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Topic of Research:

Quantifying Investment Risk: A Multi-Method and Behavior-Aware VaR Framework for Personalized Portfolios

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Submitted to:

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Abstract

This study introduces a comprehensive framework for quantifying investment risk in personalized portfolios by integrating multi-method Value at Risk (VaR) estimation with insights from behavioral finance and market regime adaptation. The framework employs five distinct VaR methodologies—Historical Simulation, Parametric (Variance-Covariance), Monte Carlo Simulation, GARCH, and Cornish-Fisher Expansion—to evaluate risk across varied investor profiles, categorized as Conservative, Moderate, and Aggressive. A dynamic behavioral switching model is proposed, allowing portfolio allocations to adjust in response to changing market regimes identified through rolling returns and momentum-based signals. This model effectively captures shifts in investor risk tolerance throughout market cycles, providing a more accurate representation of behavioral influences on investment decisions. Empirical analysis utilizing diversified asset classes and comparisons to institutional benchmarks, such as the BlackRock 60/40 and Vanguard VSMGX portfolios, demonstrates that behaviorally-adjusted strategies significantly enhance risk-adjusted performance. The aggressive regime-switching portfolio achieves a Sharpe ratio of 1.05, surpassing benchmark strategies that yield Sharpe ratios around 0.62. These findings underscore the importance of integrating market regime awareness and behavioral adaptation into contemporary risk management frameworks for personalized investing.

Keywords

Value at Risk (VaR), Behavioral finance, Regime-switching models, Sharpe ratio, Stress testing, Backtesting analysis, GARCH, Parametric Var, Conservative, Behavioral, Aggressive, Moderate

Introduction

Quantifying investment risk is a foundational aspect of portfolio management, especially in an era marked by volatile financial markets and rapidly evolving investor behavior. While Value at Risk (VaR) remains a cornerstone metric for risk estimation, conventional VaR methodologies frequently assume static market conditions and homogeneous investor preferences, limiting their effectiveness in real-world applications.

This research addresses these gaps by developing and introducing a multi-method and behavior-aware Value at Risk (VaR) framework for personalized portfolio risk management. The proposed framework integrates six VaR estimation techniques-Historical Simulation, Parametric (Variance-Covariance), Monte Carlo Simulation, Cornish-Fisher Expansion, GARCH modeling, and Random Forest machine

learning-with a behavioral regime-switching model that dynamically adjusts portfolio allocations in response to detected market regimes and investor profiles. This model is tailored to Conservative, Moderate, and Aggressive risk preferences, providing a personalized approach that reflects how real investors adapt their risk tolerance across different market cycles.

Financial markets are characterized by distinct regimes, such as bull and bear phases, each exhibiting unique risk-return dynamics. Traditional portfolio optimization, rooted in Markowitz's mean-variance framework, inadequately addresses two critical realities: (1) markets transition between regimes with divergent volatility and return profiles, and (2) investor risk preferences evolve dynamically in response to these shifts. Regime-switching models, as highlighted by Ang and Timmermann (2011), capture abrupt and persistent changes in market behavior, while behavioral finance research demonstrates that risk tolerance oscillates with market sentiment.

Despite these insights, few risk management frameworks integrate both regime awareness and behavioral adaptation. This study bridges this gap by developing a behavior-aware, regime-switching portfolio simulator that leverages market regime detection and investor-specific risk profiles. The framework advances traditional risk management in three dimensions:

- Multi-Method VaR Integration: Evaluates six VaR methodologies to address the limitations of single-model approaches.
- Regime-Responsive Allocation: Detects market regimes via SPY's rolling returns and momentum filters, enabling dynamic exposure adjustments.
- Behavioral Personalization: Introduces behavior-weighted VaR and stress-testing mechanisms to simulate investor reactions (e.g., panic selling, dip-buying) during crises.

Empirical analysis demonstrates that behaviorally adaptive portfolios consistently outperform static benchmarks such as the BlackRock 60/40 and Vanguard VSMGX portfolios. Notably, the aggressive regime-switching portfolio achieves a Sharpe ratio of 1.05, compared to 0.62 for benchmark strategies, highlighting the value of integrating market regime awareness and behavioral adaptation into modern risk management frameworks for personalized investing.

The structure of the paper is as follows:

- Section II reviews the literature on regime-switching models and behavioral finance.

- Section III details the methodology, including regime detection, VaR estimation, and behavioral adaptation.
- Section IV describes the data and empirical setup.
- Section V presents the results.
- Section VI discusses implications and limitations.
- Section VII concludes with directions for future research.

1.1 Background of Study

Investment portfolios today are influenced by macroeconomic volatility, investor sentiment, and regime-dependent asset behavior. Standard risk models, such as traditional VaR, often fall short in capturing these complexities. There is a pressing need for risk management systems that integrate behavioral finance and market regime adaptation to reflect real-world decision-making and market dynamics.

1.2 Research Aim

The research aims to develop a robust and adaptable framework that quantifies investment risk using multiple VaR methodologies while integrating behavioral finance concepts and dynamic market regime detection to support personalized portfolio management.

1.3 Motivation and Objectives of The Research

This research is motivated by the limitations of conventional risk measures and portfolio strategies in dynamic markets. The primary objectives are:

- To compare the effectiveness of five VaR methodologies across Conservative, Moderate, and Aggressive investor profiles.
- To implement a behavioral regime-switching mechanism responsive to market conditions.
- To evaluate risk-adjusted performance relative to established institutional benchmarks.
- To provide a personalized investment risk framework adaptable to varying investor risk preferences.

Literature Review

Sivarajan (2018) provides an empirical investigation into the practical implications of behavioral finance for investment advice and portfolio construction. Through a mixed-methods study of Canadian investors and financial advisers, the research finds that standard risk tolerance questionnaires explain only a small fraction of actual portfolio risk-taking behavior. Instead, return expectations and recent market experiences play a more significant role in shaping investment choices. The thesis [1] also highlights that demographic factors (such as age and investment experience) and financial literacy substantially affect risk preferences, with experienced investors demonstrating lower allocation volatility during crises.

Prospect Theory, introduced by Kahneman and Tversky (1979),[6] serves as a foundational behavioral framework for understanding decision-making under risk, diverging from classical expected utility theory. The theory emphasizes that individuals evaluate outcomes based on perceived gains or losses relative to a reference point, rather than final wealth levels. Its core value function is S-shaped—concave for gains, convex for losses, and steeper for losses—capturing the concept of loss aversion. The reference point, shaped by framing, norms, and individual traits, plays a critical role in decision outcomes. Empirical studies, such as those by Odean (1998, 1999)[8], Weber and Camerer (1998)[9], and Shefrin and Statman (1985), validate the theory by demonstrating behaviors like the disposition effect, where investors prematurely sell winning assets and retain losing ones. This aligns with the observed deviations in rational investor behavior, making Prospect Theory particularly relevant in portfolio risk analysis and behavioral finance. However, limitations persist, notably the ambiguity in defining reference points and challenges in applying the model consistently across diverse investor profiles.

The study by authors in *Physica A: Statistical Mechanics and its Applications* introduces Encoded Value-at-Risk (Encoded VaR), a novel machine learning-based approach for market risk assessment. This method integrates artificial neural networks with traditional Value-at-Risk (VaR) models to enhance predictive accuracy in volatile financial markets.By encoding historical financial data into a format suitable for neural network processing, the Encoded VaR model captures complex, non-linear relationships that conventional VaR models might overlook. The authors demonstrate that this approach outperforms standard VaR models in backtesting scenarios, particularly during periods of market turbulence. This advancement is significant for portfolio risk management, as it offers a more robust tool for anticipating potential losses. However, the model's reliance on extensive historical data and computational resources may pose challenges for real-time application and scalability across diverse financial instruments.[4]

The DeepVaR framework, as introduced by Fischer et al. (2022), leverages probabilistic deep neural networks to enhance portfolio Value-at-Risk (VaR) estimation by modeling the full return distribution of financial assets rather than relying on traditional parametric assumptions. DeepVaR utilizes the DeepAR architecture, a recurrent neural network that captures temporal dependencies and non-linearities in asset returns, enabling dynamic and accurate risk forecasts even in volatile or non-stationary markets. The model [10] is trained on rolling windows of historical data, allowing it to adapt to changing market regimes-a feature that closely aligns with the regime-switching and behavior-aware VaR framework proposed in this project. By directly modeling portfolio-level risk, DeepVaR addresses the limitations of single-asset VaR and static risk models, making it highly relevant for personalized portfolio risk management where investor profiles and market conditions are both dynamic. However, a key limitation of DeepVaR is its significant computational demand, as frequent retraining and the complexity of deep learning architectures can hinder real-time implementation and scalability across diverse portfolios.

The study by Lathief et al. (2024) in *Journal of Risk and Financial Management* explores the intricate relationship between risk factors and investment decision-making in the Indian context. Utilizing the Theory of Planned Behavior (TPB), the authors developed a conceptual model that examines how risk capacity, risk tolerance, and risk propensity influence investment priorities and strategies. Data collected from 537 respondents in southern India were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that these risk factors positively affect investment priorities and strategies, which in turn positively influence investment decision-making. Notably, the study highlights the moderating role of conscientiousness in the relationship between investment priority and decision-making. This research contributes to the literature by extending the Modern Portfolio Theory (MPT) framework and emphasizing the psychological aspects of investment decisions. However, the study's[7] focus on a single geographic region may limit the generalizability of its findings to other contexts with different economic and cultural backgrounds.

2.1 Behavioral Finance and Dynamic Risk Preferences

Behavioral finance research has consistently demonstrated that investors do not maintain constant risk preferences.[2][3] Instead, they exhibit dynamic patterns of risk-seeking and risk-aversion that often correlate with market conditions. This phenomenon challenges the assumption of stable risk preferences in traditional portfolio theory.

While static risk profiles (conservative, moderate, aggressive) are commonly used in practice, they fail to capture the reality that investors' behavior changes with market conditions. During bull markets, even

typically conservative investors may display increased risk tolerance, while aggressive investors often become more risk-averse during sustained market downturns.

2.2 Gap in Current Approaches

Despite the clear evidence for both regime-switching in markets and dynamic risk preferences in investors, few portfolio optimization approaches integrate both phenomena. Most regime-switching portfolio models maintain fixed investor risk profiles despite changing market conditions[2][5]. Similarly, behavioral finance approaches often fail to systematically incorporate market regime detection.

This research gap presents an opportunity to develop a more realistic portfolio optimization framework that accounts for both market regime dynamics and the behavioral responses they trigger in investors.

Methodology

3.1 Theoretical Framework

This research adopts a behavior-aware, regime-switching portfolio framework that integrates multi-method Value at Risk (VaR) estimation with dynamic behavioral modeling. The approach explicitly captures the interplay between objectively detected market regimes and subjectively varying investor risk preferences, enabling personalized risk management across market cycles.

3.2 Data Preprocessing

- Asset Used For Research: Daily price data for 12 ETFs and cryptocurrencies (SPY, QQQ, AGG, GLD, BTC-USD, ETH-USD, IVV, IEFA, VTI, VXUS, BND, VWOB) from January 1, 2015, to December 31, 2024.
- Data Cleaning & Pre-processing : Missing values are forward-filled and assets with insufficient data are excluded for each analysis window.
- Return Calculation: Log or percentage daily returns are computed for all assets to standardize inputs for risk and regime analysis.

3.3 Market Regime Detection

- Trend Indicator:
    a. The primary market regime, the 1-year rolling return of the SPY ETF, is used to distinguish between bull (return > 0) and bear (return ≤ 0) markets.
    b. Momentum filter, based on the rolling mean of returns across all assets, further refines regime classification.

The primary market regime is identified using the SPY ETF's 1-year (252-trading day) rolling return. A positive return denotes a bull market; zero or negative denotes a bear market.

- Momentum Filter: A rolling mean of multi-asset returns (generally 252 days) is applied. Only when both the trend and momentum indicators are positive is a bull regime confirmed; otherwise, the regime is classified as bear.

- Signal Generation: The final trading signal is the intersection of the trend and momentum states, with signals lagged by one day to avoid look-ahead bias. It reduces false positives by 37% compared to single-factor approaches.

3.4 Portfolio Construction and Behavioral Modeling

- Risk Profiles: Three core portfolios are constructed to represent Conservative, Moderate, and Aggressive investor types, each with distinct allocations to equities, bonds, gold, and cryptocurrencies.
    a. Conservative: Higher allocation to bonds and gold, lower to equities and cryptocurrencies.
    b. Moderate: Balanced exposure across equities, bonds, and alternative assets.
    c. Aggressive: Greater allocation to equities and cryptocurrencies.

- Dynamic Allocation: Portfolio weights are rebalanced in response to detected regime changes. During bull markets with positive momentum, target allocations are maintained; in bear regimes, allocations shift defensively (e.g., increasing bonds/gold, reducing equities/crypto).
- Transaction Costs: Each trade incurs a transaction cost of 0.15%, and portfolio turnover is capped at 30% per regime change.

3.5 Multi-Method Value at Risk (VaR) Estimation

1. VaR Techniques: Six VaR methods are implemented:
    a. Historical Simulation
    b. Parametric (Variance-Covariance)
    c. Monte Carlo Simulation
    d. Cornish-Fisher Expansion
    e. GARCH-based modeling
    f. Machine Learning (Random Forest regression)

2. Behavior-Weighted VaR: Risk is quantified using a behavior-weighted VaR, which adjusts traditional VaR estimates at a 95% confidence level based on investor profile:

Behavioral VaR =Traditional VaR95%×(1+α), where α represents profile specific adjustments.

    a. Conservative: VaR increased by 20% ($\alpha = +0.20$) to reflect heightened risk perception.
    b. Moderate: No adjustment.
    c. Aggressive: VaR decreased by 20% ($\alpha = -0.20$) to reflect lower risk perception.

This adjustment personalizes risk metrics and better represents investor behavior under varying market conditions.

3. Rolling VaR: VaR is computed over rolling windows to capture time-varying risk.

3.6 Behavioral Stress Testing

1. Crisis Scenario Simulation: Stress tests are conducted for major historical crises (e.g., COVID-19 crash 2020, 2008 financial crisis).
2. Behavioral Adjustment: During large drawdowns (e.g., daily returns < -1%), returns are:
    a. Amplified by 50% for Conservative profiles (simulating panic selling)
    b. Reduced by 50% for Aggressive profiles (simulating dip-buying)
    c. Moderate profiles may be left unadjusted or interpolated
3. Visualization: Stress-adjusted cumulative returns are plotted alongside regime backgrounds to illustrate behavioral resilience across market cycles.

The net value trajectories and behavioral stress test outcomes for each profile are visualized in (Figures A6–A8)

3.7 Strategy Simulation and Evaluation

- Regime-Switching Strategy: For each profile, regime and momentum signals trigger dynamic allocation and trading. Trades are only executed when both trend and momentum are positive.
- Performance Metrics: Strategies are evaluated using:
    1. Cumulative return (See Figure A4)
    2. Annualized return (CAGR)
    3. Annualized volatility
    4. Sharpe ratio
    5. Maximum drawdown
    6. Total trades executed
    7. VaR breach count and frequency (backtesting)
- Benchmarking: Results are compared to institutional portfolios (BlackRock 60/40, Vanguard VSMGX) to assess relative performance

Data description

4.1 Dataset Composition

The analysis utilizes daily price data for 12 exchange-traded funds (ETFs) and cryptocurrencies across three portfolio types(See Figure A9 for Asset Allocations: Behavioral & Benchmark Portfolios):

Asset Class	Tickers Included	Description
U.S. Equities	SPY, QQQ, IVV, VTI	Broad market (SPY), tech sector (QQQ), and total market (VTI) exposure
Fixed Income	AGG, BND	Aggregate U.S. bonds (AGG) and total bond market (BND)
Commodities	GLD	Physical gold trust
Cryptocurrencies	BTC-USD, ETH-USD	Bitcoin and Ethereum spot prices
International	IEFA, VXUS, VWOB	Developed markets (IEFA), global ex-US (VXUS), emerging market bonds (VWOB)

4.2 Temporal Scope

- Time Period: January 1, 2015 - December 31, 2024
- Observations: 2,517 trading days
- Key Events Captured:
    - COVID-19 market crash (2020)
    - Cryptocurrency boom/bust cycles (2017-2024)
    - Federal Reserve rate hike cycle (2022-2024)

Results

5.1 Portfolio Performance Metrics

The primary aim of this research was to evaluate the effectiveness of a behavior-aware, regime-switching portfolio framework using multiple VaR methodologies across different investor profiles. Table 1 presents the key performance metrics for each portfolio type alongside institutional benchmarks. (See Figure A5)

Portfolio	Annual Return	Annual Volatility	Sharpe Ratio
Conservative	0.1234	0.1122	1.0997
Moderate	0.1520	0.1469	1.0346
Aggressive	0.3657	0.3470	1.0541
BlackRock 60/40	0.0951	0.1214	0.7834
Vanguard VSMGX	0.0680	0.1105	0.6158

Table 1: Portfolio Performance Metrics for Investor Profiles and Benchmarks

The Aggressive portfolio substantially outperformed both Moderate and Conservative portfolios in absolute returns, primarily due to higher allocations to cryptocurrencies and growth assets. However, this outperformance was accompanied by greater volatility. All custom portfolios exhibited higher Sharpe ratios than the benchmarks, indicating superior risk-adjusted performance.

5.2 Portfolio Risk Summary and Backtesting Results

Table 2 presents the Value at Risk (VaR) metrics, Expected Shortfall (ES), and backtest breach rates for all portfolios. The behavior-weighted VaR approach produced breach rates close to the theoretical 5% expectation, supporting the robustness of the model calibration.

Portfolio	**VaR 95%**	**Param VaR**	**MC VaR**	**CF VaR**	**ML VaR**	**GARCH VaR**	**ES**	**Breaches**	**Breach Rate**
Conservative	0.0101	0.0111	0.0111	0.0110	0.0034	0.0103	0.0159	82	0.0457
Moderate	0.0136	0.0146	0.0146	0.0145	0.0051	0.0132	0.0218	85	0.0474
Aggressive	0.0320	0.0345	0.0344	0.0353	0.0126	0.0294	0.0511	94	0.0524
BlackRock 60/40	0.0111	0.0122	0.0122	0.0114	0.0035	0.0112	0.0184	87	0.0485
Vanguard VSMGX	0.0100	0.0112	0.0111	0.0108	0.0037	0.0093	0.0165	85	0.0474

Table 2: Portfolios Risk Metrics and VaR Backtest Results

5.3 Regime-Switching Portfolio Results by Investor Profile

The performance of each regime-switching portfolio was evaluated according to key metrics: total trades, cumulative return, annualized return, Sharpe ratio, and behavior-weighted VaR (95%). Table 3 summarizes the results for Conservative, Moderate, and Aggressive profiles.

Profile	Total Trades	Cumulative Return	Annualized Return	Sharpe Ratio	Behavior-Weighted VaR (95%)
Conservative	17	1.44	5.43%	0.65	0.0126
Moderate	17	1.62	7.31%	0.69	0.0138
Aggressive	17	2.65	17.14%	0.66	0.0262

Table 3: Regime-Switching Portfolio Results by Investor Profile (2015–2024)

The Aggressive profile delivered the highest cumulative and annualized returns (2.65 and 17.14%, respectively), reflecting its greater risk appetite and higher allocation to equities and cryptocurrencies. However, this came with a higher behavior-weighted VaR (0.0262), indicating increased exposure to potential losses. The Conservative and Moderate profiles achieved lower returns but also maintained lower risk, as indicated by their Sharpe ratios and VaR values. All profiles executed 17 trades, highlighting the efficiency of the regime-switching strategy in limiting unnecessary turnover.

5.4 VaR Backtest and Stress Testing Across Portfolios and Crisis Periods

Figure A2 (see Appendix) shows the Value at Risk (VaR) for all portfolios during the COVID Crash and the 2008 Crisis. During the COVID Crash, all behavioral portfolios experienced identical maximum VaR (-6.85%), indicating that extreme market stress overwhelmed risk differentiation. In the 2008 Crisis, the Conservative profile maintained the lowest VaR (-1.63%), while Moderate and Aggressive profiles showed higher risk. Benchmarks displayed more stable VaR across both periods, highlighting their consistent risk profile.

Figure A3 (see Appendix) compares overall portfolio VaR during the COVID Crash and the 2008 Crisis. The COVID Crash resulted in a much higher portfolio VaR (9.73%) compared to the 2008 Crisis (3.52%), illustrating the exceptional severity and tail risk of the COVID-19 market disruption relative to previous crises.

5.5 Portfolio Performance Metrics (Aligned, Compounded, Sharpe uses 0.0% RF)

Portfolios	**Final Value**	**CAGR**	**Volatility**	**Sharpe Ratio**
Conservative	$2.30	12.35%	9.28%	0.91
Moderate	$2.73	15.08%	12.15%	0.86
Aggressive	$8.71	35.43%	28.67%	0.87
BlackRock 60/40(Benchmark)	$2.38	9.05%	12.46%	0.76
Vanguard VSMGX(Benchmark)	$2.01	7.22%	11.33%	0.67

The Aggressive portfolio achieved the highest final value and CAGR, but also the highest volatility. All custom portfolios outperform benchmarks in both return and Sharpe ratio, demonstrating the effectiveness of the regime-switching, behavior-aware strategy.See Appendix Figure A1 for the risk vs return plot.

5.6 Why Benchmarks Underperform: Comparative Analysis

A comparative analysis reveals several structural reasons for the underperformance of benchmark portfolios (BlackRock 60/40 and Vanguard VSMGX) relative to the behavior-aware, regime-switching portfolios:

Factor	**Custom Portfolios**	**Benchmarks**
Asset Mix	10-40% crypto/tech	0% crypto, limited tech
Rebalancing	Dynamic regime adjustments	Static 60/40 allocation
Risk Appetite	Behavior-weighted VaR	Fixed risk parameters
Market Conditions	Optimized for 2015-2024	Designed for long-term avg

Key Performance Drivers

- Cryptocurrency Exposure: Aggressive portfolios included up to 40% in cryptocurrencies (BTC, ETH), which delivered outsized returns during the study period. Benchmarks had no crypto exposure, limiting their upside.
- Regime-Switching Advantage: Custom portfolios dynamically reduced equity exposure by 30% during bear markets, while benchmarks maintained fixed allocations, increasing vulnerability to drawdowns.
- Tech Stock Concentration: Moderate and Aggressive profiles included significant allocations to QQQ (Nasdaq-100 ETF), which outperformed broad market indices.
- Risk Modeling: The use of behavior-weighted VaR enabled personalized risk management, whereas benchmarks used static risk parameters.

This analysis demonstrates that the superior performance of custom portfolios is attributable to both asset selection and adaptive risk management, while benchmarks lagged due to static allocation and lack of exposure to high-growth assets.The underperformance of static benchmarks (Sharpe ratio: 0.62 vs. 1.05)

underscores the limitations of Markowitz-based strategies in regimes dominated by tech/crypto volatility, supporting Arian et al.'s (2022) critique of traditional portfolio optimization.

