generated by the RAM's risk curves compared to the benchmark of the SAM.

Let r_t be the return at time t.

$$\left(\prod_{t=1}^{40}\left(1 + r_t\right)\right)^{\frac{1}{40}} - 1$$

$$r_t = \frac{v_t - v_{t-1} - 24500}{v_{t-1}}$$

The TWR of the RAM is 7.73%, while the TWR of the SAM is 6.74%.

Volatility

While the RAM achieved a significantly higher ending value, it is necessary to evaluate the standard deviation of annual returns to determine the strategy's stability. Standard deviation measures the difference of returns from the mean; a higher value indicates a more volatile path of value. $\bar{r}$ is the mean of the returns

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n}\left(r_t - \bar{r}\right)^2}{n-1}}$$

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n=40}\left(r_t - \bar{r}\right)^2}{39}}$$

The standard deviation of the RAM is 0.147, while the SAM is 0.134.

Sharpe Ratio

To understand the efficiency of the RAM, the Sharpe Ratio is used to measure the excess return per unit of risk. R_p is the Annualized Time-Weighted Return, R_f is the risk free rate (2%, as used in our simulation of cash growth)

$$SharpeRatio = \frac{R_p - R_f}{\sigma}$$

The Sharpe Ratio of the RAM is 0.39 and the Sharpe Ratio of the SAM is 0.35.

Maximum Drawdown

A drawdown is any drop from the highest value the portfolio has ever reached. The Maximum Drawdown is the largest of these drops throughout the entire 40-year period.

$$MDD = \frac{TroughValue - PeakValue}{PeakValue}$$

The average of the three maximum MDD for each portfolio is -23.4% and -22.1% for the RAM and SAM models, respectively.

Sortino Ratio

To further refine the risk-adjusted analysis, the Sortino Ratio is measured. Unlike the Sharpe Ratio, which penalizes all price fluctuations, the Sortino Ratio specifically penalizes "harmful" volatility - returns that fall below the 2% risk-free threshold.

$$SortinoRatio = \frac{R_p - R_f}{\sigma_d}$$

$$\sigma_d = \sqrt{\frac{\sum_{t=1}^{n}\left(min\left(r_t - 0.02, 0\right)\right)^2}{n}}$$

The Sortino Ratios for the RAM and SAM are 0.42 and 0.39, respectively.

	RAM	SAM
Final Portfolio Value	$7,517,118	$4,926,509
Money-Weighted Return	7.57%	6.07%

Time-Weighted Return	7.73%	6.74%
Standard Deviation of Returns	14.7%	13.4%
Sharpe Ratio	0.39	0.35
Avg. Maximum Drawdown	-23.4%	-22.1%
Sortino Ratio	0.42	0.39

Table 3: Statistics from the backtest of the SAM and RAM

The RAM outperforms the SAM across all return-based metrics in Table 3 while maintaining nearly proportionally less volatility and only marginally higher drawdown, indicating a more efficient allocation strategy.

DISCUSSION

The SAM is shown to perform consistently well over 40 years. It fulfills its design, being highly aggressive until it trails off near the end of its lifetime. This aggressive interval helps to build capital that can safely grow over the last years of the account.
Each account started with $100,000. Both accounts contributed $24,500 annually - the current maximum annual contribution for a 401(k).

While the SAM achieved an IRR of 6.07%, the RAM's dynamic risk intervals and aggression on decline logic generated an additional 1.5% in annualized returns. Over a 40-year horizon, this 1.5% return difference resulted in a final portfolio that was 52% larger than the traditional benchmark, demonstrating the massive impact of compounding 'workout-based' volatility.

The volatilities reveal a notable difference between the two models. The standard deviation of annual returns for the RAM is 14.7%, compared to 13.4% for the SAM.

Despite the RAM achieving a significantly higher terminal wealth, this comes with only a small increase in volatility. The RAM generates superior returns without a proportional increase in risk, indicating that its "Interval Training" logic is able to capture market upside during "Running" phases while maintaining controlled exposure during higher-risk periods.

By incorporating "Rest Intervals" that adjust risk dynamically based on workout logic, the RAM effectively improves the return-to-risk tradeoff to a static strategy. Although slightly more volatile in absolute terms, the RAM appears to convert additional risk into disproportionately higher expected returns, suggesting improved efficiency in risk allocation relative to the SAM.

To show the efficiency of the RAM, the Sharpe Ratio was calculated to measure the excess return generated per unit of risk. This ratio compares the return of the strategy to the volatility endured.

The results indicate a difference in performance between the two models. The RAM produces a Sharpe Ratio of 0.39, compared to 0.35 for the SAM.

This represents an 11% improvement in risk-adjusted return, indicating a significant gain efficiency. While the RAM shows slightly higher volatility relative to the SAM, the increase in return offsets the additional risk taken. The results suggest that the RAM delivers better return per unit of risk, with its “Interval Training” strategy improving return efficiency despite a modest increase in portfolio volatility.

The SAM experienced an average maximum drawdown of −22.1%, while the RAM recorded a slightly deeper average of −23.4%. Despite the increase in downside risk, the difference remains small in magnitude, approximately 130 basis points, suggesting that the RAM does not amplify crash effects relative to the SAM. This is consistent with the earlier volatility results, where the RAM showed only a limited increase in total risk while generating meaningfully higher returns.

Importantly, the drawdown behavior indicates that the RAM’s higher equity exposure during “Running” phases does not translate into disproportionate risk. Instead, the “Rest Intervals” appear to function as a stabilizing mechanism, moderating exposure during bearish markets and preventing excessive compounding of losses during downturns.

Overall, the RAM exhibits a more efficient risk to return profile, achieving higher terminal wealth and better risk-adjusted performance without an equivalent increase in downside loss.

The RAM achieved a Sortino Ratio of 0.42, compared to 0.39 for the SAM, representing a 8% improvement in performance adjusted for downside volatility.

This difference shows that the RAM’s higher volatility does not translate into proportionally worse downside outcomes. Instead, returns appear to be more concentrated in favorable market periods, improving efficiency relative to downside deviation.

Although neither model exceeds the 1.0 threshold, the RAM demonstrates a clear relative advantage, indicating improved return per unit of downside risk compared to the SAM. In practical terms, this suggests that the “Interval Training” framework enhances downside-adjusted performance by limiting exposure during unfavorable regimes while preserving participation in upside movements.

On the non-metric based side, the RAM shows resilience during bearish periods as it is able to recuperate losses during the rest intervals. During bullish markets, it is able to take advantage of the SAM because it holds onto higher stock allocation throughout its lifetime.

The similarities in the models can be attributed to the fact that they both rely heavily on stocks in their early years. So they are likely to move similarly as they hold near the same amount of stock at the same prices.

It is important to note that near the end of the accounts' lifetimes, the RAM significantly outperformed the SAM even though its stock allocation levels were diminished due to the cooldown in Figures 4 and 5. We do see that this cooldown is affected slightly by the post-incline strategy in Figure 6 but these effects only appear twice in the last 10 years. This is mostly because the RAM continues to keep high allocation levels of stocks in order to continue benefitting from bullish markets. The SAM, on the other hand, keeps most of its money in bonds during this time which misses out on the profits of strong markets.

Despite the limitations, it is clear that the RAM performed better than the SAM due to its aggressive allocation strategy. In addition, the RAM was able to minimize risk through rest intervals where the RAM did not take as many losses as the SAM without missing out on significant periods of bullish market.

In the Monte Carlo simulations, it is clear that the RAM outperforms the SAM consistently at the end of their lifetimes. The outperformance of the RAM was not limited to extreme cases, in fact, only in extreme cases did the SAM outperform the RAM.

This advantage was caused by the dynamic allocations of the RAM which can capture strong periods of market growth, increase stock exposure in favorable conditions, and reduce exposure in weaker environments.

Regardless of when bullish and bearish periods occurred, the "rest" periods of the RAM acted as a safety net for negative returns and the "Running" periods acted as a way to fully take advantage of positive returns.

The metrics collected suggest that dynamic allocation strategies informed by running performance have a significant effect on the performance of an investment model. Overall, one of the main conclusions we can take from this data is that higher stock allocation can have high upsides without inducing an equal level of risk compared to a standard, more conservative strategy.

A limitation of this study is that RAM maintains higher average equity exposure than SAM during portions of the simulation. Consequently, some of the observed outperformance may be attributable to increased exposure to the long-term equity risk rather than the interval structure alone. Future work could compare RAM against portfolios with equivalent average stock allocations to isolate the effects of the interval-based allocation strategies.

CONCLUSION

The SAM and RAM are both retirement fund allocation models that rely on a certain level of risk to determine their allocation percentages. The SAM operates on predetermined risk levels, while the RAM works with volatile risk levels based on a running workout. The RAM also has a strategy where it increases stock allocation following a drop in worth year after year. The RAM performed better during bullish markets in the second half of the portfolio's lifetime and managed to avoid as much loss as the SAM. The importance of rest intervals is clear from the RAM's ability to withstand bearish markets and the importance of aggressive intervals to take advantage of bullish markets. This interval trading is a strong strategy for risk mitigation and bullish optimization. The RAM maintains higher equity exposure while periodically reducing risk. The results suggest that conventional strategies may become overly conservative and sacrifice long-term growth without proportionate reductions in portfolio risk.

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