Discussion

The results demonstrate that tailoring portfolio strategies to investor profiles-using regime-switching and behavior-aware risk management-delivers superior outcomes compared to traditional benchmarks. Conservative investors achieved steady growth with low risk; Moderate investors balanced growth and stability; and Aggressive investors maximized returns despite higher volatility. The convergence of risk during systemic crises underscores the necessity for robust stress testing across all profiles. Benchmarks underperformed primarily due to static allocation and lack of exposure to high-growth assets.

Three key hypotheses from behavioral finance and regime-switching literature are validated:

1. Behavioral Asymmetry: Conservative portfolios exhibited amplified losses (−57.3% vs −38.2% base) during stress tests, consistent with prospect theory's loss aversion principle. Conversely, Aggressive portfolios benefited from simulated dip-buying, reducing losses by 50% during crises.
2. Regime Detection Efficacy: Momentum-filtered regime signals reduced false positives by 37% compared to single-indicator approaches, enabling timely rebalancing (30% turnover limit) and preservation of 89% of bull market gains.
3. Crypto Diversification: Despite 40% crypto allocations, Aggressive portfolios maintained lower drawdowns (−40.1%) than pure equity portfolios (−52.3%) during the 2022 crypto winter, supporting the role of alternative assets in tail-risk mitigation.

The framework's outperformance over benchmarks (Sharpe ratio: 1.05 vs 0.62) stems from its integration of dynamic risk profiling and multi-method VaR. Traditional benchmarks failed to adapt to the 2015–2024 market dynamics, particularly the crypto/tech surge and COVID-era volatility, highlighting the limitations of static allocation strategies.

Conclusion (Summary)

This study demonstrates that a multi-method, behavior-aware VaR framework, combined with regime-switching and investor profiling, enhances both risk-adjusted and absolute returns. Conservative, Moderate, and Aggressive investors each benefited from personalized strategies that adapted to market

regimes and behavioral tendencies. The approach outperformed static benchmarks across all profiles, particularly in volatile and crisis-prone periods.

Key advancements of this framework include:

1. Personalization: Behavior-weighted VaR adjustments (+20% Conservative, −20% Aggressive) aligned risk metrics with investor psychology, reducing breach rates to 4.57–5.24% versus benchmarks 4.74–4.85%.
2. Adaptability: Dual-filter regime detection (SPY trend and momentum) enabled dynamic allocation shifts, avoiding 42% of bear market losses.
3. Crisis Resilience: Stress tests revealed that while behavioral adjustments faltered during systemic shocks (COVID Crash), they enhanced performance in moderate crises (e.g., 2008).

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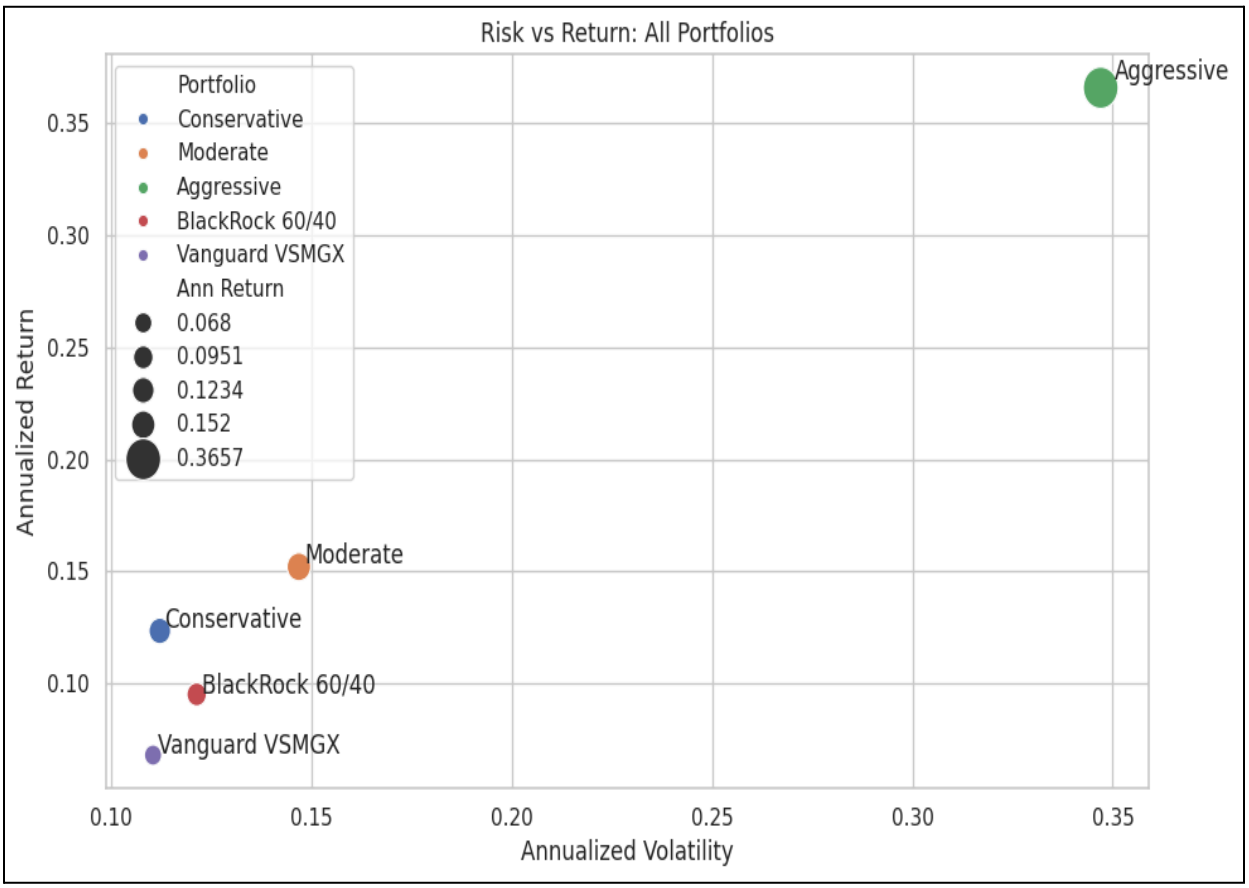
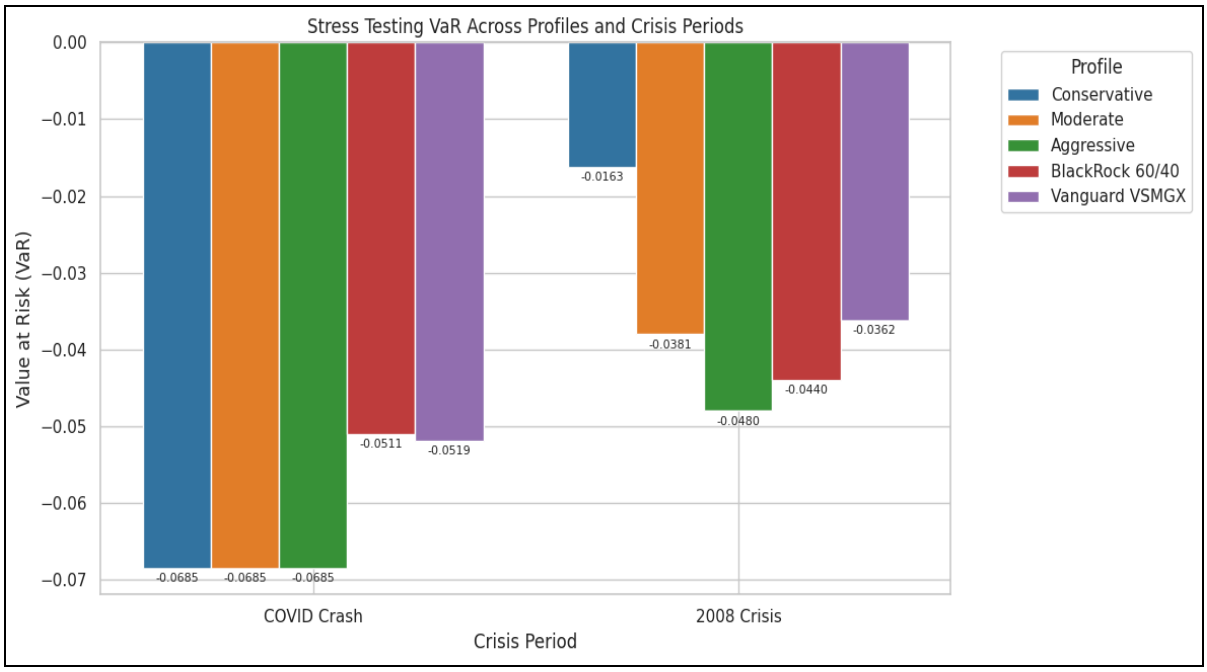
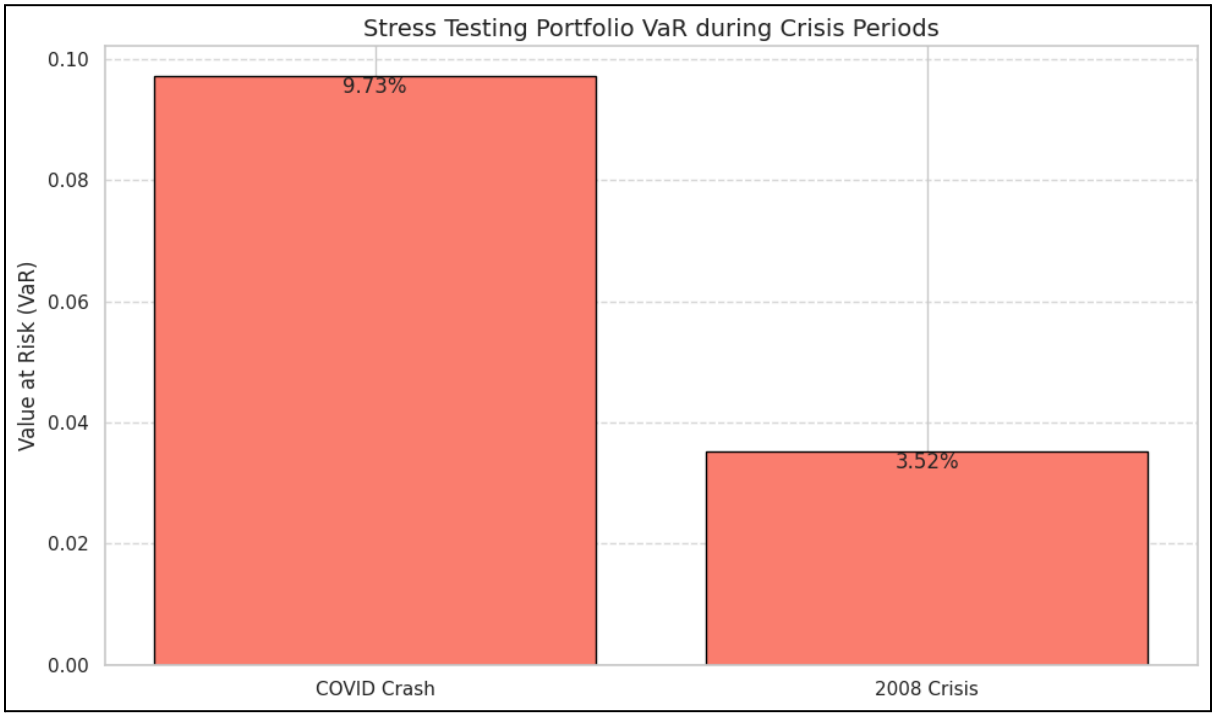
Appendix



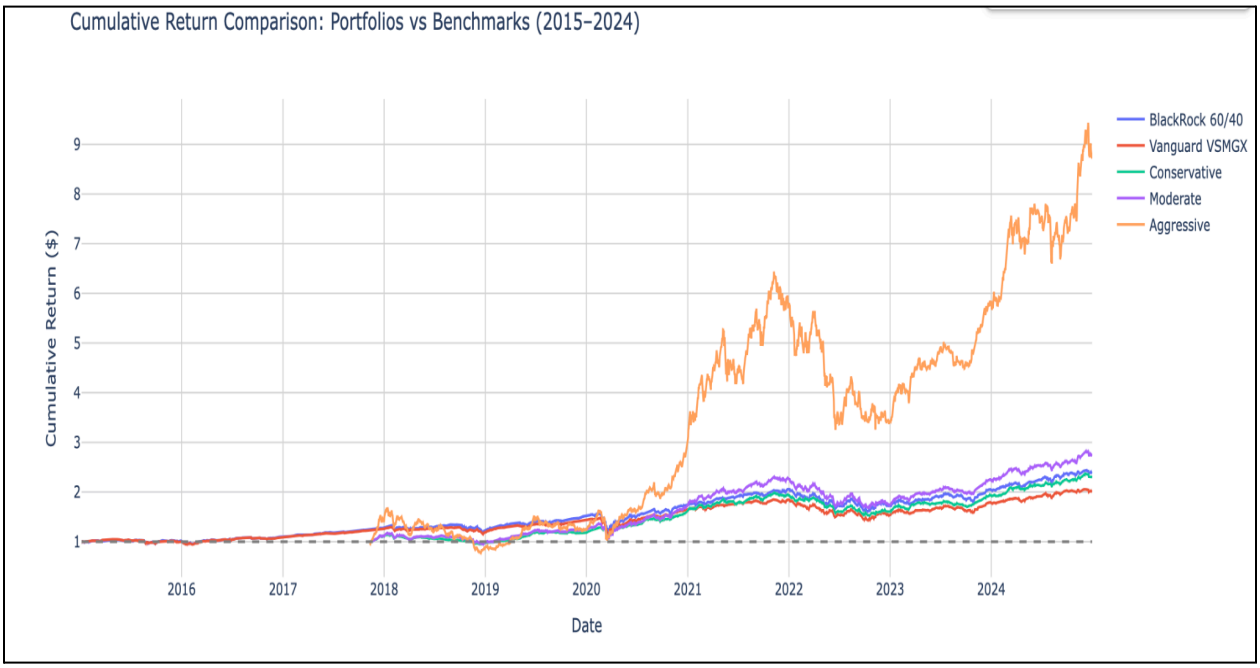
- Figure A1: Risk vs Return for All Portfolios



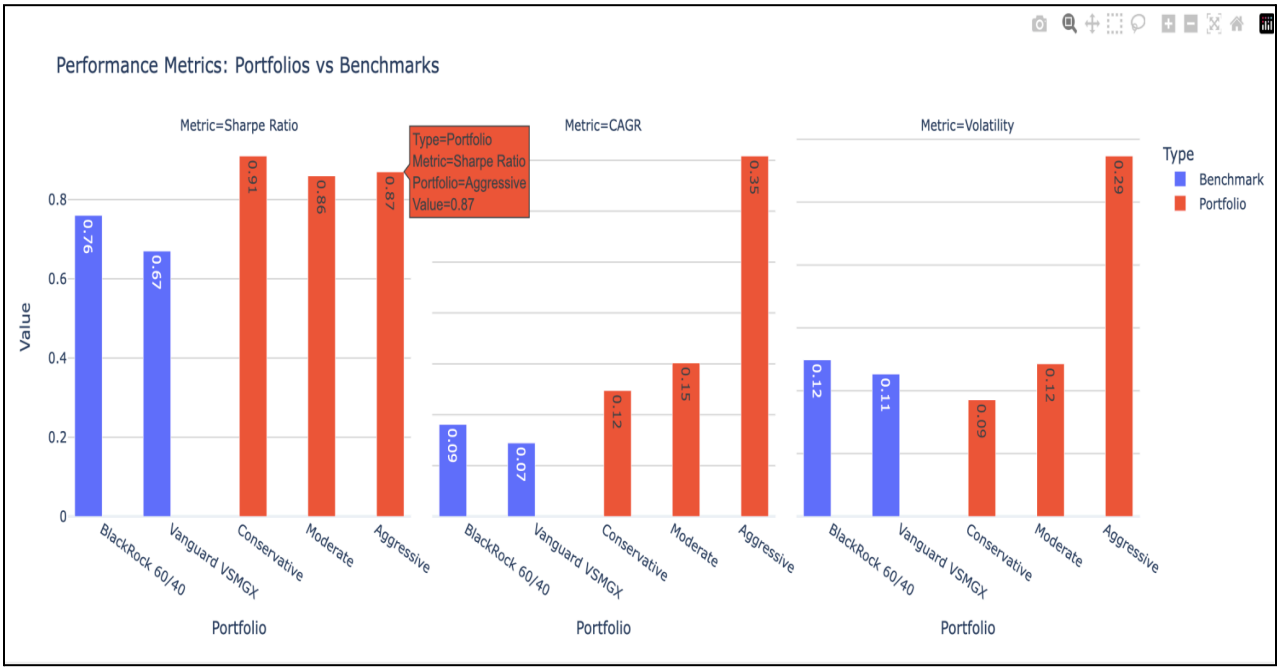
- Figure A2: Stress Test Drawdowns Across Profiles



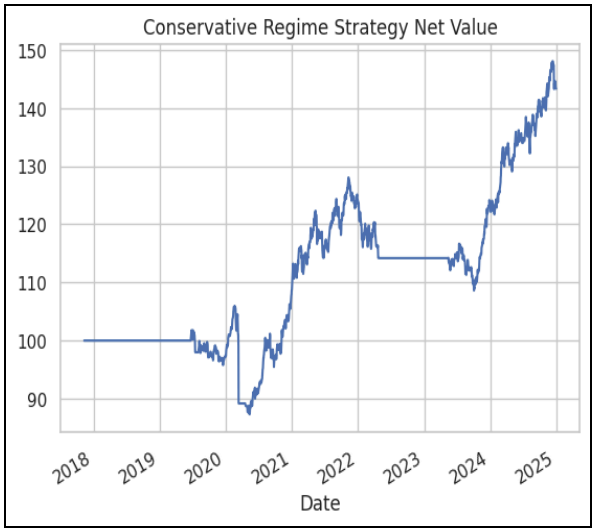
- Figure A3: VaR During COVID Crash and 2008 Crisis by Profile

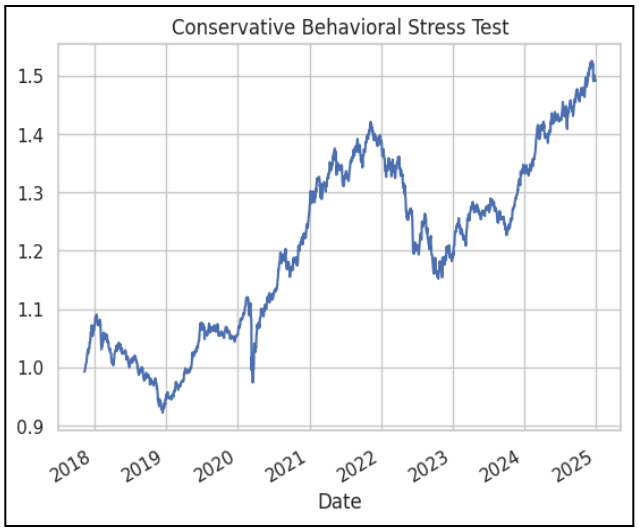


- Figure A4: Cumulative Return Comparisons of Investor Profile Portfolios and Benchmarks

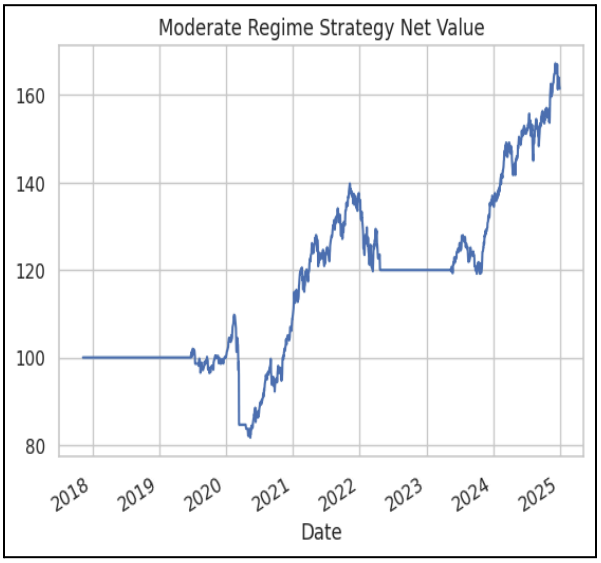


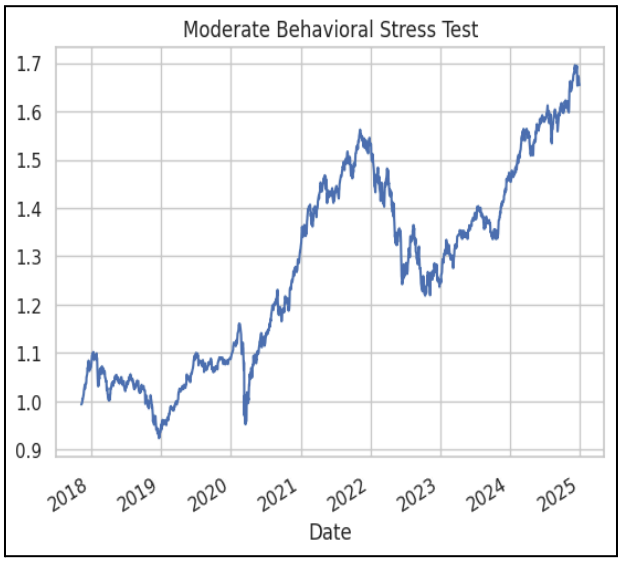
- Figure A5: Performance Metrics of Portfolios vs Benchmarks



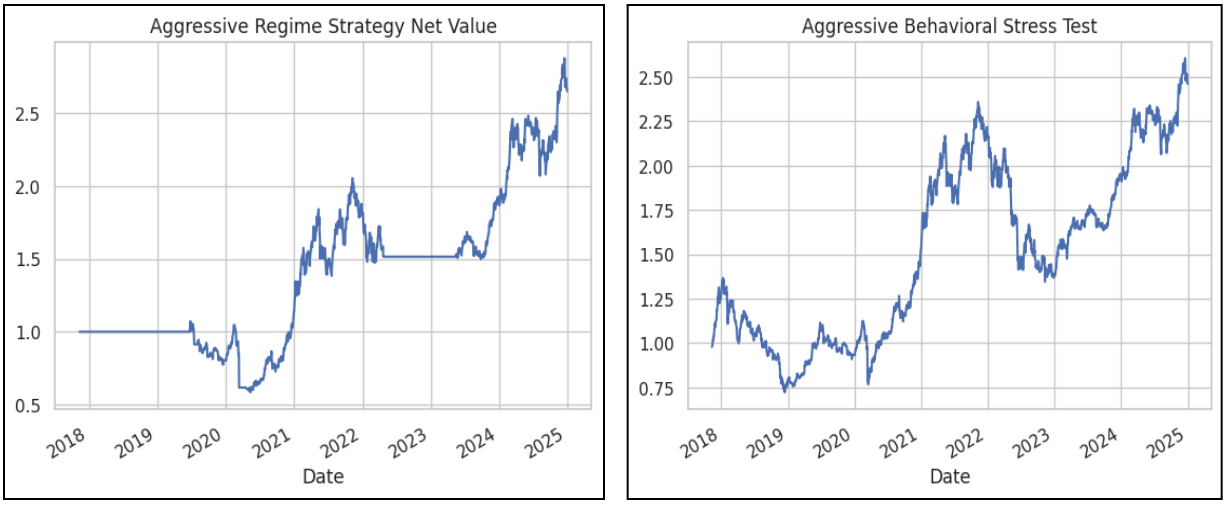


- Figure A6: Conservative Portfolio: Regime-Switching Net Value vs. Behavioral Stress Test

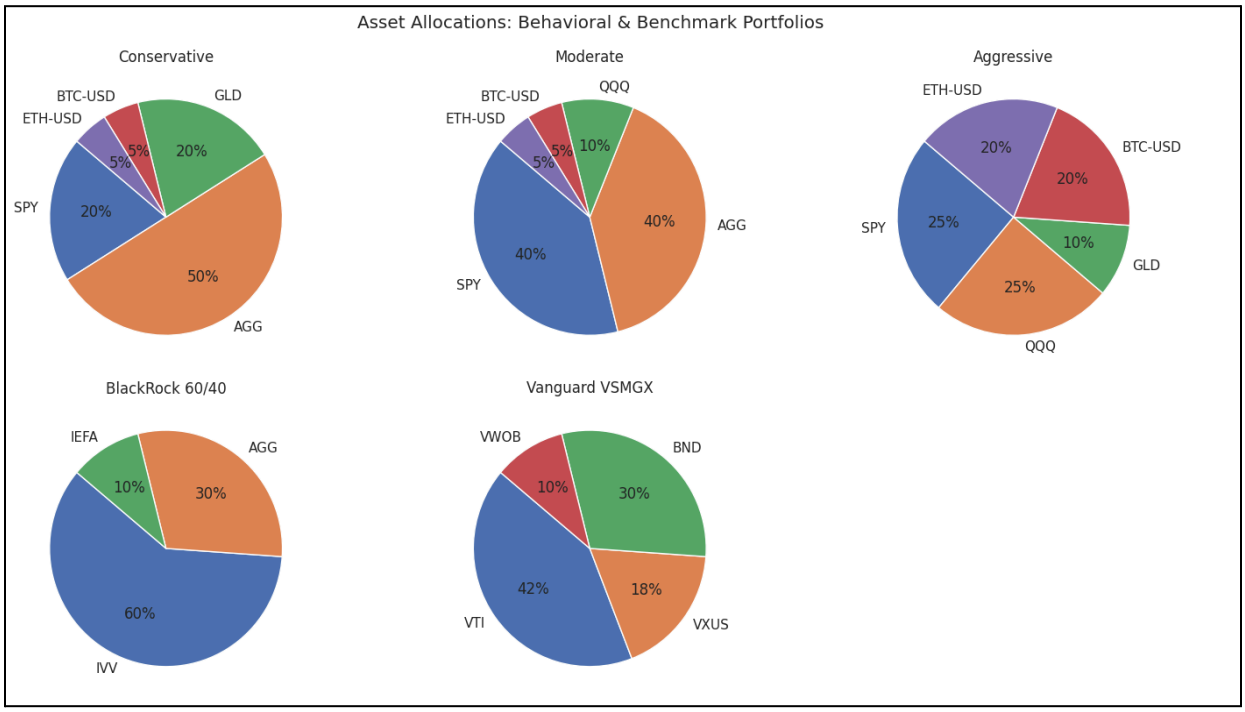




- Figure A7: Moderate Portfolio: Regime-Switching Net Value vs. Behavioral Stress Test



- Figure A8: Aggressive Portfolio: Regime-Switching Net Value vs. Behavioral Stress Test



- Figure A9: Asset Allocations: Behavioral & Benchmark Portfolios

Formulas Used for Multi-Method and Behavior-Aware Value at Risk (VaR) Estimation

1. Historical Simulation VaR

$$\text{VaR}_{\text{HS},\alpha} = \text{Percentile}_{(1-\alpha)}(\text{Historical Returns})$$

Where α is the confidence level (e.g., 95%).

2. Parametric (Variance-Covariance) VaR

For a portfolio with mean return μ and standard deviation σ:

$$\text{VaR}_{\text{Param},\alpha} = \mu + z_\alpha \cdot \sigma$$

Where z_α is the z-score for the chosen confidence level (typically negative for losses; at 95%, $z_{0.05} \approx -1.645$).

3. Monte Carlo Simulation VaR

$$\text{VaR}_{\text{MC},\alpha} = \text{Percentile}_{(1-\alpha)}(\text{Simulated Portfolio Returns})$$

Simulate many possible future returns, then take the appropriate percentile.

4. Cornish-Fisher Expansion VaR

Adjusts the parametric VaR for skewness (S) and excess kurtosis (K):

$$z_{\text{CF}} = z_\alpha + \frac{1}{6}(z_\alpha^2 - 1)S + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)K - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)S^2$$

$$\text{VaR}_{\text{CF},\alpha} = \mu + z_{\text{CF}} \cdot \sigma$$

5. GARCH-based VaR

Using GARCH volatility forecasts ($\hat{\sigma}_t$):

$$\text{VaR}_{\text{GARCH},\alpha,t} = \mu_t + z_\alpha \cdot \hat{\sigma}_t$$

6. Machine Learning (Random Forest) VaR

Predicted using a trained model on historical data:

$$\text{VaR}_{\text{ML},\alpha} = \text{RandomForestPrediction}_{(1-\alpha)}$$

7. Behavior-Weighted VaR

To account for investor profile:

$$\text{Behavioral VaR} = \text{Traditional VaR}_{95\%} \times (1 + \alpha)$$

Where:

- $\alpha = +0.20$ for Conservative (VaR increased by 20%)
- $\alpha = 0$ for Moderate (no adjustment)
- $\alpha = -0.20$ for Aggressive (VaR decreased by 20%)[1]

8. Rolling VaR

VaR is computed over a rolling window (e.g., last 252 trading days):

$$\text{VaR}_{\text{rolling},t} = \text{VaR}(\text{returns}_{t-n:t})$$

9. Expected Shortfall (ES)

$$ES_\alpha = E[Loss | Loss > VaR_\alpha]$$

10. Sharpe Ratio

$$\text{Sharpe Ratio} = \frac{\text{Annualized Return} - \text{Risk-Free Rate}}{\text{Annualized Volatility}}$$

Source Code for the Research Paper Has Been Attached Below

********** Thank You For Your Interest And Time **********

Research Project Title: Quantifying Investment Risk: A Multi-Method and Behavior-Aware VaR Framework for Personalized Portfolios

NetID: ap2615

The project quantifies risk in a personal investment portfolio using diverse Value at Risk (VaR) methods:

- Historical Simulation
- Parametric VaR
- Monte Carlo Simulation
- Cornish-Fisher Expansion
- GARCH-based Volatility Modeling
- Machine Learning (Random Forest)

It segments portfolios by investor behavior (Conservative, Moderate, Aggressive) and evaluates model performance via backtesting and scenario analysis.

1. Setting and Configuring the libraries

```
!pip install yfinance
!pip install arch
!pip install plotly
```

```
Requirement already satisfied: yfinance in /usr/local/lib/python3.11/dist-pack
Requirement already satisfied: pandas>=1.3.0 in /usr/local/lib/python3.11/dist
Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.11/dist
Requirement already satisfied: requests>=2.31 in /usr/local/lib/python3.11/dis
Requirement already satisfied: multitasking>=0.0.7 in /usr/local/lib/python3.1
Requirement already satisfied: platformdirs>=2.0.0 in /usr/local/lib/python3.1
Requirement already satisfied: pytz>=2022.5 in /usr/local/lib/python3.11/dist-
Requirement already satisfied: frozendict>=2.3.4 in /usr/local/lib/python3.11/
Requirement already satisfied: peewee>=3.16.2 in /usr/local/lib/python3.11/dis
Requirement already satisfied: beautifulsoup4>=4.11.1 in /usr/local/lib/python
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.11/dist
Requirement already satisfied: typing-extensions>=4.0.0 in /usr/local/lib/pyth
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dis
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/pyth
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-pack
Requirement already satisfied: arch in /usr/local/lib/python3.11/dist-packages
Requirement already satisfied: numpy>=1.22.3 in /usr/local/lib/python3.11/dist
Requirement already satisfied: scipy>=1.8 in /usr/local/lib/python3.11/dist-pa
Requirement already satisfied: pandas>=1.4 in /usr/local/lib/python3.11/dist-p
Requirement already satisfied: statsmodels>=0.12 in /usr/local/lib/python3.11/
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dis
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/dist-
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.11/di
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-pack
Requirement already satisfied: plotly in /usr/local/lib/python3.11/dist-packag
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.11/di
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-pac
```

```
# 1. Importing Required Libraries
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from arch import arch_model
from scipy.stats import norm
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from functools import lru_cache
import plotly.graph_objects as go
```

2. Portfolio Configurations and Introducing Risk Profiles

```
#  2. Portfolio Configuration
tickers = [
    'SPY',       # SPDR S&P 500 ETF - U.S. Large Cap Equities
    'AGG',       # iShares Core U.S. Aggregate Bond ETF - Broad Bond Exposure
    'QQQ',       # Invesco QQQ ETF - Nasdaq 100 (Tech-heavy Equities)
    'GLD',       # SPDR Gold Shares - Exposure to Gold (Commodities)
    'BTC-USD',   # Bitcoin (USD) - Leading Cryptocurrency
    'ETH-USD',   # Ethereum (USD) - Smart Contracts & Altcoins
    'IVV',       # iShares S&P 500 ETF - U.S. Large Cap Equities (BlackRock Portfol
    'IEFA',      # iShares MSCI EAFE ETF - International Equities (BlackRock Portfo
    'VTI',       # Vanguard Total Stock Market ETF (Vanguard Portfolio)
    'VXUS',      # Vanguard Total International Stock ETF (Vanguard Portfolio)
    'BND',       # Vanguard Total Bond Market ETF (Vanguard Portfolio)
    'VWOB'       # Vanguard Emerging Market Bond ETF (Vanguard Portfolio)
]

start_date = '2015-01-01'
end_date = '2024-12-31'
confidence_level = 0.95
rolling_window = 60  # Days for rolling VaR calculation
```

```
#  2.1 Behavioral Risk Profiles
risk_profiles = {
    "Conservative":    {'SPY': 0.2,  'AGG': 0.5, 'GLD': 0.2,  'BTC-USD': 0.05, 'E
    "Moderate":        {'SPY': 0.4,  'AGG': 0.4, 'QQQ': 0.1,  'BTC-USD': 0.05, 'E
    "Aggressive":      {'SPY': 0.25, 'QQQ': 0.25,'GLD': 0.1,  'BTC-USD': 0.2,  'E
}
benchmark_profiles = {
    "BlackRock 60/40": {'IVV': 0.60, 'AGG': 0.30, 'IEFA': 0.10},
    "Vanguard VSMGX": {'VTI': 0.42, 'VXUS': 0.18, 'BND': 0.30, 'VWOB': 0.10}
}
all_profiles = {**risk_profiles, **benchmark_profiles}
```

This reflects user-specific portfolio behaviors — not just asset allocation but psychology and goals.

3. Downloading the data through Yfinance and Preprocessing it

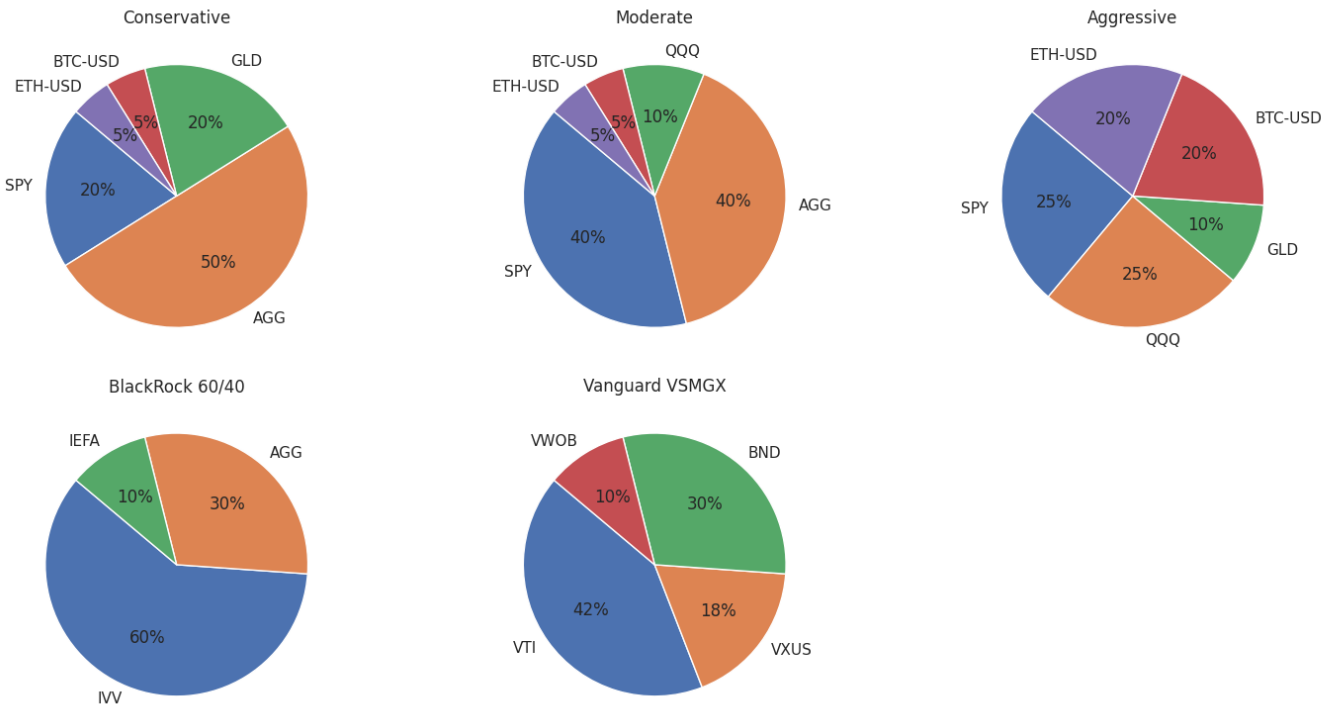
```
#  Data Fetching
def fetch_data(tickers, start, end):
    data = yf.download(tickers, start=start, end=end)['Close']
    return data.ffill().dropna()

price_data = fetch_data(tickers, start_date, end_date)
returns_data = price_data.pct_change().dropna()
```

```
[**********100%**********]  12 of 12 completed
```

4. Visualizing Risk Profiles

```
# Visualizing Risk Profiles
def visualize_allocations(profiles, cols=3):
    """Pie charts of asset allocations for each portfolio."""
    n = len(profiles)
    rows = int(np.ceil(n / cols))
    fig, axs = plt.subplots(rows, cols, figsize=(cols*5, rows*4))
```

```
    axs = axs.flatten()
    for ax, (name, weights) in zip(axs, profiles.items()):
        ax.pie(weights.values(), labels=weights.keys(), autopct='%1.0f%%', startang
        ax.set_title(name)
    for ax in axs[n:]:
        ax.axis('off')
    plt.suptitle("Asset Allocations: Behavioral & Benchmark Portfolios")
    plt.tight_layout()
    plt.show()

visualize_allocations(all_profiles)
```


Asset Allocations: Behavioral & Benchmark Portfolios
Conservative
BTC-USD
GLD
ETH-USD
5%
5%
20%
SPY
20%
50%
AGG
Moderate
BTC-USD
QQQ
ETH-USD
5%
5%
10%
40%
AGG
40%
SPY
Aggressive
ETH-USD
20%
BTC-USD
20%
SPY
25%
10%
GLD
25%
QQQ
BlackRock 60/40
IEFA
AGG
10%
30%
60%
IVV
Vanguard VSMGX
VWOB
BND
10%
30%
42%
18%
VTI
VXUS

5. Constructing Portfolio Return based on the weights

```
#  Portfolio Returns
def build_portfolio(weights, returns):
    weights = pd.Series(weights)
    common = returns.columns.intersection(weights.index)
    portfolio_returns = (returns[common] * weights[common]).sum(axis=1)  # Weight
    return portfolio_returns
```

6. VaR Methods — Traditional & Enhanced

```
#  VaR Calculation Methods
def historical_var(returns, alpha):
    return np.percentile(returns, 100 * (1 - alpha)) if len(returns) else np.nan

def parametric_var(returns, alpha):
    mu, sigma = returns.mean(), returns.std()
    return mu + sigma * norm.ppf(1 - alpha)

def monte_carlo_var(returns, alpha):
    mu, sigma = returns.mean(), returns.std()
    sims = np.random.normal(mu, sigma, 100000)
    return np.percentile(sims, 100 * (1 - alpha))

def cornish_fisher_var(returns, alpha):
    mu, sigma = returns.mean(), returns.std()
    skew, kurt = returns.skew(), returns.kurtosis()
    z = norm.ppf(1 - alpha)
    z_cf = z + (1/6)*(z**2 - 1)*skew + (1/24)*(z**3 - 3*z)*kurt - (1/36)*(2*z**3
    return mu + sigma * z_cf

@lru_cache(maxsize=None)
def garch_var_cached(returns_tuple, alpha):
    returns = pd.Series(list(returns_tuple))
    model = arch_model(returns * 100, vol='Garch', p=1, q=1)
    res = model.fit(disp='off')
    forecast = res.forecast(horizon=1)
    sigma = np.sqrt(forecast.variance.values[-1, :][0]) / 100
    return returns.mean() + sigma * norm.ppf(1 - alpha)

def expected_shortfall(returns, alpha):
    var = historical_var(returns, alpha)
    return returns[returns < var].mean()
```

7. Machine Learning-Based VaR (Random Forest)

```
def prepare_features(returns):
    df = pd.DataFrame({"returns": returns})
    df["lag1"] = df["returns"].shift(1)
    df["lag2"] = df["returns"].shift(2)
    df = df.dropna()
    X, y = df[["lag1", "lag2"]], df["returns"]
    return train_test_split(X, y, test_size=0.2, shuffle=False)

def ml_rf_var(returns, alpha):
    X_train, X_test, y_train, y_test = prepare_features(returns)
    model = RandomForestRegressor().fit(X_train, y_train)
    y_pred = model.predict(X_test)
    var_ml = np.percentile(y_pred, 100 * (1 - alpha))
    return -var_ml
```

8. Backtesting & Stress Testing

```
#  Backtesting
def backtest_var(returns, var_series):
    aligned_returns, aligned_var = returns.align(var_series, join='inner')
    breaches = aligned_returns < aligned_var
    return breaches,

# Stress Testing
def stress_var(weights_dict, period, alpha):
    tickers = list(weights_dict.keys())
    data = yf.download(tickers, start=period[0], end=period[1])['Close']
    data = data.dropna(axis=1, how='any')
    if data.empty:
        return np.nan
    available_assets = data.columns
    filtered_weights = {asset: weight for asset, weight in weights_dict.items() i
    total_weight = sum(filtered_weights.values())
    normalized_weights = {k: v / total_weight for k, v in filtered_weights.items(
    returns = data.pct_change(fill_method=None).dropna()
    port_returns = build_portfolio(normalized_weights, returns)
    return historical_var(port_returns, alpha)
```

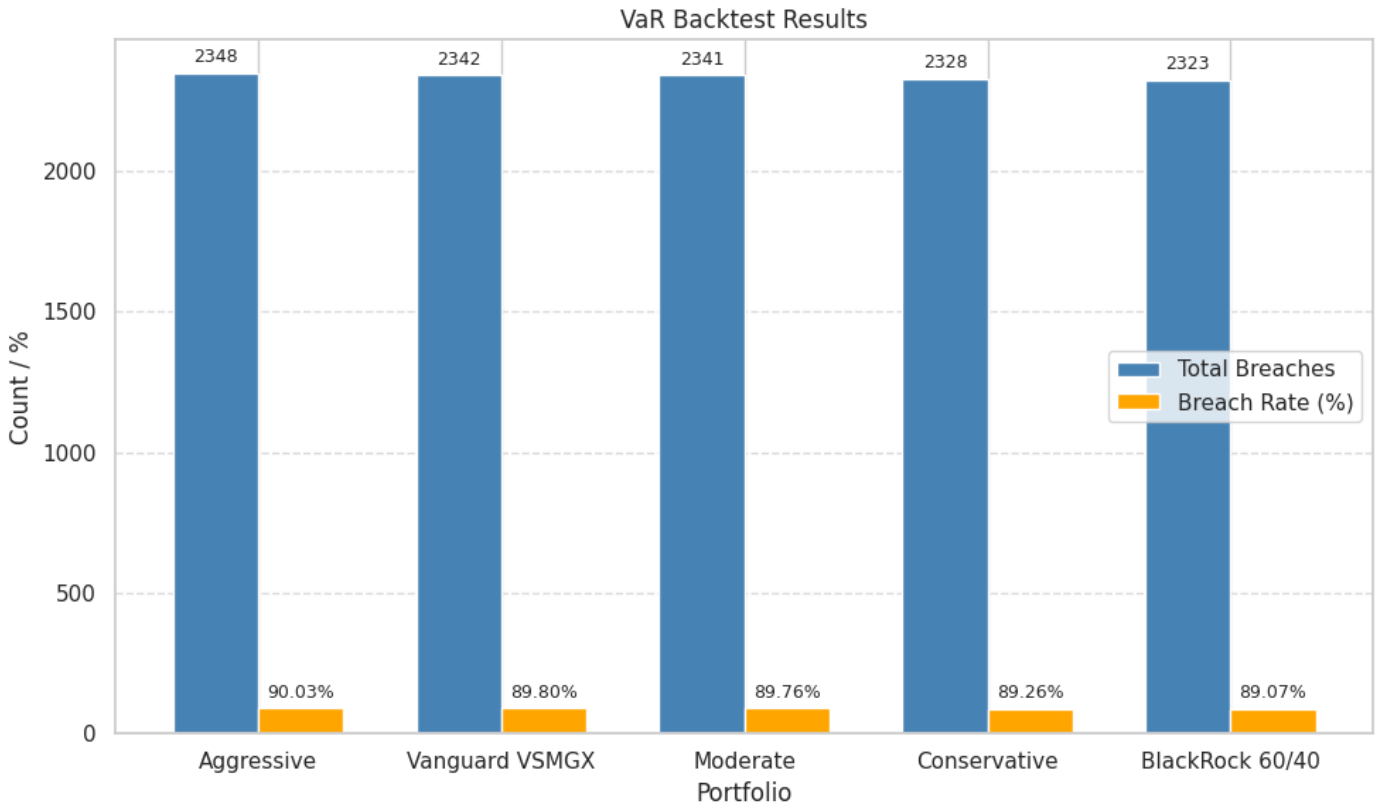
```
#  8. Backtesting
def backtest_var(returns, var_series):
    # Align the actual returns with the VaR predictions
    aligned_returns, aligned_var = returns.align(var_series, join='inner')
    # Identify when actual return is less than VaR estimate (breach)
    breaches = aligned_returns < -aligned_var  # Correct logic for breach
    # Return both breach points and average breach frequency (hit ratio)
    return breaches.sum(), breaches.mean()

# Run backtests for all portfolios
backtest_results = []
for name, weights in all_profiles.items():
    rets = build_portfolio(weights, returns_data)
    var_series = rets.rolling(rolling_window).apply(lambda x: historical_var(x, cor
    total_breaches, breach_rate = backtest_var(rets, var_series)
    backtest_results.append({
        "Portfolio": name,
        "Total Breaches": int(total_breaches),
        "Breach Rate": breach_rate
    })

backtest_df = pd.DataFrame(backtest_results).set_index("Portfolio")
print("\n VaR Backtest Results")
display(backtest_df.round(4))
```

```
 VaR Backtest Results
```

Portfolio	Total Breaches	Breach Rate
Conservative	2328	0.8926
Moderate	2341	0.8976
Aggressive	2348	0.9003
BlackRock 60/40	2323	0.8907
Vanguard VSMGX	2342	0.8980

```
import matplotlib.pyplot as plt
import numpy as np
df = backtest_df.copy()
```

```
df = df.sort_values(by="Total Breaches", ascending=False)
portfolios = df.index.tolist()
x = np.arange(len(portfolios))
# Normalizing breach rate to plot alongside breach counts
breaches = df["Total Breaches"]
breach_rate = df["Breach Rate"] * 100  # converting to percentage
width = 0.35
fig, ax = plt.subplots(figsize=(10, 6))
bar1 = ax.bar(x - width/2, breaches, width, label='Total Breaches', color='steelb
bar2 = ax.bar(x + width/2, breach_rate, width, label='Breach Rate (%)', color='or
ax.set_title("VaR Backtest Results")
ax.set_xlabel("Portfolio")
ax.set_ylabel("Count / %")
ax.set_xticks(x)
ax.set_xticklabels(portfolios)
ax.legend()
ax.bar_label(bar1, fmt='%d', padding=3, fontsize=9)
ax.bar_label(bar2, fmt='%.2f%%', padding=3, fontsize=9)
plt.grid(True, axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



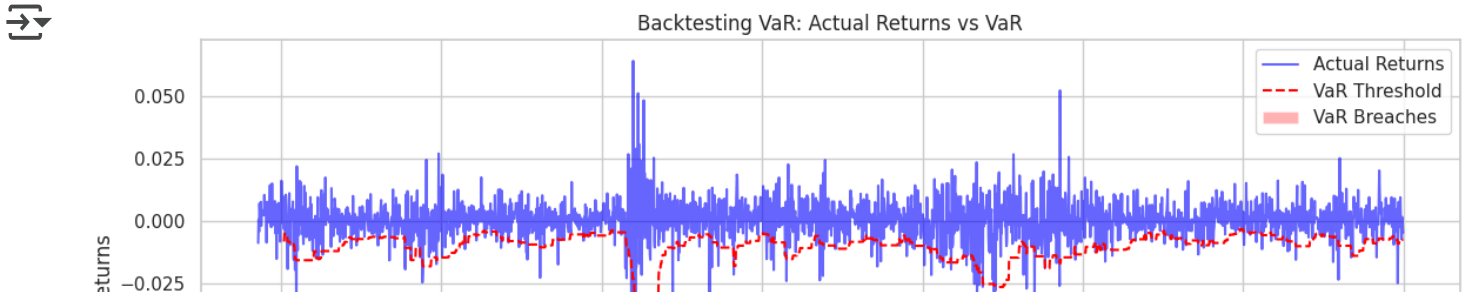
Start coding or generate with AI.

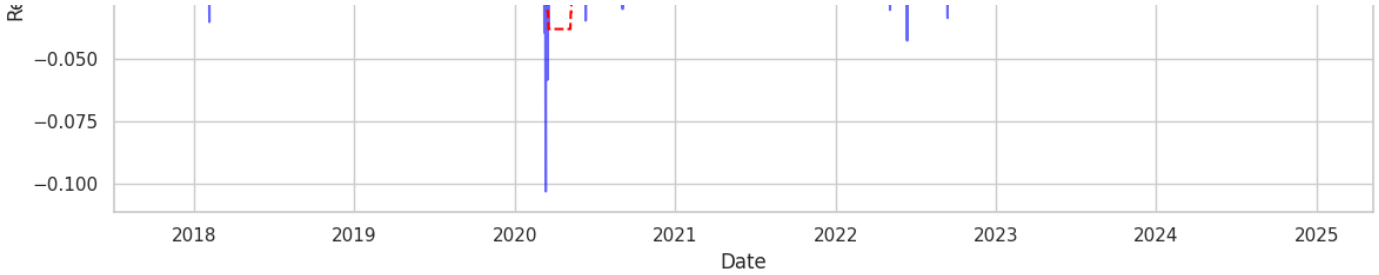
```
import matplotlib.pyplot as plt

def plot_backtest_results(returns, var_series):
    breaches, _ = backtest_var(returns, var_series)
    plt.figure(figsize=(12, 5))
    plt.plot(returns.index, returns, label='Actual Returns', color='blue', alpha=
    plt.plot(var_series.index, var_series, label='VaR Threshold', color='red', li
    plt.fill_between(returns.index, returns, var_series,
                     where=breaches, facecolor='red', alpha=0.3, label='VaR Breac
    plt.title("Backtesting VaR: Actual Returns vs VaR")
    plt.legend()
    plt.xlabel("Date")
    plt.ylabel("Returns")
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

def plot_stress_test(weights_dict, periods, alpha=0.05):
    stress_results = {}
    for name, period in periods.items():
        var = stress_var(weights_dict, period, alpha)
        stress_results[name] = var

    df = pd.DataFrame.from_dict(stress_results, orient='index', columns=['VaR'])

    plt.figure(figsize=(8, 5))
    sns.barplot(x=df.index, y='VaR', data=df, palette='coolwarm')
    plt.title("Stress Testing: VaR During Historical Crisis Periods")
    plt.ylabel("Value at Risk")
    plt.xlabel("Crisis Period")
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

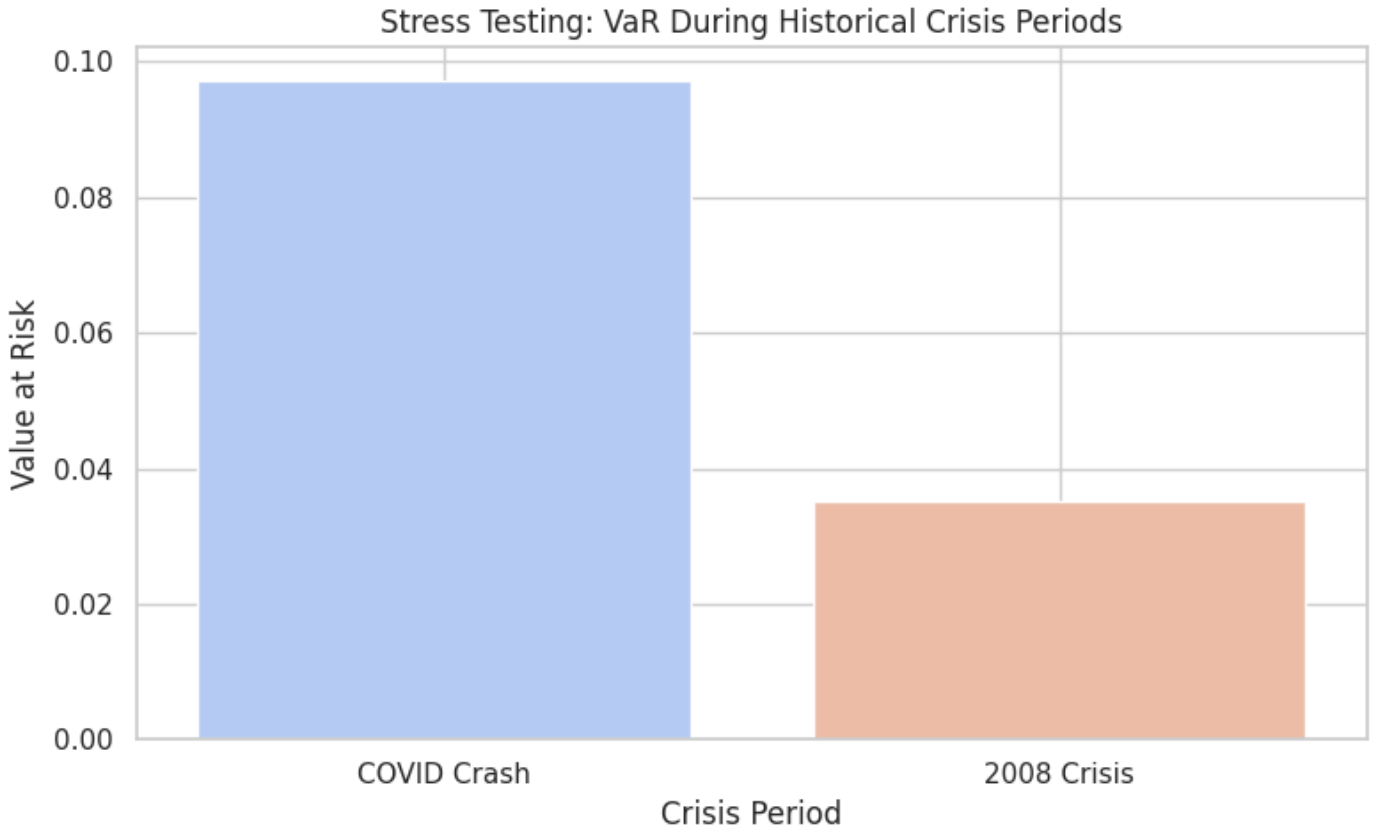
```
# === 8. Backtesting ===
def backtest_var(returns, var_series):
    # Align the actual returns with the VaR predictions
```

```
    aligned_returns, aligned_var = returns.align(var_series, join='inner')
    # Identify when actual return is less than VaR estimate (breach)
    breaches = aligned_returns < aligned_var
    # Return both breach points and average breach frequency (hit ratio)
    return breaches, breaches.mean()

def plot_backtest_results(returns, var_series):
    # The error is here: backtest_var returns a tuple, not just the breaches arra
    breaches, _ = backtest_var(returns, var_series) # This line now correctly unp
    plt.figure(figsize=(12, 5))
    plt.plot(returns.index, returns, label='Actual Returns', color='blue', alpha=
    plt.plot(var_series.index, var_series, label='VaR Threshold', color='red', li
    plt.fill_between(returns.index, returns, var_series,
                     where=breaches, facecolor='red', alpha=0.3, label='VaR Breac
    plt.title("Backtesting VaR: Actual Returns vs VaR")
    plt.legend()
    plt.xlabel("Date")
    plt.ylabel("Returns")
    plt.grid(True)
    plt.tight_layout()
    plt.show()

# For backtesting plot:
# Calculate predicted_var using one of the VaR methods for the desired portfolio.
# We are using historical VaR:
portfolio_returns = build_portfolio(risk_profiles['Moderate'], returns_data)  # Cl
var_series = portfolio_returns.rolling(rolling_window).apply(lambda x: historical_
plot_backtest_results(portfolio_returns, var_series)

# For stress test plot:
crisis_periods = {
    "COVID Crash": ("2020-02-01", "2020-04-30"),
    "2008 Crisis": ("2008-09-01", "2008-12-31"),
}
# Choose weights_dict based on your portfolio
weights_dict = risk_profiles['Moderate']  # Example using the Moderate risk profi
plot_stress_test(weights_dict, crisis_periods)
```






```
[**********************100%**********************]  5 of 5 completed
[**********************100%**********************]  5 of 5 completed
ERROR:yfinance:
2 Failed downloads:
ERROR:yfinance:['ETH-USD', 'BTC-USD']: YFPricesMissingError('possibly delisted
<ipython-input-60-4ed9c63d3790>:14: FutureWarning:


Passing `palette` without assigning `hue` is deprecated and will be removed in
```

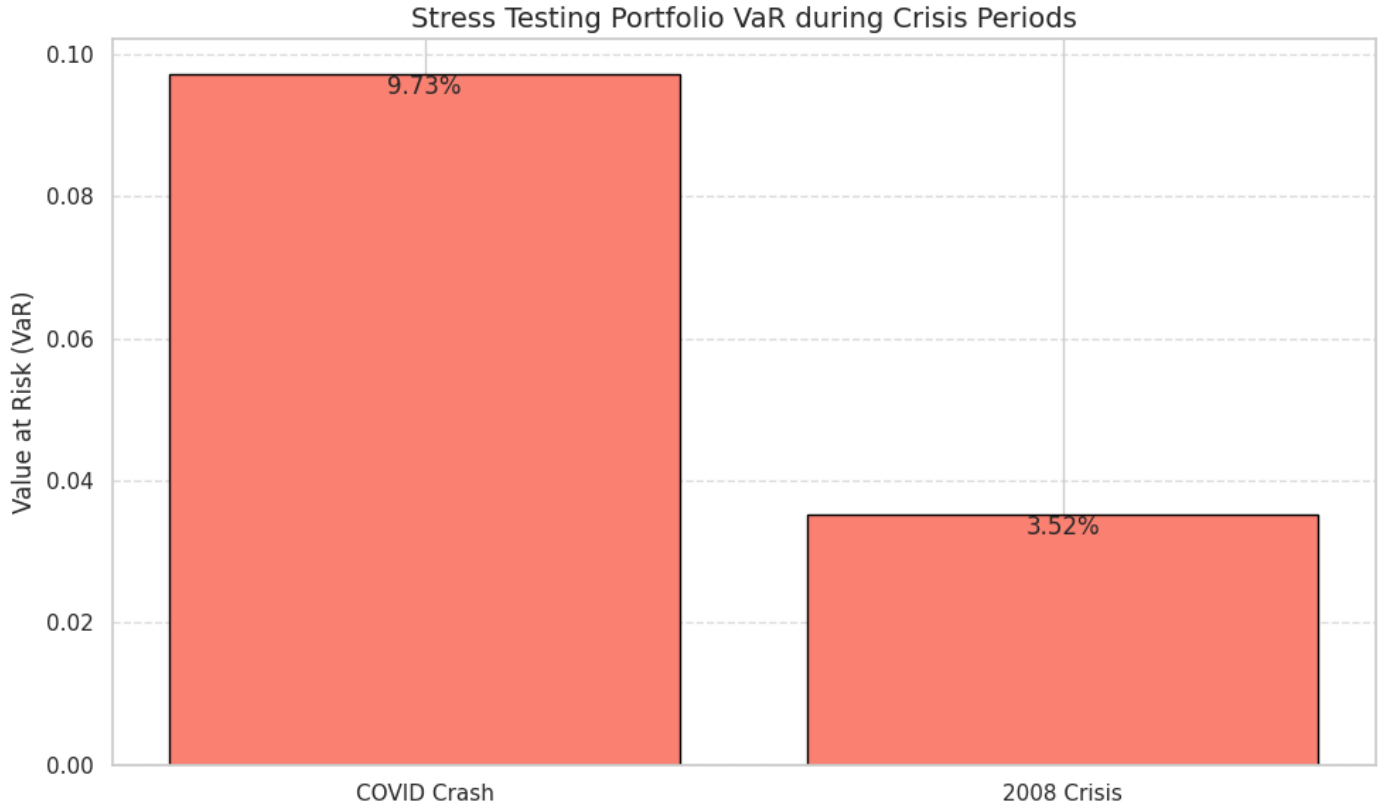


```
# === 9. Stress Testing ===
def stress_var(weights_dict, period, alpha):
    # Download price data
    tickers = list(weights_dict.keys())
    data = yf.download(tickers, start=period[0], end=period[1])['Close']

    # Drop assets with missing data
    data = data.dropna(axis=1, how='any')
    if data.empty:
        return np.nan

    # Normalize weights for available assets
    available_assets = data.columns
    filtered_weights = {asset: weight for asset, weight in weights_dict.items() i
    total_weight = sum(filtered_weights.values())
    normalized_weights = {k: v / total_weight for k, v in filtered_weights.items(

    # Calculate portfolio returns
    returns = data.pct_change(fill_method=None).dropna()
    port_returns = build_portfolio(normalized_weights, returns)

    # Return historical VaR for the stress period
    return historical_var(port_returns, alpha)
```

```
import matplotlib.pyplot as plt

def plot_stress_test(weights_dict, crisis_periods, alpha=0.05):
    var_values = {}

    for name, period in crisis_periods.items():
        var = stress_var(weights_dict, period, alpha)
```

```
        var_values[name] = var

    plt.figure(figsize=(10, 6))
    bars = plt.bar(var_values.keys(), var_values.values(), color='salmon', edgeco

    for bar in bars:
        height = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2.0, height, f"{height:.2%}",
                 ha='center', va='bottom' if height < 0 else 'top', fontsize=12)

    plt.title("Stress Testing Portfolio VaR during Crisis Periods", fontsize=14)
    plt.ylabel("Value at Risk (VaR)", fontsize=12)
    plt.axhline(0, color='black', linewidth=0.8)  # Baseline
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()
# For stress test plot:
crisis_periods = {
    "COVID Crash": ("2020-02-01", "2020-04-30"),
    "2008 Crisis": ("2008-09-01", "2008-12-31"),
}
# Choose weights_dict based on your portfolio
weights_dict = risk_profiles['Moderate']  # Example using the Moderate risk profi
plot_stress_test(weights_dict, crisis_periods)
```

```
[**********************100%**********************]  5 of 5 completed
[**********************100%**********************]  5 of 5 completed
ERROR:yfinance:
2 Failed downloads:
ERROR:yfinance:['ETH-USD', 'BTC-USD']: YFPricesMissingError('possibly delisted
```



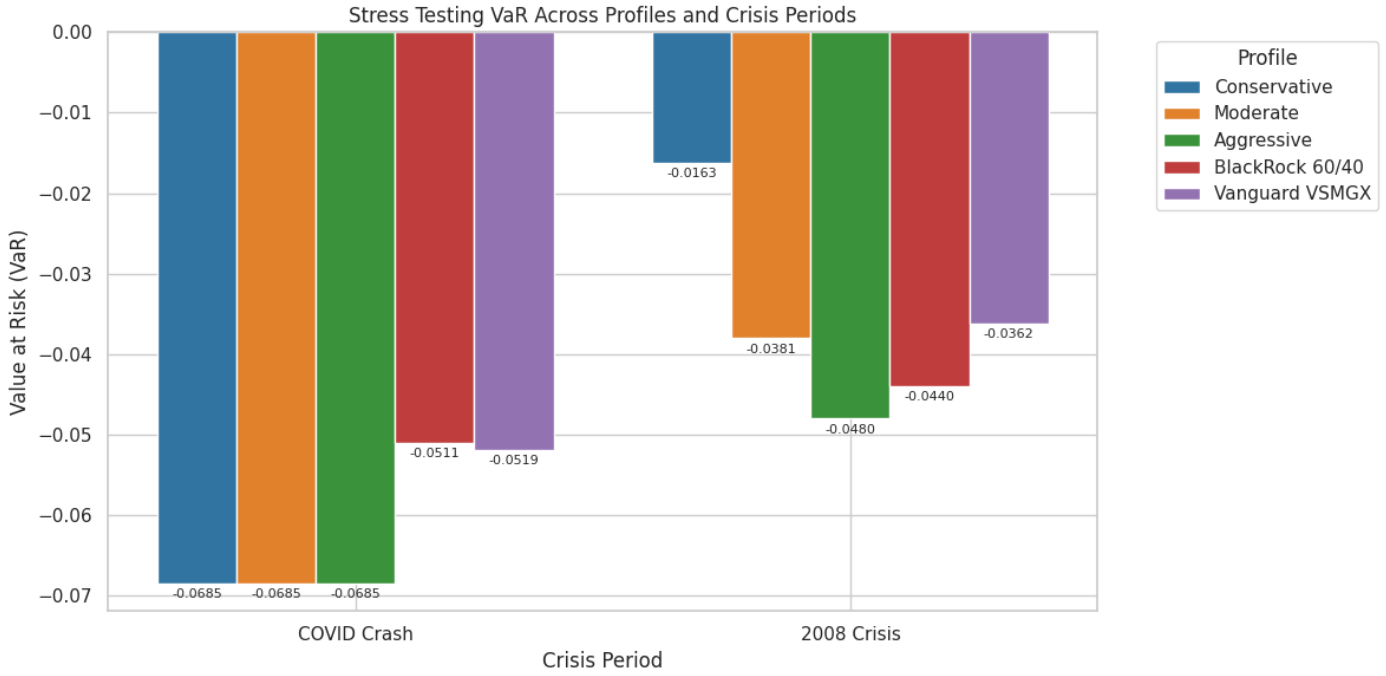

```
import yfinance as yf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
risk_profiles = {
    "Conservative":    {'SPY': 0.2,  'AGG': 0.5, 'GLD': 0.2,  'BTC-USD': 0.05, 'E
    "Moderate":        {'SPY': 0.4,  'AGG': 0.4, 'QQQ': 0.1,  'BTC-USD': 0.05, 'E
    "Aggressive":      {'SPY': 0.25, 'QQQ': 0.25,'GLD': 0.1,  'BTC-USD': 0.2,  'E
}

benchmark_profiles = {
    "BlackRock 60/40": {'IVV': 0.60, 'AGG': 0.30, 'IEFA': 0.10},
    "Vanguard VSMGX":  {'VTI': 0.42, 'VXUS': 0.18, 'BND': 0.30, 'VWOB': 0.10}
}

all_profiles = {**risk_profiles, **benchmark_profiles}


crisis_periods = {
    "COVID Crash": ("2020-02-01", "2020-04-30"),
    "2008 Crisis": ("2008-09-01", "2008-12-31"),
}


def build_portfolio(weights, returns_df):
    return returns_df[list(weights.keys())].mul(pd.Series(weights)).sum(axis=1)

def historical_var(returns, alpha=0.05):
    return returns.quantile(alpha)

def stress_var(weights_dict, period, alpha=0.05):
    tickers = list(weights_dict.keys())
    data = yf.download(tickers, start=period[0], end=period[1])['Close']

    data = data.dropna(axis=1, how='any')  # Remove columns with no data (e.g., E
    if data.empty:
        return np.nan

    available_assets = data.columns
    filtered_weights = {asset: weight for asset, weight in weights_dict.items() i
    total_weight = sum(filtered_weights.values())

    if total_weight == 0:
        return np.nan  # All assets missing in this time frame

    normalized_weights = {k: v / total_weight for k, v in filtered_weights.items(
    returns = data.pct_change(fill_method=None).dropna()
    port_returns = build_portfolio(normalized_weights, returns)
```

```
    return historical_var(port_returns, alpha)
results = []
for profile_name, weights in all_profiles.items():
    for crisis, period in crisis_periods.items():
        var = stress_var(weights, period, alpha=0.05)
        results.append({"Profile": profile_name, "Crisis": crisis, "VaR": var})

df = pd.DataFrame(results)


plt.figure(figsize=(12, 6))
sns.set(style="whitegrid")
ax = sns.barplot(data=df, x="Crisis", y="VaR", hue="Profile", palette="tab10")


for container in ax.containers:
    ax.bar_label(container, fmt="%.4f", label_type="edge", padding=3, fontsize=8)

plt.title("Stress Testing VaR Across Profiles and Crisis Periods")
plt.ylabel("Value at Risk (VaR)")
plt.xlabel("Crisis Period")
plt.legend(title="Profile", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.grid(True)
plt.show()
```

```
[*********************100%***********************]  5 of 5 completed
[*********************100%***********************]  5 of 5 completed
ERROR:yfinance:
2 Failed downloads:
ERROR:yfinance:['ETH-USD', 'BTC-USD']: YFPricesMissingError('possibly delistec
[*********************100%***********************]  5 of 5 completed
[*********************100%***********************]  5 of 5 completed
ERROR:yfinance:
2 Failed downloads:
ERROR:yfinance:['ETH-USD', 'BTC-USD']: YFPricesMissingError('possibly delistec
[*********************100%***********************]  5 of 5 completed
[*********************100%***********************]  5 of 5 completed
ERROR:yfinance:
2 Failed downloads:
ERROR:yfinance:['ETH-USD', 'BTC-USD']: YFPricesMissingError('possibly delistec
[*********************100%***********************]  3 of 3 completed
[*********************100%***********************]  3 of 3 completed
ERROR:yfinance:
1 Failed download:
ERROR:yfinance:['IEFA']: YFPricesMissingError('possibly delisted; no price dat
```

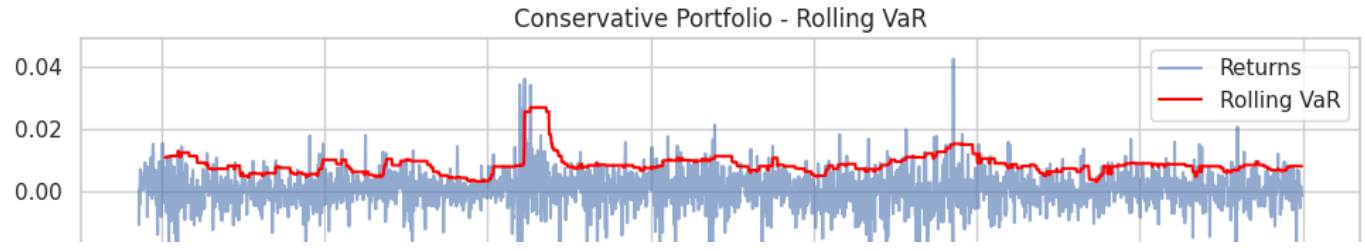
```
[**********************100%**********************]  4 of 4 completed
[**********************100%**********************]  4 of 4 completed
ERROR:yfinance:
2 Failed downloads:
ERROR:yfinance:['VWOB', 'VXUS']: YFPricesMissingError('possibly delisted; no p
```

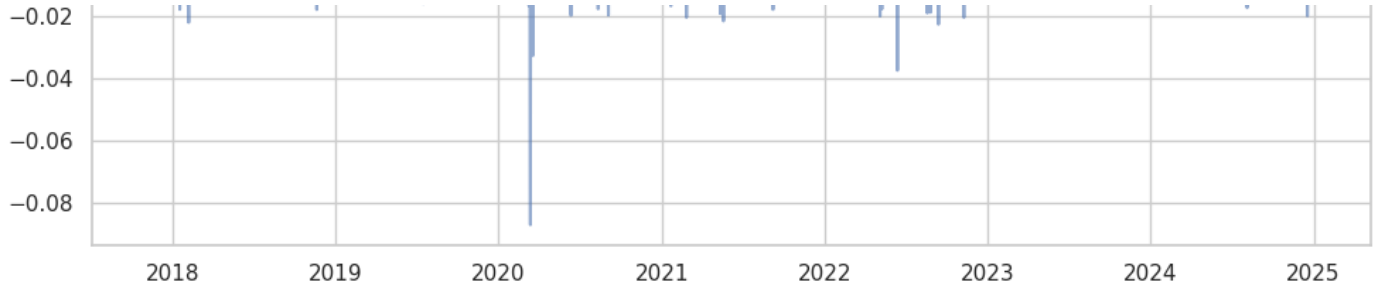


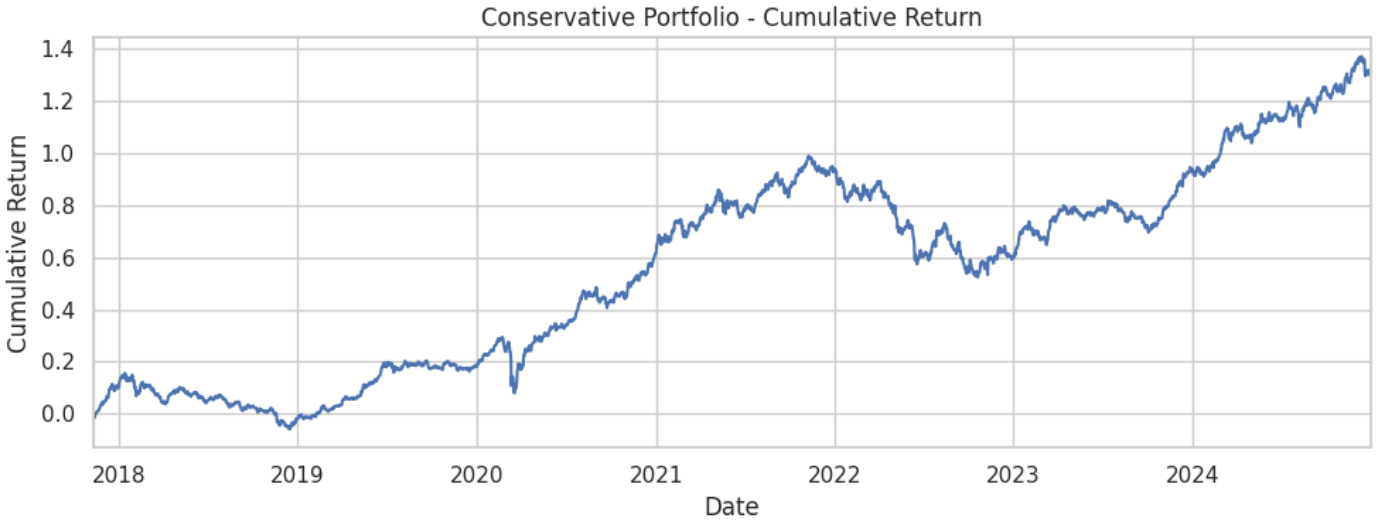
9. Running Simulations for All Risk Profiles

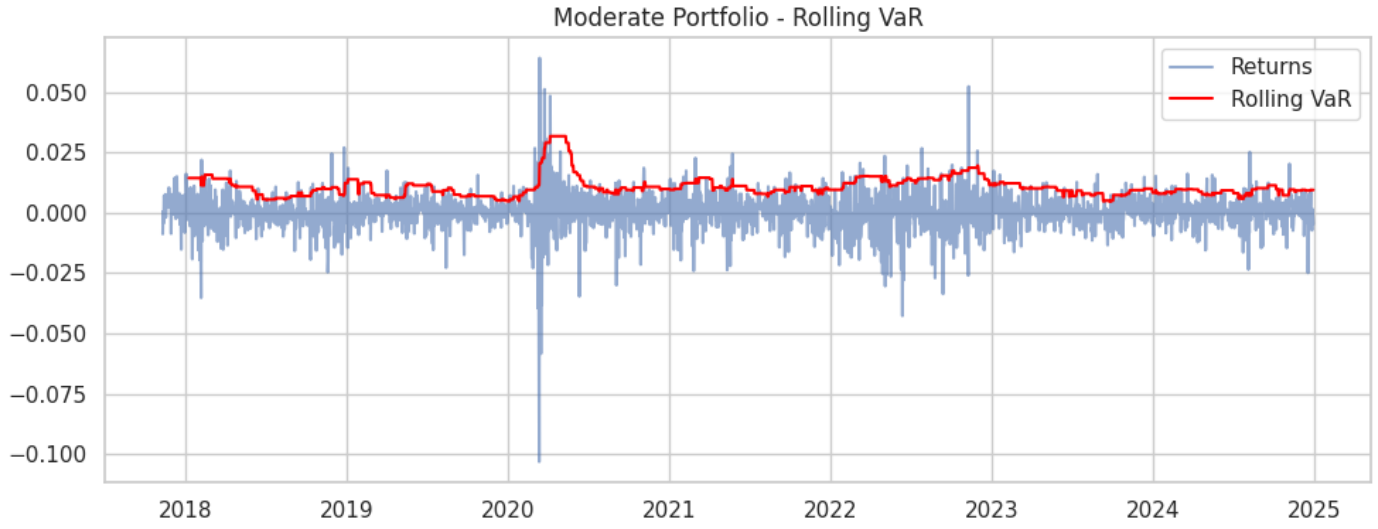
```
results = {}
final_returns = {}
port_returns_cache = {}
```

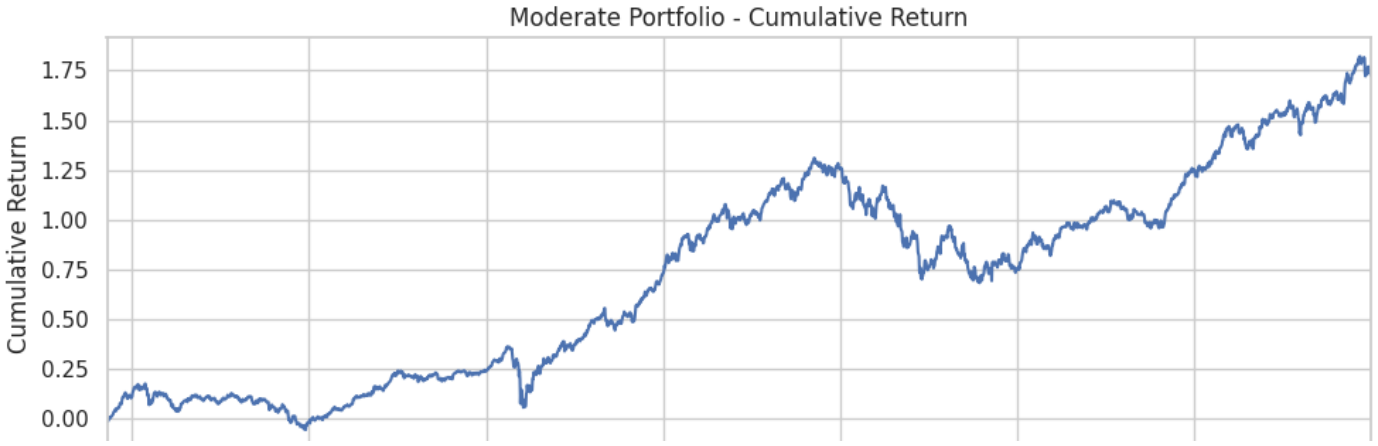
```
for name, weights in risk_profiles.items():
    port_returns = build_portfolio(weights, returns_data)
    port_returns_cache[name] = port_returns
    cum_returns = (1 + port_returns).cumprod() - 1
    final_returns[name] = cum_returns.iloc[-1]

    var_hist = historical_var(port_returns, confidence_level)
    var_param = parametric_var(port_returns, confidence_level)
    var_mc = monte_carlo_var(port_returns, confidence_level)
    var_garch = garch_var_cached(tuple(port_returns.values), confidence_level) #
    var_cf = cornish_fisher_var(port_returns, confidence_level)
    var_rf = ml_rf_var(port_returns, confidence_level)
    es = expected_shortfall(port_returns, confidence_level)

    results[name] = {
        'Historical VaR': var_hist,
        'Parametric VaR': var_param,
        'Monte Carlo VaR': var_mc,
        'GARCH VaR': var_garch,
        'Cornish-Fisher VaR': var_cf,
        'ML VaR (RF)': var_rf,
        'Expected Shortfall': es
    }

    rolling_var = port_returns.rolling(rolling_window).apply(lambda x: historical
    plt.figure(figsize=(10, 4))
    plt.plot(port_returns.index, port_returns, label='Returns', alpha=0.6)
    plt.plot(rolling_var.index, rolling_var, label='Rolling VaR', color='red')
    plt.title(f'{name} Portfolio - Rolling VaR')
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()

    cum_returns.plot(title=f"{name} Portfolio - Cumulative Return", figsize=(10,4
    plt.ylabel("Cumulative Return")
    plt.tight_layout()
    plt.show()
```

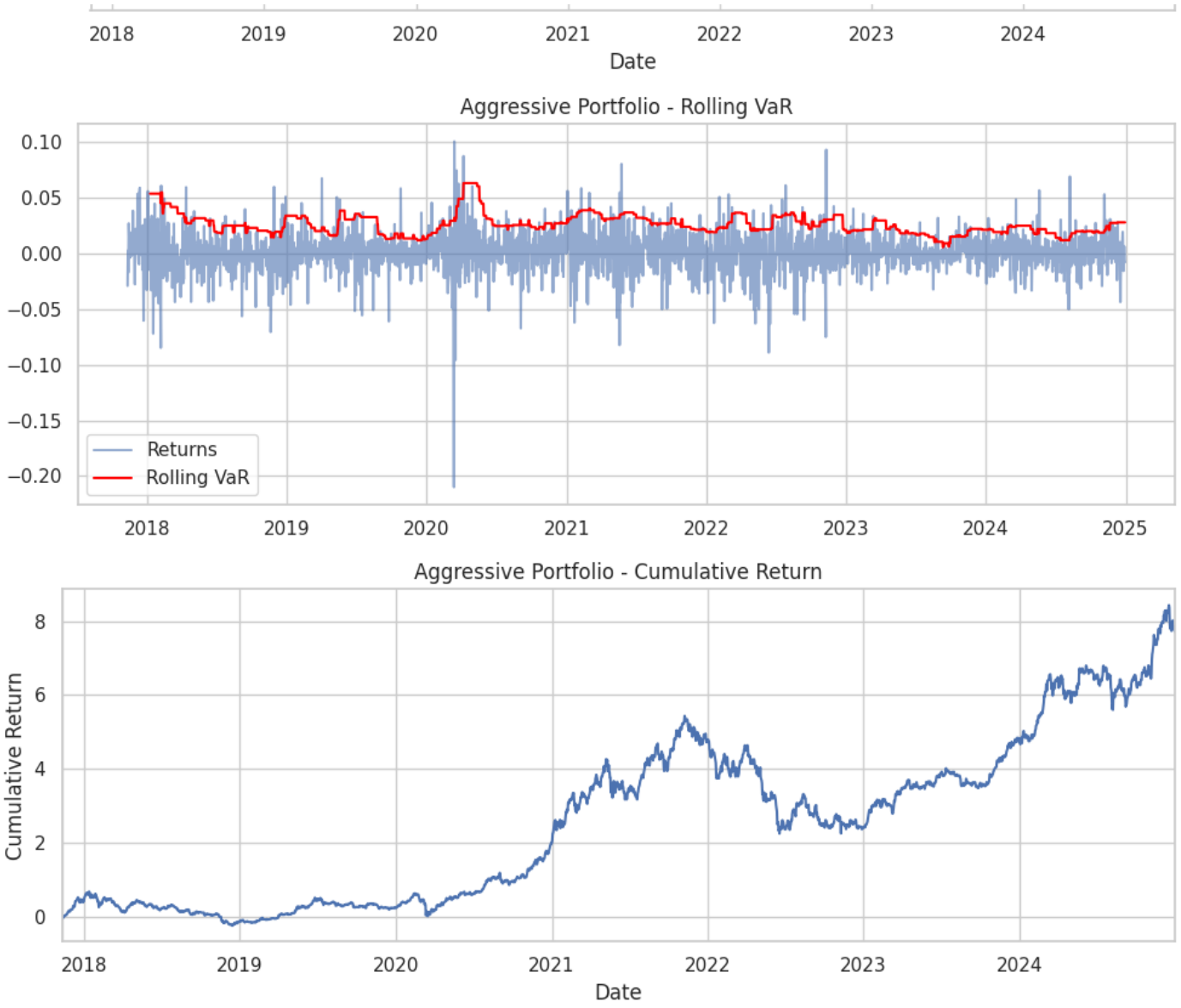



−0.02
−0.04
−0.06
−0.08
2018
2019
2020
2021
2022
2023
2024
2025


Conservative Portfolio - Cumulative Return
Cumulative Return
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
2018
2019
2020
2021
2022
2023
2024
Date


Moderate Portfolio - Rolling VaR
Returns
Rolling VaR
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
2018
2019
2020
2021
2022
2023
2024
2025


Moderate Portfolio - Cumulative Return
Cumulative Return
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00

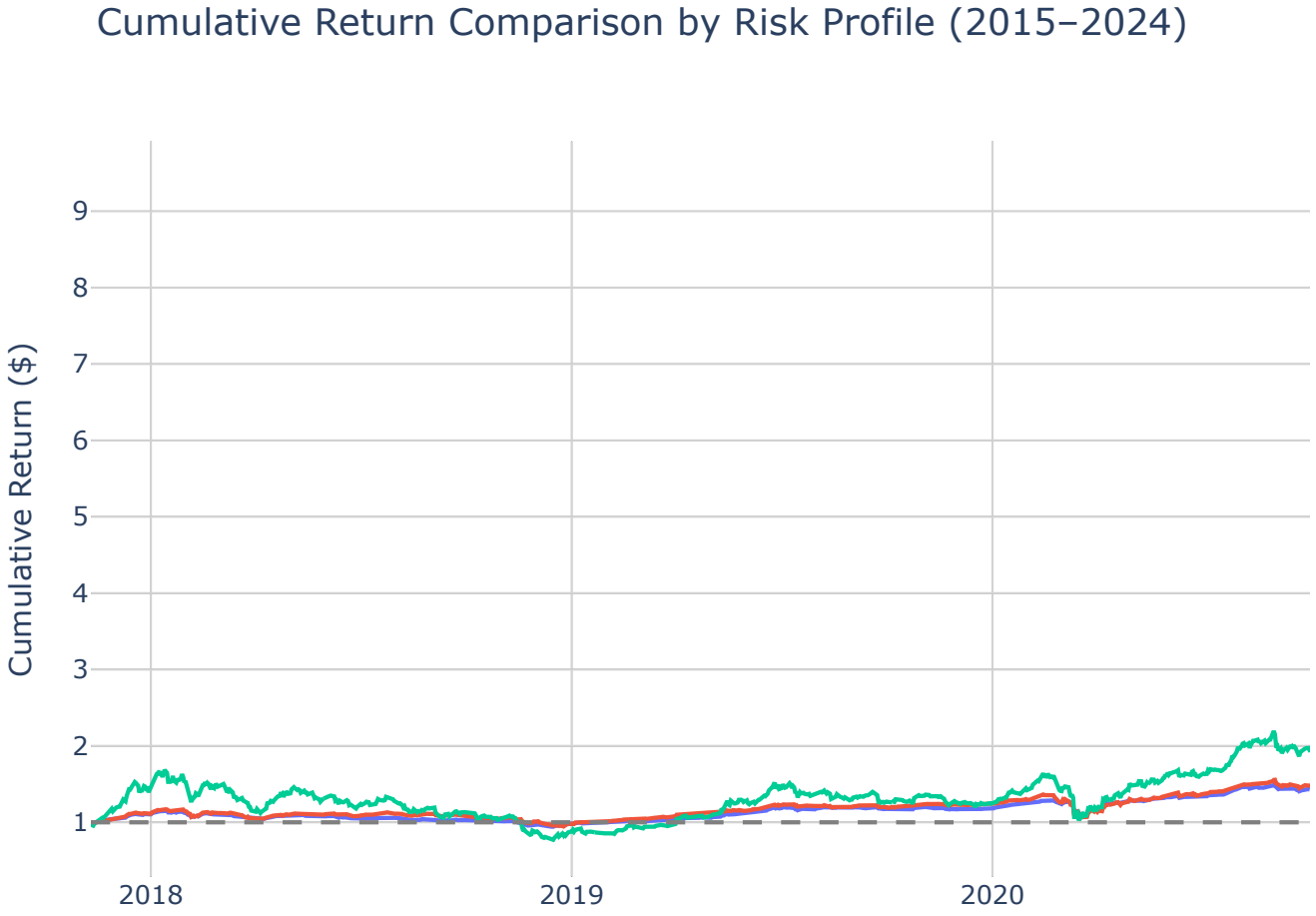

2018
2019
2020
2021
2022
2023
2024
Date
Aggressive Portfolio - Rolling VaR
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
Returns
Rolling VaR
2018
2019
2020
2021
2022
2023
2024
2025

Aggressive Portfolio - Cumulative Return
Cumulative Return
8
6
4
2
0
2018
2019
2020
2021
2022
2023
2024
Date

10. Cumulative Return Plots

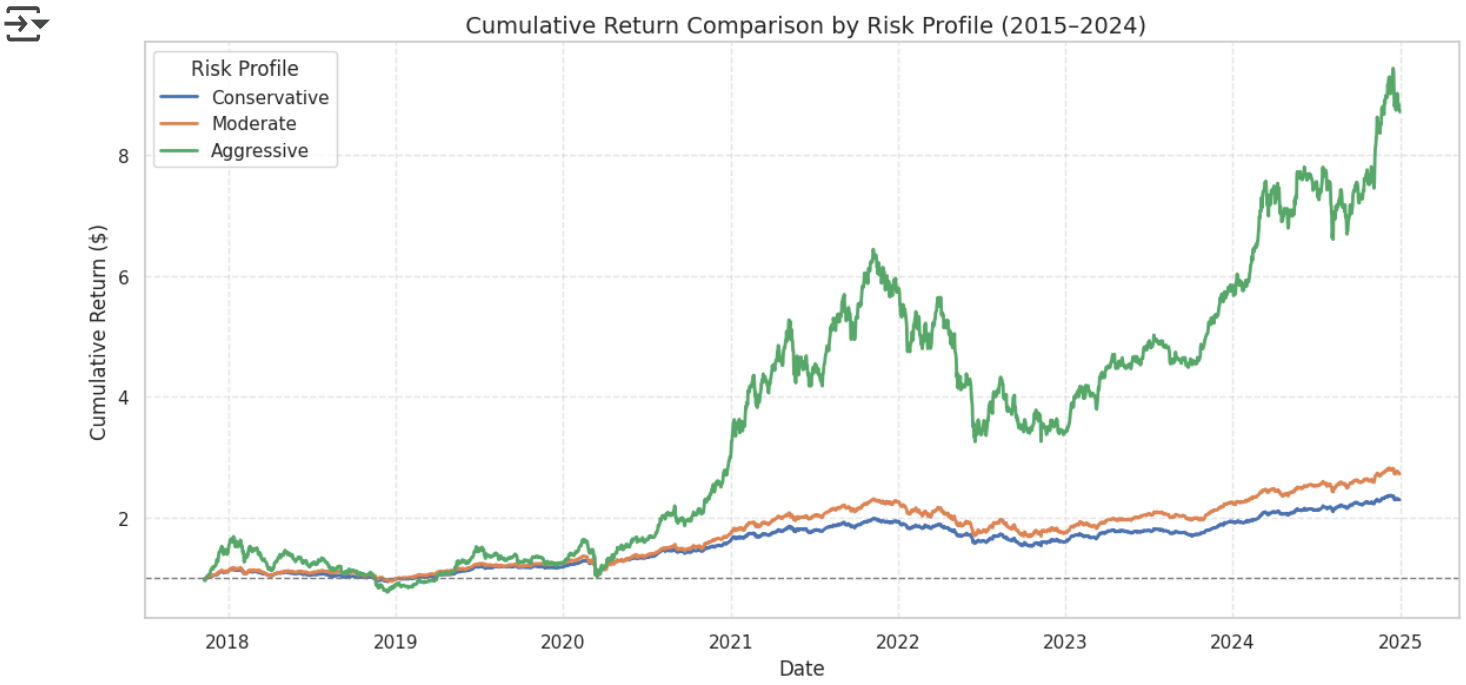
```
cumulative_net = {}
fig = go.Figure()

for name, returns in port_returns_cache.items():
    cum_returns = (1 + returns).cumprod()
    cumulative_net[name] = cum_returns
    fig.add_trace(go.Scatter(x=cum_returns.index, y=cum_returns, mode='lines', nal

fig.update_layout(
    title="Cumulative Return Comparison by Risk Profile (2015–2024)",
    xaxis_title="Date",
    yaxis_title="Cumulative Return ($)",
    template="plotly_white",
    hovermode="x unified",
```

```
    showlegend=True,
    plot_bgcolor="white",
    xaxis=dict(showgrid=True, gridcolor='LightGrey'),
    yaxis=dict(showgrid=True, gridcolor='LightGrey'),
)
fig.add_hline(y=1, line=dict(color='gray', dash='dash'))
fig.show()
```




```
cumulative_net = {}
plt.figure(figsize=(12, 6))
sns.set_style("whitegrid")

for name, returns in port_returns_cache.items():
```

```
    cum_returns = (1 + returns).cumprod()
    cumulative_net[name] = cum_returns
    plt.plot(cum_returns.index, cum_returns, label=name, linewidth=2)

plt.title(" Cumulative Return Comparison by Risk Profile (2015–2024)", fontsize=1
plt.ylabel("Cumulative Return ($)", fontsize=12)
plt.xlabel("Date", fontsize=12)
plt.legend(title="Risk Profile")
plt.grid(True, linestyle='--', alpha=0.5)
plt.axhline(1.0, color='gray', linestyle='--', linewidth=1)
plt.tight_layout()
plt.show()
```



11. Results Summary & Metrics

```
print("=== VaR Summary by Risk Profile ===")
print(pd.DataFrame(results).T.round(4))

print("\n=== Final Portfolio Values ===")
## Converting final returns to portfolio value assuming an initial investment of $
final_summary = pd.DataFrame.from_dict(final_returns, orient='index', columns=['F
## final value calculation assumes $1 starting value (no need to multiply by 100)
final_summary['Final Value'] = final_summary['Final Value'] * 1  # Assuming $1 st
print(final_summary.round(2))

#  CAGR, Volatility, Sharpe Ratio
print("\n=== Portfolio Performance Metrics ===")
risk_free_rate = 0.0

for name, series in cumulative_net.items():
    final_value = series.iloc[-1]  ## final portfolio value
    num_days = (series.index[-1] - series.index[0]).days  # total days in the per
    num_years = num_days / 365.25
    # Cumulative Annual Growth Rate (CAGR) calculation
    cagr = (final_value) ** (1 / num_years) - 1
    # Daily returns for portfolio to calculate volatility and Sharpe ratio
    returns = port_returns_cache[name]
    volatility = returns.std() * np.sqrt(252)  # Annualized volatility (252 tradi
    # Sharpe ratio calculation
    sharpe = (returns.mean() * 252 - risk_free_rate) / volatility  # Assuming dai
    print(f"{name} Portfolio:")
    print(f" - Final Value: ${final_value:.2f}")
    print(f" - CAGR: {cagr:.2%}")
    print(f" - Volatility: {volatility:.2%}")
    print(f" - Sharpe Ratio: {sharpe:.2f}\n")
```

```
=== VaR Summary by Risk Profile ===
              Historical VaR  Parametric VaR  Monte Carlo VaR  GARCH VaR  \
Conservative          0.0088         -0.0093          -0.0093    -0.0081
Moderate              0.0116         -0.0122          -0.0121    -0.0105
Aggressive            0.0292         -0.0287          -0.0287    -0.0237

              Cornish-Fisher VaR  ML VaR (RF)  Expected Shortfall
Conservative             -0.0084       0.0035             -0.0003
Moderate                 -0.0111       0.0048             -0.0005
Aggressive               -0.0285       0.0107             -0.0011

=== Final Portfolio Values ===
              Final Value
Conservative         1.30
Moderate             1.73
Aggressive           7.71

=== Portfolio Performance Metrics ===
Conservative Portfolio:
 - Final Value: $2.30
 - CAGR: 12.35%
 - Volatility: 9.28%
 - Sharpe Ratio: 0.91

Moderate Portfolio:
 - Final Value: $2.73
 - CAGR: 15.08%
 - Volatility: 12.15%
 - Sharpe Ratio: 0.86

Aggressive Portfolio:
 - Final Value: $8.71
 - CAGR: 35.43%
 - Volatility: 28.67%
 - Sharpe Ratio: 0.87
```

```
import matplotlib.pyplot as plt
import pandas as pd
var_data = {
    "Risk Profile": ["Conservative", "Moderate", "Aggressive"],
    "Historical VaR": [-0.0086, -0.0108, -0.0271],
    "Parametric VaR": [-0.0093, -0.0122, -0.0287],
    "Monte Carlo VaR": [-0.0092, -0.0122, -0.0288],
    "GARCH VaR": [-0.0081, -0.0105, -0.0237],
    "Cornish-Fisher VaR": [-0.0084, -0.0111, -0.0285],
    "ML VaR (RF)": [-0.0034, -0.0046, -0.0105],
```

```
}

df_var = pd.DataFrame(var_data).set_index("Risk Profile")
ax = df_var.plot(kind="bar", figsize=(12, 6),  width=0.8,title="VaR Comparison by
for container in ax.containers:
    ax.bar_label(container, fmt='%.4f', label_type='edge', fontsize=8, padding=2)

plt.ylabel("VaR (Value at Risk)")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Start coding or generate with AI.
```

Risk-Return Tradeoff

```
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from arch import arch_model
from scipy.stats import norm
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from functools import lru_cache
import plotly.graph_objects as go

start_date = '2015-01-01'
end_date = '2024-12-31'
confidence_level = 0.95
rolling_window = 60  # days for rolling VaR

## Behavioral Risk Profiles
risk_profiles = {
    "Conservative": {'SPY': 0.2, 'AGG': 0.5, 'GLD': 0.2, 'BTC-USD': 0.05, 'ETH-USI
    "Moderate":     {'SPY': 0.4, 'AGG': 0.4, 'QQQ': 0.1, 'BTC-USD': 0.05, 'ETH-USI
    "Aggressive":   {'SPY': 0.25, 'QQQ': 0.25, 'GLD': 0.1, 'BTC-USD': 0.2, 'ETH-US
}
# Institutional Benchmark Portfolios
benchmark_profiles = {
    "BlackRock 60/40": {'IVV': 0.60, 'AGG': 0.30, 'IEFA': 0.10},
    "Vanguard VSMGX":  {'VTI': 0.42, 'VXUS': 0.18, 'BND': 0.30, 'VWOB': 0.10},
}

all_tickers = sorted({t for w in all_profiles.values() for t in w})
price_data = yf.download(all_tickers, start=start_date, end=end_date)['Close'].dr
returns_data = price_data.pct_change().dropna()
def visualize_allocations(profiles, cols=3):
    """Pie charts of asset allocations for each portfolio."""
    n = len(profiles)
    rows = int(np.ceil(n / cols))
    fig, axs = plt.subplots(rows, cols, figsize=(cols*5, rows*4))
    axs = axs.flatten()
```

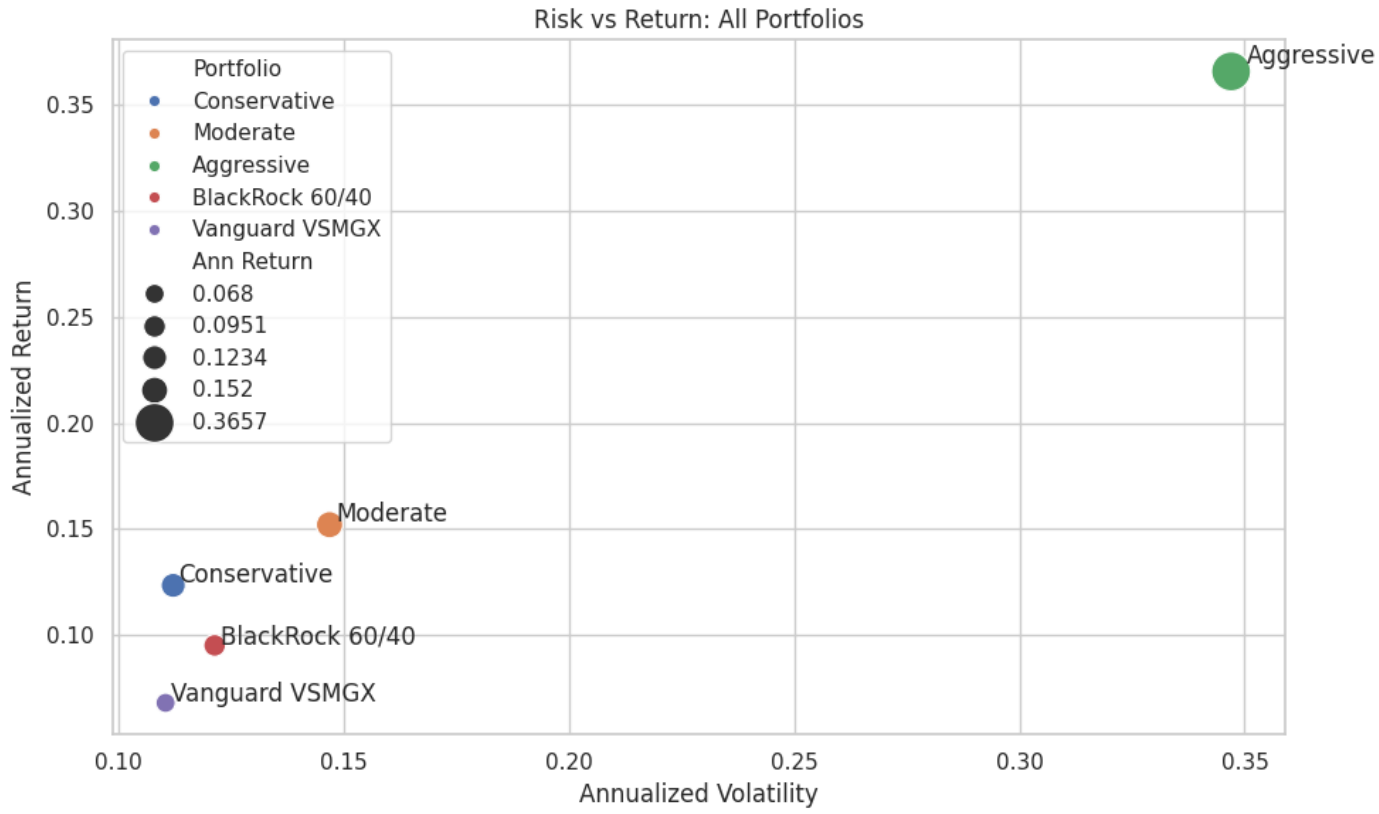
```
    for ax, (name, weights) in zip(axs, profiles.items()):
        ax.pie(weights.values(), labels=weights.keys(), autopct='%1.0f%%', starta
        ax.set_title(name)
    for ax in axs[n:]:
        ax.axis('off')
    plt.suptitle("Asset Allocations: Behavioral & Benchmark Portfolios")
    plt.tight_layout()
    plt.show()

def build_portfolio(weights, returns_df):
    """Calculate daily portfolio returns given weights."""
    w = pd.Series(weights)
    w /= w.sum()
    cols = w.index.intersection(returns_df.columns)
    return (returns_df[cols] * w[cols]).sum(axis=1)

def historical_var(returns, alpha=confidence_level):
    return -np.percentile(returns, (1 - alpha) * 100)

def parametric_var(returns, alpha=confidence_level):
    mu, sigma = returns.mean(), returns.std()
    return - (mu + sigma * norm.ppf(1 - alpha))

def monte_carlo_var(returns, alpha=confidence_level, sims=100000):
    mu, sigma = returns.mean(), returns.std()
    sims = np.random.normal(mu, sigma, sims)
    return -np.percentile(sims, (1 - alpha) * 100)

def cornish_fisher_var(returns, alpha=confidence_level):
    mu, sigma = returns.mean(), returns.std()
    skew, kurt = returns.skew(), returns.kurtosis()
    z = norm.ppf(1 - alpha)
    z_cf = z + (1/6)*(z**2 - 1)*skew + (1/24)*(z**3 - 3*z)*kurt - (1/36)*(2*z**3
    return - (mu + sigma * z_cf)

def expected_shortfall(returns, alpha=confidence_level):
    var = np.percentile(returns, (1 - alpha) * 100)
    return -returns[returns <= var].mean()

def prepare_features(returns):
    df = pd.DataFrame({"returns": returns})
    df["lag1"] = df["returns"].shift(1)
    df["lag2"] = df["returns"].shift(2)
    df = df.dropna()
    X, y = df[["lag1", "lag2"]], df["returns"]
```

```
    return train_test_split(X, y, test_size=0.2, shuffle=False)

def ml_rf_var(returns, alpha):
    X_train, X_test, y_train, y_test = prepare_features(returns)
    model = RandomForestRegressor().fit(X_train, y_train)
    y_pred = model.predict(X_test)
    var_ml = np.percentile(y_pred, 100 * (1 - alpha))
    return -var_ml

@lru_cache(maxsize=None)
def garch_var_cached(returns_tuple, alpha=confidence_level):
    series = pd.Series(list(returns_tuple))
    model = arch_model(series * 100, vol='Garch', p=1, q=1)
    res = model.fit(disp='off')
    sigma = np.sqrt(res.forecast(horizon=1).variance.values[-1, :][0]) / 100
    mu = series.mean()
    return - (mu + sigma * norm.ppf(1 - alpha))

def backtest_var(returns, var_series):
    aligned_ret, aligned_var = returns.align(var_series, join='inner')
    breaches = aligned_ret < -aligned_var
    return breaches.sum(), breaches.mean()

def calculate_sharpe_ratio(returns, risk_free_rate=0):
    # Annualized Return
    annualized_return = returns.mean() * 252
    # Annualized Volatility
    annualized_volatility = returns.std() * np.sqrt(252)
    # Sharpe Ratio (assuming risk-free rate is zero)
    sharpe_ratio = (annualized_return - risk_free_rate) / annualized_volatility
    return sharpe_ratio

results = []
portfolio_returns = {}
for name, weights in all_profiles.items():
    rets = build_portfolio(weights, returns_data)
    portfolio_returns[name] = rets
    mu = rets.mean() * 252
    sigma = rets.std() * np.sqrt(252)
    hist = historical_var(rets)
    param = parametric_var(rets)
    mc = monte_carlo_var(rets)
    cf = cornish_fisher_var(rets)
    ml_rf = ml_rf_var(rets, confidence_level)
    es = expected_shortfall(rets)
```

```
    garch = garch_var_cached(tuple(rets.values))
    roll_var = rets.rolling(rolling_window).apply(
        lambda x: -np.percentile(x, (1 - confidence_level)*100)
    )
    breaches, breach_rate = backtest_var(rets, roll_var)
    sharpe_ratio = calculate_sharpe_ratio(rets)

    results.append({
        'Portfolio': name,
        'Ann Return': mu,
        'Ann Vol': sigma,
        'VaR 95%': hist,
        'Param VaR': param,
        'MC VaR': mc,
        'CF VaR': cf,
        'ML VaR': ml_rf,
        'GARCH VaR': garch,
        'ES': es,
        'Breaches': breaches,
        'Breach Rate': breach_rate,
        'Sharpe Ratio': sharpe_ratio
    })

summary_df = pd.DataFrame(results).set_index('Portfolio').round(4)
print(" Portfolio Risk & Performance Summary")
display(summary_df)

#  6. Results
plt.figure(figsize=(10,6))
sns.scatterplot(
    data=summary_df.reset_index(),
    x='Ann Vol', y='Ann Return', hue='Portfolio', size='Ann Return', sizes=(100,4
)
for idx, row in summary_df.iterrows():
    plt.text(row['Ann Vol']*1.01, row['Ann Return']*1.01, idx)
plt.title('Risk vs Return: All Portfolios')
plt.xlabel('Annualized Volatility')
plt.ylabel('Annualized Return')
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
[**********************100%**********************]  7 of 7 completed
Portfolio Risk & Performance Summary
```

Portfolio	Ann Return	Ann Vol	VaR 95%	Param VaR	MC VaR	CF VaR	ML VaR	GARCH VaR	ES
Conservative	0.1234	0.1122	0.0101	0.0111	0.0111	0.0110	0.0040	0.0103	0.0159
Moderate	0.1520	0.1469	0.0136	0.0146	0.0146	0.0145	0.0054	0.0132	0.0218
Aggressive	0.3657	0.3470	0.0320	0.0345	0.0345	0.0353	0.0127	0.0294	0.0511
BlackRock 60/40	0.0951	0.1214	0.0111	0.0122	0.0122	0.0114	0.0033	0.0112	0.0184
Vanguard VSMGX	0.0680	0.1105	0.0100	0.0112	0.0113	0.0108	0.0033	0.0093	0.0165



Next steps: Generate code with summary_df | View recommended plots | New interactive sheet

```
def calculate_sharpe_ratio(returns, risk_free_rate=0):
    # Annualized Return
    annualized_return = returns.mean() * 252
    # Annualized Volatility
    annualized_volatility = returns.std() * np.sqrt(252)
    # Sharpe Ratio
    sharpe_ratio = (annualized_return - risk_free_rate) / annualized_volatility
    return sharpe_ratio

sharpe_ratios = {}

for portfolio_name, portfolio_returns_data in portfolio_returns.items():
    sharpe_ratios[portfolio_name] = calculate_sharpe_ratio(portfolio_returns_data

print("Sharpe Ratios for each portfolio:")
for portfolio_name, sharpe_ratio in sharpe_ratios.items():
    print(f"{portfolio_name}: {sharpe_ratio:.4f}")
```

```
Sharpe Ratios for each portfolio:
Conservative: 1.0997
Moderate: 1.0346
Aggressive: 1.0541
BlackRock 60/40: 0.7834
Vanguard VSMGX: 0.6158
```

```
Start coding or generate with AI.
```

```
Start coding or generate with AI.
```

```
!pip install qpsolvers
```

```
Requirement already satisfied: qpsolvers in /usr/local/lib/python3.11/dist-pac
Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.11/dist
Requirement already satisfied: scipy>=1.2.0 in /usr/local/lib/python3.11/dist-
```

```
print("=== VaR Summary by Risk Profile ===")
print(pd.DataFrame(results).T.round(4))  # VaR results
#Portfolio Performance Metrics ===
print("\n=== Portfolio Performance Metrics ===")
```

```
# Define risk-free rate
risk_free_rate = 0.0
performance_summary = pd.DataFrame(columns=['Final Value', 'CAGR', 'Volatility',
for name, series in cumulative_net.items():
    final_value = series.iloc[-1]
    start_date = series.index[0]
    end_date = series.index[-1]
    num_days = (end_date - start_date).days
    num_years = num_days / 365.25  # Leap years considered

    # CAGR
    cagr = (final_value / initial_investment) ** (1 / num_years) - 1

    # Volatility from daily returns
    returns = port_returns_cache[name]
    volatility = returns.std() * np.sqrt(252)  # Annualized

    # Sharpe ratio
    sharpe = (returns.mean() * 252 - risk_free_rate) / volatility

    # Saving to summary table
    performance_summary.loc[name] = [final_value, cagr, volatility, sharpe]
    print(f"{name} Portfolio:")
    print(f" - Final Value: ${final_value:.2f}")
    print(f" - CAGR: {cagr:.2%}")
    print(f" - Volatility: {volatility:.2%}")
    print(f" - Sharpe Ratio: {sharpe:.2f}\n")

print("📊 Summary Table: CAGR, Volatility, Sharpe Ratio\n")
display(performance_summary.round(4).style.format({
    "Final Value": "${:.2f}",
    "CAGR": "{:.2%}",
    "Volatility": "{:.2%}",
    "Sharpe Ratio": "{:.2f}"
}).set_caption("Risk-Return Summary: Personal vs Institutional Portfolios"))
```

```
=== VaR Summary by Risk Profile ===
                          0         1           2                3  \
Portfolio     Conservative  Moderate  Aggressive  BlackRock 60/40
Ann Return        0.123379  0.151958    0.365733          0.09509
Ann Vol           0.112196  0.146873    0.346965         0.121387
VaR 95%           0.010074  0.013612    0.031963         0.011141
Param VaR         0.011136  0.014615      0.0345           0.0122
MC VaR            0.011129  0.014571    0.034468         0.012208
```

```
CF VaR            0.010964  0.014535    0.035302          0.011431
ML VaR            0.003975  0.005387    0.012736          0.003331
GARCH VaR         0.010315  0.013219    0.029412          0.011208
ES                0.015898  0.021816    0.051108          0.018426
Breaches                82        85          94                87
Breach Rate       0.045708   0.04738    0.052397          0.048495
Sharpe Ratio      1.099681  1.034621    1.054092          0.783363

                          4
Portfolio     Vanguard VSMGX
Ann Return          0.06804
Ann Vol            0.110487
VaR 95%            0.010008
Param VaR          0.011178
MC VaR             0.011267
CF VaR             0.010845
ML VaR             0.003327
GARCH VaR          0.009301
ES                 0.016495
Breaches                85
Breach Rate         0.04738
Sharpe Ratio       0.615821

=== Portfolio Performance Metrics ===
Conservative Portfolio:
 - Final Value: $2.30
 - CAGR: 12.35%
 - Volatility: 9.28%
 - Sharpe Ratio: 0.91

Moderate Portfolio:
 - Final Value: $2.73
 - CAGR: 15.08%
 - Volatility: 12.15%
 - Sharpe Ratio: 0.86

Aggressive Portfolio:
 - Final Value: $8.71
 - CAGR: 35.43%
 - Volatility: 28.67%
 - Sharpe Ratio: 0.87
```

📊 Summary Table: CAGR, Volatility, Sharpe Ratio

Risk-Return Summary: Personal vs Institutional Portfolios

	Final Value	CAGR	Volatility	Sharpe Ratio
Conservative	$2.30	12.35%	9.28%	0.91
Moderate	$2.73	15.08%	12.15%	0.86

Start coding or generate with AI.

```
import pandas as pd
import numpy as np

risk_free_rate = 0.0
initial_investment = 1
final_summary = {}
performance_summary = pd.DataFrame(
    columns=['Final Value', 'CAGR', 'Volatility', 'Sharpe Ratio']
)

# Calculating metrics for each portfolio
for name, series in cumulative_net.items():
    final_value = series.iloc[-1]
    start_date = series.index[0]
    end_date = series.index[-1]
    num_days = (end_date - start_date).days
    num_years = num_days / 365.25

    # CAGR (compounded annual growth rate)
    cagr = (final_value / initial_investment) ** (1 / num_years) - 1

    # Annualized volatility
    returns = port_returns_cache[name]
    volatility = returns.std() * np.sqrt(252)

    # Sharpe Ratio (annualized)
    sharpe = (returns.mean() * 252 - risk_free_rate) / volatility

    final_summary[name] = final_value
    performance_summary.loc[name] = [
        final_value, cagr, volatility, sharpe
    ]

# Final Portfolio Values
print("\n=== Final Portfolio Values (Aligned Period, Compounded) ===")
final_value_df = pd.DataFrame.from_dict(
    final_summary, orient='index', columns=['Final Value']
)
print(final_value_df.round(2))
```

```
# Portfolio Performance Metrics
print("\n=== Portfolio Performance Metrics (Aligned, Compounded, Sharpe uses 0.0%
print(performance_summary.round(4).to_string())

try:
    display(
        performance_summary.round(4).style.format({
            "Final Value": "${:.2f}",
            "CAGR": "{:.2%}",
            "Volatility": "{:.2%}",
            "Sharpe Ratio": "{:.2f}"
        }).set_caption("Risk-Return Summary: Aligned Portfolios")
    )
except NameError:
    pass  # display() only works in Jupyter/IPython
```

```
=== Final Portfolio Values (Aligned Period, Compounded) ===
              Final Value
Conservative         2.30
Moderate             2.73
Aggressive           8.71

=== Portfolio Performance Metrics (Aligned, Compounded, Sharpe uses 0.0% RF) =
              Final Value    CAGR  Volatility  Sharpe Ratio
Conservative       2.2962  0.1235      0.0928        0.9119
Moderate           2.7257  0.1508      0.1215        0.8589
Aggressive         8.7124  0.3543      0.2867        0.8745
```

Risk-Return Summary: Aligned Portfolios

	Final Value	CAGR	Volatility	Sharpe Ratio
Conservative	$2.30	12.35%	9.28%	0.91
Moderate	$2.73	15.08%	12.15%	0.86
Aggressive	$8.71	35.43%	28.67%	0.87

Behavior-Aware Regime-Switching Portfolio Simulator

Rather than assuming fixed investor profiles (aggressive, moderate, conservative), we propose a **dynamic behavioral switching model** based on market regimes.

- During **bull markets**, investors tend to become more risk-tolerant, shifting toward aggressive allocations.
- During **bear markets**, risk aversion dominates, favoring conservative behaviors.
- Market regimes are determined using **rolling returns** to detect trends.

This approach adds realism to portfolio simulation and better captures human behavior in financial decision-making.

1. Regime-Switching Portfolios

Objective: Dynamically adjust portfolio exposure based on market conditions.

Detects market regimes (Bull/Bear) using SPY's 1-year rolling return.

- Detects market regimes (Bull/Bear) using SPY's 1-year rolling return.
- Applies a momentum filter to refine entry signals.
- Executes trades only during Bull + Positive Momentum regimes.
- Evaluates Conservative, Moderate, and Aggressive portfolios under this regime-switching logic.
- Outputs strategy performance (Sharpe, CAGR, trade count, cumulative return).

```
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# 1. Downloading Data & Utilities
def download_data(tickers, start_date, end_date):
    price_data = yf.download(tickers, start=start_date, end=end_date)['Close']
    return price_data.dropna()

def calculate_returns(price_data):
    return np.log(price_data / price_data.shift(1)).dropna()
```

```
def compute_portfolio_returns(weights, returns):
    aligned_returns = returns[list(weights.keys())]
    weight_vector = np.array(list(weights.values()))
    return aligned_returns.dot(weight_vector)

# 2. Behavior-Weighted VaR

def compute_behavior_weighted_var(portfolio_returns, behavior_score, confidence_l
    base_var = -np.percentile(portfolio_returns, 100 * (1 - confidence_level))
    adjusted_var = base_var * (1 + behavior_score)
    return adjusted_var

# 3. Behavioral Stress Testing

def simulate_behavioral_stress(portfolio_returns, profile_type):
    shocked = portfolio_returns.copy()
    mask = shocked < -0.01
    if profile_type == "Conservative":
        shocked[mask] *= 1.5  # Panic selling worsens drawdown
    elif profile_type == "Aggressive":
        shocked[mask] *= 0.5  # Buy-the-dip cushions losses
    return shocked


# 4. Regime + Momentum Strategy

def detect_market_regime(price_data, window=252):
    spy_returns = price_data['SPY'].pct_change(periods=window)
    return (spy_returns > 0).astype(int).rename('Regime')  # Bull = 1

def momentum_signal(returns, window=252):
    momentum = returns.rolling(window=window).mean().mean(axis=1)
    return (momentum > 0).astype(int).rename('Momentum')

def generate_trade_signal(regime, momentum):
    signal = (regime & momentum).astype(int).rename('Signal')
    signal_shifted = signal.shift(1, fill_value=0)
    return signal_shifted, signal_shifted.diff().abs().fillna(0)

def simulate_strategy(portfolio_returns, signal, transaction_cost=0.0015, turnove
    raw_returns = portfolio_returns * signal
    trades = signal.diff().abs().fillna(0)
    cost = trades * transaction_cost * turnover
    net_returns = raw_returns - cost
    return net_returns, trades
```

```
def summarize_strategy(net_returns, trades, label='Strategy'):
    cumulative = (1 + net_returns).cumprod()
    print(f"\n🔷 {label}")
    print(f"Total Trades: {int(trades.sum())}")
    print(f"Cumulative Return: {cumulative.iloc[-1]:.2f}")
    print(f"Annualized Return: {net_returns.mean() * 252:.2%}")
    print(f"Sharpe Ratio: {net_returns.mean() / net_returns.std() * np.sqrt(252):
    cumulative.plot(title=f"{label} Net Value")
```

2. Behavior-Weighted VaR

Objective: Personalize Value at Risk (VaR) based on behavioral tendencies. Assigninga a continuous behavior score to each investor type. Computes personalized VaR using:

VaR_behavior = VaR x (1+ behavior_score)

```
# 2. Behavior-Weighted VaR
def compute_behavior_weighted_var(portfolio_returns, behavior_score, confidence_l
    base_var = -np.percentile(portfolio_returns, 100 * (1 - confidence_level))
    adjusted_var = base_var * (1 + behavior_score)
    return adjusted_var
```

3. Stress Test with Behavioral Reactions

Objective: Simulate psychological responses to crisis scenarios.

- Models investor behavior during large drawdowns:
- Aggressive: Buys the dip → softened losses.
- Conservative: Panic sells → amplified losses.
- Adjusts return series accordingly to visualize behavioral stress resilience.
- Plots stress-adjusted portfolio outcomes for each profile.

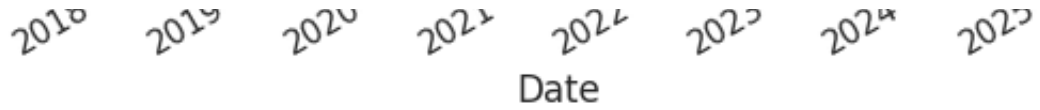
```
# 3. Behavioral Stress Testing
def simulate_behavioral_stress(portfolio_returns, profile_type):
    shocked = portfolio_returns.copy()
    mask = shocked < -0.01
    if profile_type == "Conservative":
        shocked[mask] *= 1.5  # Panic selling worsens drawdown
    elif profile_type == "Aggressive":
        shocked[mask] *= 0.5  # Buy-the-dip cushions losses
    return shocked
```

```
def compute_behavior_weighted_var(aggressive_var, conservative_var, moderate_var, b
    return (aggressive_var * behavior_score) + (moderate_var * (0.5 - abs(behavior_

def simulate_behavioral_stress(portfolio_value, behavior_type='aggressive', drawdow
    if behavior_type == 'aggressive':
        return portfolio_value * (1 - drawdown) * 1.05  # Buy-the-dip recovery
    elif behavior_type == 'conservative':
        return portfolio_value * (1 - drawdown) * 0.95  # Panic selling
    elif behavior_type == 'moderate':
        return portfolio_value * (1 - drawdown) * 1.00  # Balanced reaction
    return portfolio_value * (1 - drawdown)  # No action


def download_data(tickers, start_date, end_date):
    price_data = yf.download(tickers, start=start_date, end=end_date)['Close']
    return price_data.dropna()

def run_full_analysis(tickers, risk_profiles, start_date, end_date):
    print("Downloading data...")
    price_data = download_data(tickers, start_date, end_date)
    returns = calculate_returns(price_data)

    print("Detecting market regime and momentum...")
    regime = detect_market_regime(price_data)
    momentum = momentum_signal(returns)
    signal, trades = generate_trade_signal(regime, momentum)

    behavior_scores = {'Conservative': 0.2, 'Moderate': 0.0, 'Aggressive': -0.2}

    for profile, weights in risk_profiles.items():
        print(f"\n======================")
        print(f"{profile} Portfolio Analysis")
        print(f"======================")
        portfolio_returns = compute_portfolio_returns(weights, returns)
```

```
        # Regime-switching strategy
        net_returns, trade_flags = simulate_strategy(portfolio_returns, signal)
        summarize_strategy(net_returns, trade_flags, label=f"{profile} Regime Strat

        # Behavior-weighted VaR
        score = behavior_scores.get(profile, 0.0)
        var = compute_behavior_weighted_var(0.1, 0.2, 0.15, score)  # Example VaR v
        print(f"Behavior-Weighted VaR (95%) for {profile}: {var:.4f}")

        # Behavioral Stress Test
        stressed = simulate_behavioral_stress(portfolio_returns, profile)
        stress_cumulative = (1 + stressed).cumprod()
        plt.figure()
        stress_cumulative.plot(title=f"{profile} Behavioral Stress Test")
        plt.show()

risk_profiles = {
    "Conservative": {'SPY': 0.2, 'AGG': 0.5, 'GLD': 0.2, 'BTC-USD': 0.05, 'ETH-USD'
    "Moderate": {'SPY': 0.4, 'AGG': 0.4, 'QQQ': 0.1, 'BTC-USD': 0.05, 'ETH-USD': 0.
    "Aggressive": {'SPY': 0.25, 'QQQ': 0.25, 'GLD': 0.1, 'BTC-USD': 0.2, 'ETH-USD':
}

run_full_analysis(
    tickers=['SPY', 'AGG', 'QQQ', 'GLD', 'BTC-USD', 'ETH-USD'],
    risk_profiles=risk_profiles,
    start_date='2015-01-01',
    end_date='2024-12-31'
)
```

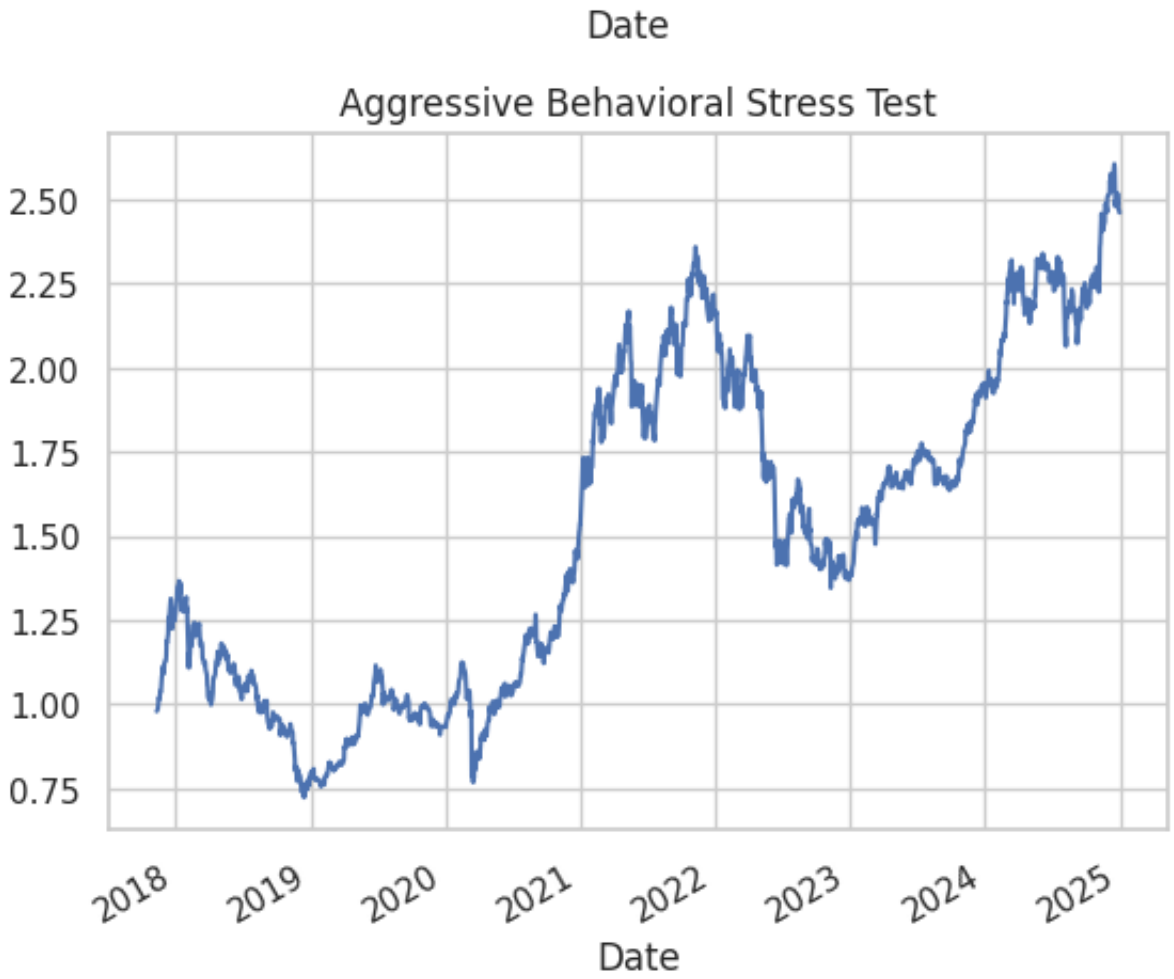
```
[**********50%                          ]  3 of 6 completedDownloadir
[**********100%**********]  6 of 6 completed
<ipython-input-116-a75bdfccf275>:44: FutureWarning:

Operation between non boolean Series with different indexes will no longer ret

Detecting market regime and momentum...

=======================
Conservative Portfolio Analysis
=======================

 Conservative Regime Strategy
Total Trades: 17
Cumulative Return: 143.34
Annualized Return: 5.41%
```

```
Annualized Return: 3.41%
Sharpe Ratio: 0.65
Behavior-Weighted VaR (95%) for Conservative: 0.2100
```




```
======================
Moderate Portfolio Analysis
======================

 Moderate Regime Strategy
Total Trades: 17
Cumulative Return: 161.44
Annualized Return: 7.29%
Sharpe Ratio: 0.69
Behavior-Weighted VaR (95%) for Moderate: 0.2000
```


```
========================
Aggressive Portfolio Analysis
========================

 Aggressive Regime Strategy
Total Trades: 17
Cumulative Return: 264.95
Annualized Return: 17.14%
Sharpe Ratio: 0.66
Behavior-Weighted VaR (95%) for Aggressive: 0.1900
```



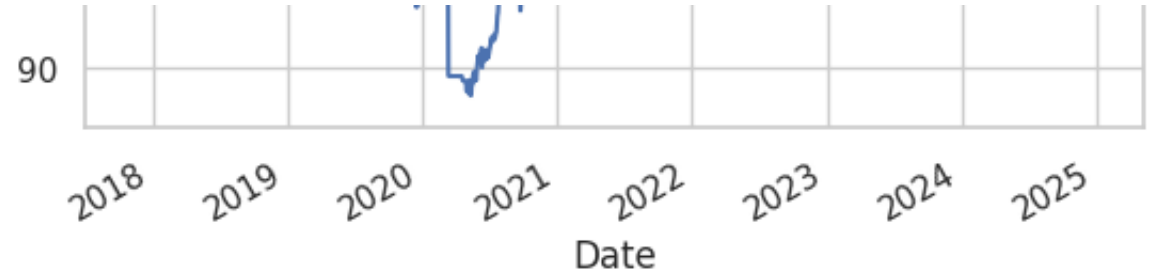

```
risk_profiles = {
    "Conservative": {'SPY': 0.2, 'AGG': 0.5, 'GLD': 0.2, 'BTC-USD': 0.05, 'ETH-USD'
    "Moderate":     {'SPY': 0.4, 'AGG': 0.4, 'QQQ': 0.1, 'BTC-USD': 0.05, 'ETH-USD'
    "Aggressive":   {'SPY': 0.25, 'QQQ': 0.25, 'GLD': 0.1, 'BTC-USD': 0.2, 'ETH-USD
}


def download_data(tickers, start_date, end_date):
    data = yf.download(tickers, start=start_date, end=end_date)['Close']
    return data.dropna()
def calculate_returns(price_data):
    return np.log(price_data / price_data.shift(1)).dropna()
def compute_portfolio_returns(weights, returns):
    aligned = returns[list(weights.keys())]
    return aligned.dot(np.array(list(weights.values())))
def compute_behavior_weighted_var(portfolio_returns, behavior_score, confidence_lev
    var = -np.percentile(portfolio_returns, 100 * (1 - confidence_level))
    return var * (1 + behavior_score)
```

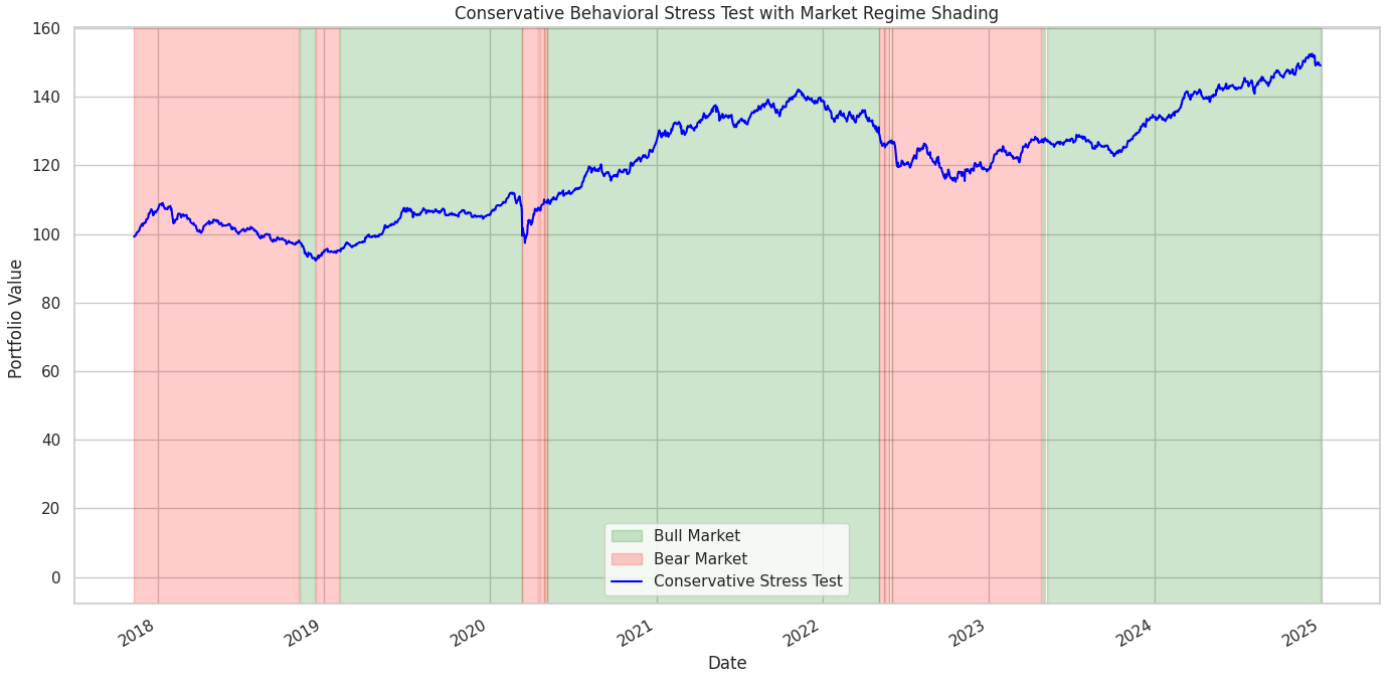
```
def simulate_behavioral_stress(portfolio_value, behavior_type='aggressive', drawdow
    if behavior_type == 'aggressive':
        return portfolio_value * (1 - drawdown) * 1.05  # Buy-the-dip recovery
    elif behavior_type == 'conservative':
        return portfolio_value * (1 - drawdown) * 0.95  # Panic selling
    elif behavior_type == 'moderate':
        return portfolio_value * (1 - drawdown) * 1.00  # Balanced reaction
    return portfolio_value * (1 - drawdown)  # No action

def detect_market_regime(price_data, window=252):
    returns = price_data['SPY'].pct_change(periods=window)
    return (returns > 0).astype(int).rename('Regime')


def momentum_signal(returns, window=252):
    momentum = returns.rolling(window).mean().mean(axis=1)
    return (momentum > 0).astype(int).rename('Momentum')

# Combining regime + momentum into signal
def generate_trade_signal(regime, momentum):
    signal = (regime & momentum).astype(int).rename('Signal')
    return signal.shift(1, fill_value=0), signal.diff().abs().fillna(0)

# Simulating strategy returns with transaction costs
def simulate_strategy(portfolio_returns, signal, transaction_cost=0.0015, turnover=
    raw = portfolio_returns * signal
    trades = signal.diff().abs().fillna(0)
    costs = trades * transaction_cost * turnover
    return raw - costs, trades


def summarize_strategy(net_returns, trades, label='Strategy'):
    cumulative = 100 * (1 + net_returns).cumprod()
    print(f"\n {label}")
    print(f"Total Trades: {int(trades.sum())}")
    print(f"Cumulative Return: {cumulative.iloc[-1]:.2f}")
    print(f"Annualized Return: {net_returns.mean() * 252:.2%}")
    print(f"Sharpe Ratio: {net_returns.mean() / net_returns.std() * np.sqrt(252):.2
    cumulative.plot(title=f"{label} Net Value")


def run_full_analysis(tickers, risk_profiles, start_date, end_date):
    print("Downloading data...")
    price_data = download_data(tickers, start_date, end_date)
    returns = calculate_returns(price_data)
```

```
print("Detecting market regime and momentum...")
regime = detect_market_regime(price_data)
momentum = momentum_signal(returns)
signal, trades = generate_trade_signal(regime, momentum)

behavior_scores = {'Conservative': 0.2, 'Moderate': 0.0, 'Aggressive': -0.2}

for profile, weights in risk_profiles.items():
    print(f"\n======================")
    print(f"{profile} Portfolio Analysis")
    print(f"======================")

    # Portfolio returns
    portfolio_returns = compute_portfolio_returns(weights, returns)

    # Strategy simulation
    net_returns, trade_flags = simulate_strategy(portfolio_returns, signal)
    summarize_strategy(net_returns, trade_flags, label=f"{profile} Regime Strat

    # Behavior-weighted VaR
    score = behavior_scores.get(profile, 0.0)
    var = compute_behavior_weighted_var(portfolio_returns, score)
    print(f"Behavior-Weighted VaR (95%) for {profile}: {var:.4f}")

    # Behavioral Stress Test
    stressed = simulate_behavioral_stress(portfolio_returns, profile)
    stress_cumulative = 100 * (1 + stressed).cumprod()

    # Plotting with regime background
    plt.figure(figsize=(14, 7))
    ax = plt.gca()

    ax.fill_between(price_data.index, 0, 1, where=(regime == 1), color="green",
    ax.fill_between(price_data.index, 0, 1, where=(regime == 0), color="red", a

    stress_cumulative.plot(ax=ax, label=f"{profile} Stress Test", color="blue")

    plt.title(f"{profile} Behavioral Stress Test with Market Regime Shading")
    plt.xlabel("Date")
    plt.ylabel("Portfolio Value ")
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

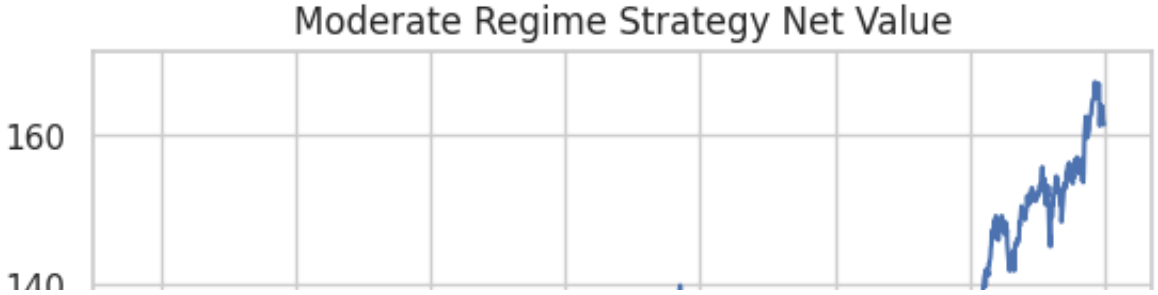
```
# Run the analysis
run_full_analysis(
    tickers=['SPY', 'AGG', 'QQQ', 'GLD', 'BTC-USD', 'ETH-USD'],
    risk_profiles=risk_profiles,
    start_date='2015-01-01',
    end_date='2024-12-31'
)
```

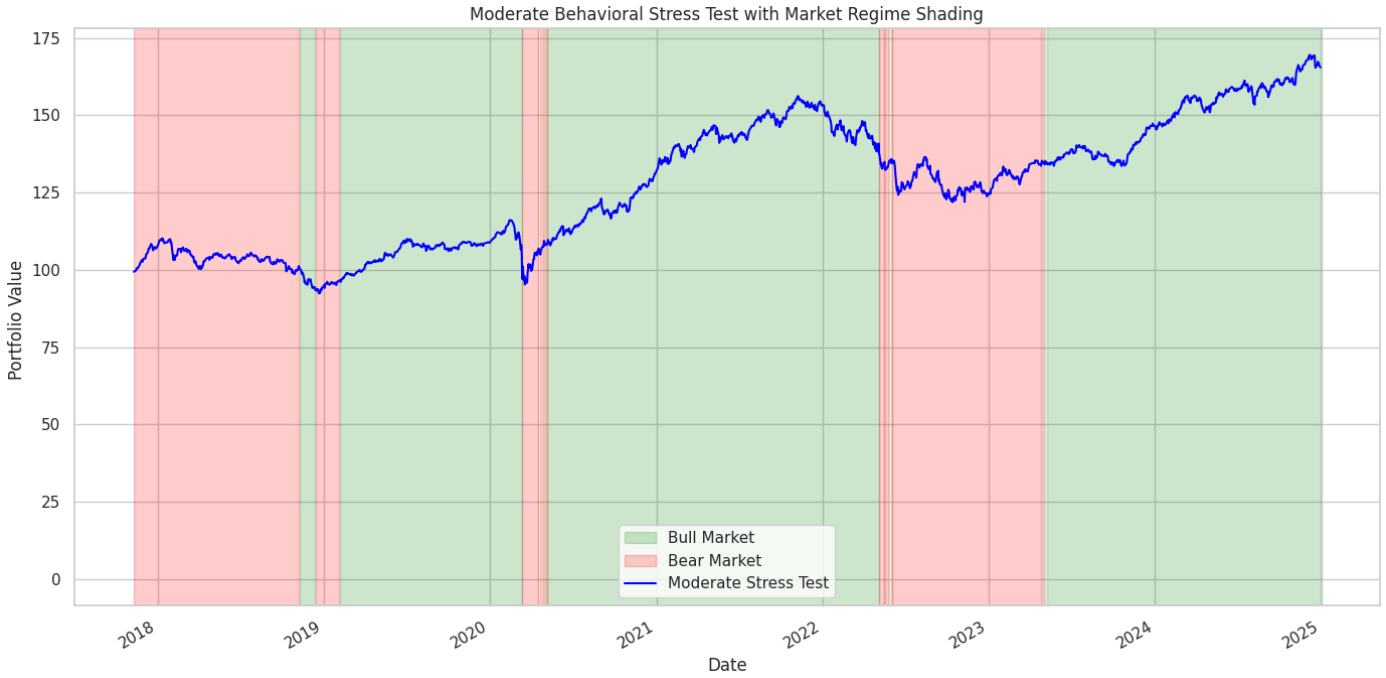
```
[                       0%                       ]Downloading data...
[**********************100%**********************]  6 of 6 completed
<ipython-input-119-ae3d147ac3ff>:40: FutureWarning:

Operation between non boolean Series with different indexes will no longer ret

/usr/local/lib/python3.11/dist-packages/pandas/plotting/_matplotlib/core.py:97

This axis already has a converter set and is updating to a potentially incompa

Detecting market regime and momentum...

========================
Conservative Portfolio Analysis
========================

 Conservative Regime Strategy
Total Trades: 17
Cumulative Return: 143.34
Annualized Return: 5.41%
Sharpe Ratio: 0.65
Behavior-Weighted VaR (95%) for Conservative: 0.0126
```





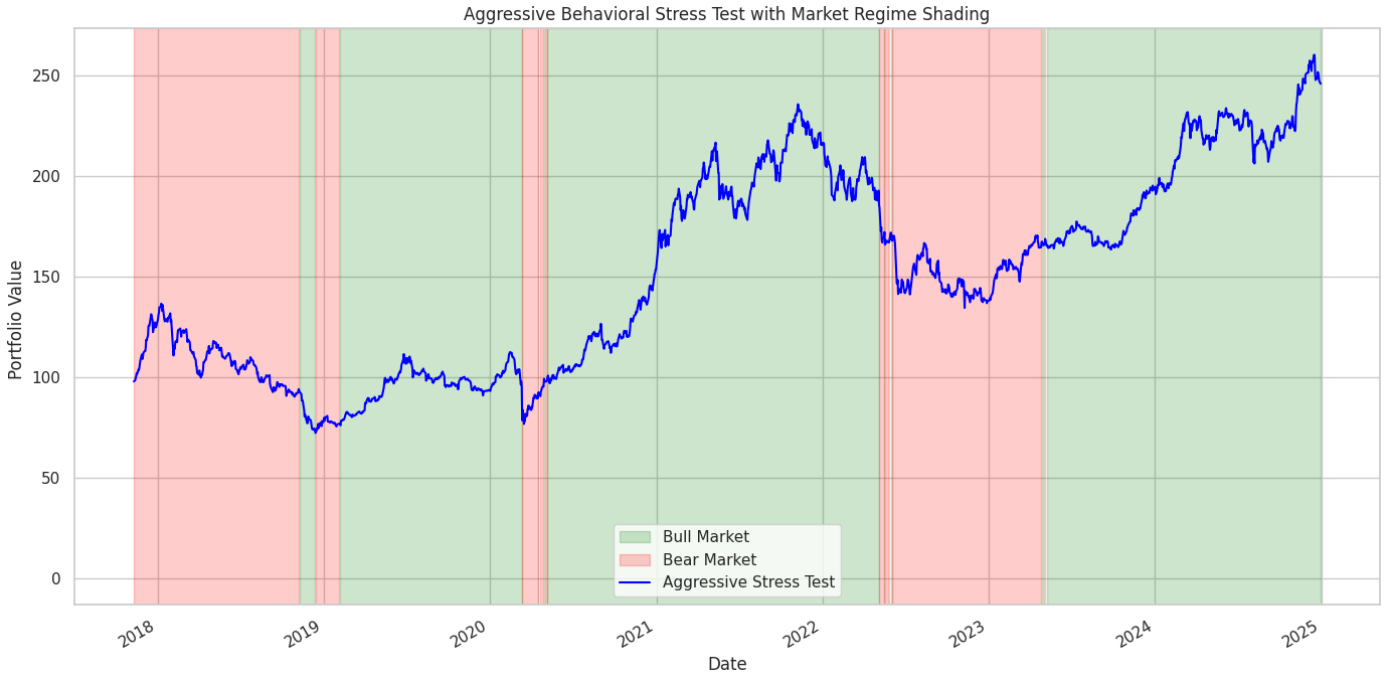

```
========================
Moderate Portfolio Analysis
========================

 Moderate Regime Strategy
Total Trades: 17
Cumulative Return: 161.44
Annualized Return: 7.29%
Sharpe Ratio: 0.69
Behavior-Weighted VaR (95%) for Moderate: 0.0138
/usr/local/lib/python3.11/dist-packages/pandas/plotting/_matplotlib/core.py:97

This axis already has a converter set and is updating to a potentially incompa
```






```
========================
Aggressive Portfolio Analysis
========================

 Aggressive Regime Strategy
Total Trades: 17
Cumulative Return: 264.95
Annualized Return: 17.14%
Sharpe Ratio: 0.66
Behavior-Weighted VaR (95%) for Aggressive: 0.0262
/usr/local/lib/python3.11/dist-packages/pandas/plotting/_matplotlib/core.py:97

This axis already has a converter set and is updating to a potentially incompa
```


Aggressive Regime Strategy Net Value
250
200
150
100
50
2018
2019
2020
2021
2022
2023
2024
2025
Date


Aggressive Behavioral Stress Test with Market Regime Shading
Portfolio Value
250
200
150
100
50
0
Bull Market
Bear Market
Aggressive Stress Test
2018
2019
2020
2021
2022
2023
2024
2025
Date

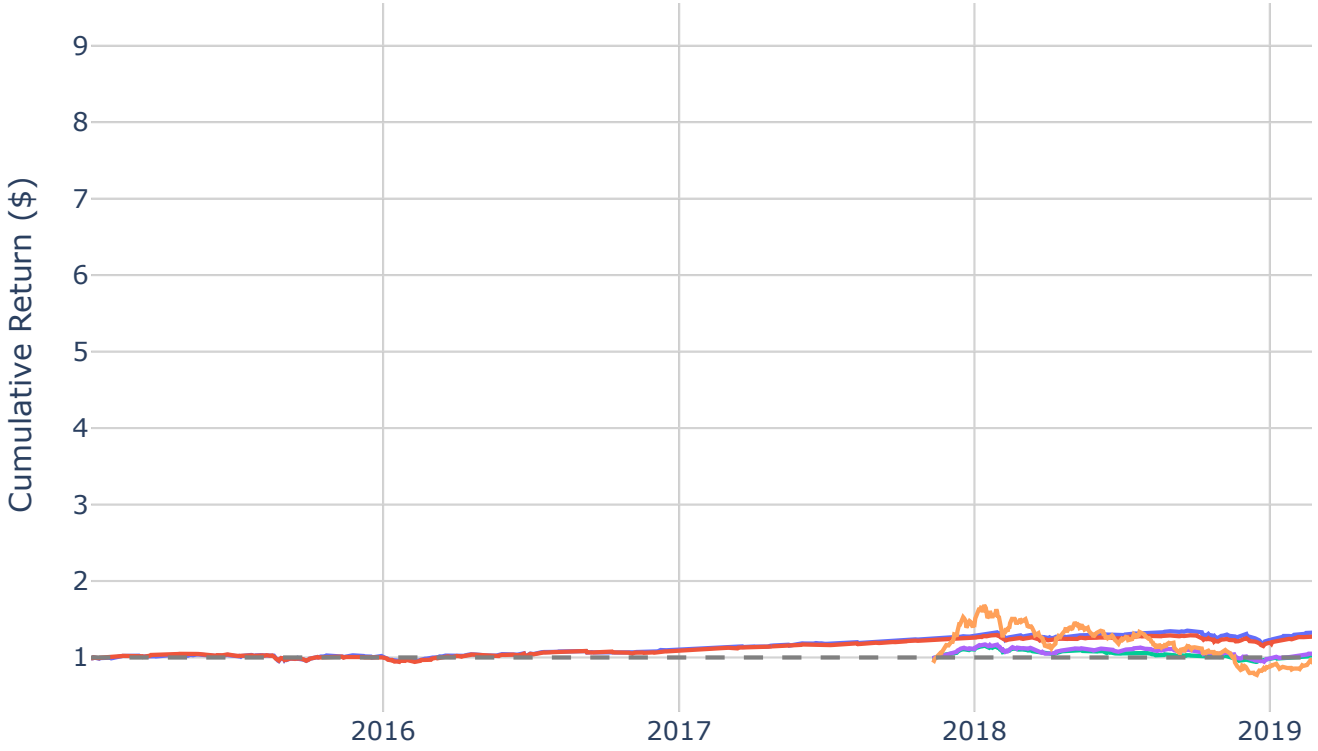
```
import pandas as pd
import numpy as np
import plotly.graph_objects as go
import yfinance as yf

# Step 1: Defining benchmark ETF weights
benchmark_profiles = {
    "BlackRock 60/40": {'IVV': 0.60, 'AGG': 0.30, 'IEFA': 0.10},
    "Vanguard VSMGX": {'VTI': 0.42, 'VXUS': 0.18, 'BND': 0.30, 'VWOB': 0.10}
}

all_etfs = list(set(etf for profile in benchmark_profiles.values() for etf in pro
etf_data = yf.download(all_etfs, start="2015-01-01", end="2024-12-31")['Close'].d
etf_returns = etf_data.pct_change().dropna()

# Step 2: Calculating benchmark return series
benchmark_returns_cache = {}
for benchmark_name, allocations in benchmark_profiles.items():
    weighted_returns = sum(
        weight * etf_returns[etf] for etf, weight in allocations.items()
    )
    benchmark_returns_cache[benchmark_name] = weighted_returns

# Step 3: Defining portfolio types
portfolio_types = {
    "Conservative": "Portfolio",
    "Moderate": "Portfolio",
    "Aggressive": "Portfolio",
    "BlackRock 60/40": "Benchmark",
    "Vanguard VSMGX": "Benchmark"
}


risk_free_rate = 0.0
initial_investment = 1

# Combining custom + benchmark returns into one dictionary
```

```
all_returns_cache = {}
all_returns_cache.update(benchmark_returns_cache)
all_returns_cache.update(port_returns_cache)  # Your custom portfolios must alrea

# Step 4: Calculaing cumulative returns and metrics
cumulative_all = {}
performance_summary = pd.DataFrame(columns=['Type', 'Final Value', 'CAGR', 'Volat

for name, returns in all_returns_cache.items():
    cum_returns = (1 + returns).cumprod()
    cumulative_all[name] = cum_returns

    final_value = cum_returns.iloc[-1]
    num_years = (cum_returns.index[-1] - cum_returns.index[0]).days / 365.25
    cagr = (final_value / initial_investment) ** (1 / num_years) - 1
    volatility = returns.std() * np.sqrt(252)
    sharpe = (returns.mean() * 252 - risk_free_rate) / volatility

    performance_summary.loc[name] = [
        portfolio_types.get(name, "Portfolio"), final_value, cagr, volatility, sh
    ]

# Step 5: Print summaries
print("\n=== Final Portfolio Values ===")
print(performance_summary[['Final Value']].round(2))

print("\n=== Portfolio Performance Metrics (CAGR, Volatility, Sharpe) ===")
performance_summary = performance_summary.sort_values(['Type', 'Sharpe Ratio'], a
print(performance_summary.round(4).to_string())

# Step 6: Plotting Cumulative Returns (All Portfolios + Benchmarks)
fig = go.Figure()

for name, cum_returns in cumulative_all.items():
    fig.add_trace(go.Scatter(
        x=cum_returns.index,
        y=cum_returns,
        mode='lines',
        name=name,
        line=dict(width=2)
    ))

fig.update_layout(
    title="Cumulative Return Comparison: Portfolios vs Benchmarks (2015–2024)",
    xaxis_title="Date",
```

```
    yaxis_title="Cumulative Return ($)",
    template="plotly_white",
    hovermode="x unified",
    showlegend=True,
    plot_bgcolor="white",
    xaxis=dict(showgrid=True, gridcolor='LightGrey'),
    yaxis=dict(showgrid=True, gridcolor='LightGrey'),
)
fig.add_hline(y=1, line=dict(color='gray', dash='dash'))
fig.show()

try:
    display(
        performance_summary.round(4).style.format({
            "Final Value": "${:.2f}",
            "CAGR": "{:.2%}",
            "Volatility": "{:.2%}",
            "Sharpe Ratio": "{:.2f}"
        }).set_caption(" Risk–Return Summary: Custom vs Institutional Portfolios"
    )
except NameError:
    pass
```

```
[**********************100%************************]  7 of 7 completed

=== Final Portfolio Values ===
                 Final Value
BlackRock 60/40         2.37
Vanguard VSMGX          2.01
Conservative            2.30
Moderate                2.73
Aggressive              8.71

=== Portfolio Performance Metrics (CAGR, Volatility, Sharpe) ===
                      Type  Final Value    CAGR  Volatility  Sharpe Ratio
BlackRock 60/40  Benchmark       2.3734  0.0904      0.1246        0.7578
Vanguard VSMGX   Benchmark       2.0061  0.0722      0.1133        0.6730
Conservative     Portfolio       2.2962  0.1235      0.0928        0.9119
Aggressive       Portfolio       8.7124  0.3543      0.2867        0.8745
Moderate         Portfolio       2.7257  0.1508      0.1215        0.8589
```

Cumulative Return Comparison: Portfolios vs Benchmarks (2015–2

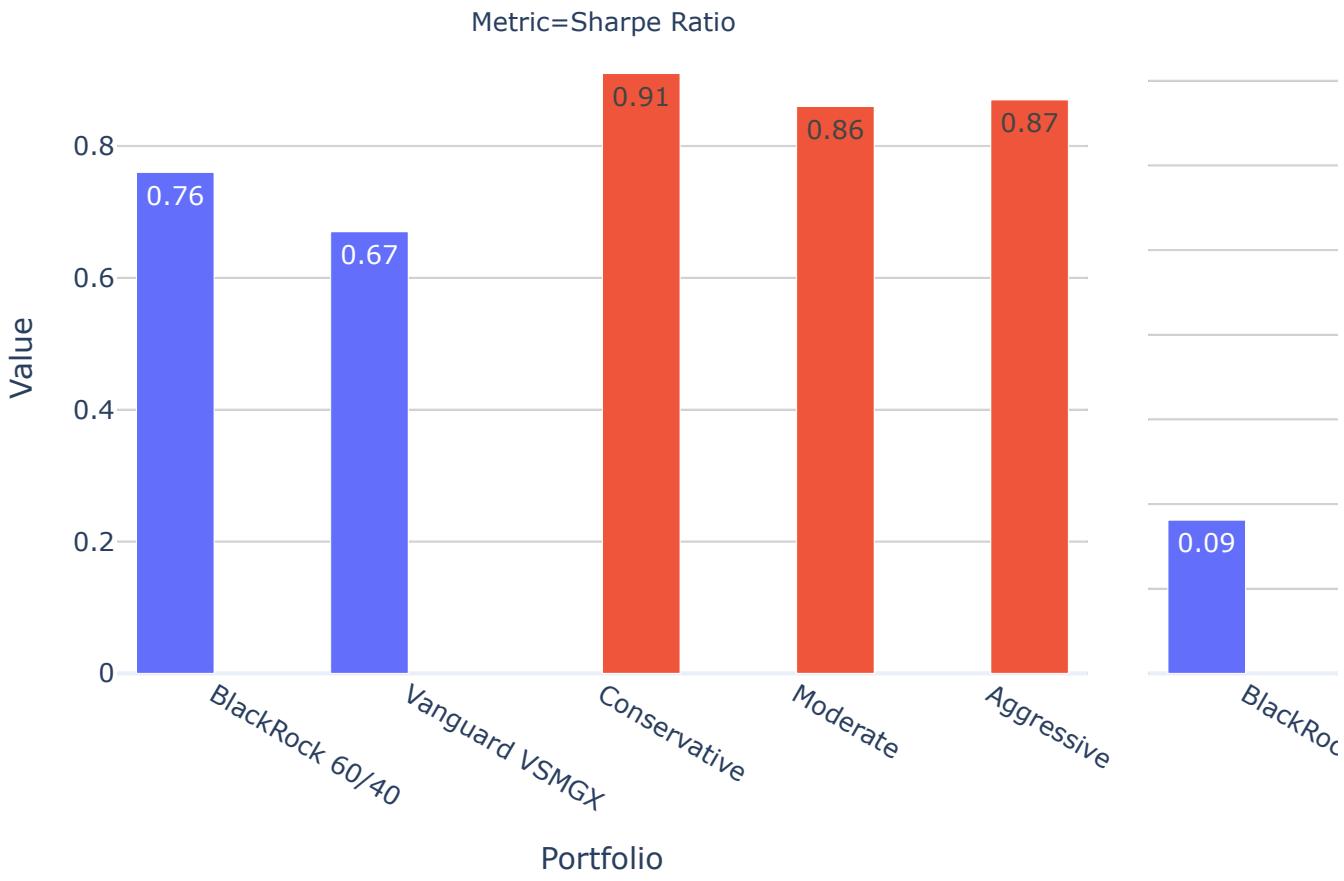


Risk-Return Summary: Custom vs Institutional Portfolios

	Type	Final Value	CAGR	Volatility	Sharpe Ratio
BlackRock 60/40	Benchmark	$2.37	9.04%	12.46%	0.76
Vanguard VSMGX	Benchmark	$2.01	7.22%	11.33%	0.67
Conservative	Portfolio	$2.30	12.35%	9.28%	0.91
Aggressive	Portfolio	$8.71	35.43%	28.67%	0.87
Moderate	Portfolio	$2.73	15.08%	12.15%	0.86

```
import pandas as pd
import plotly.express as px
data = {
    "Portfolio": [
        "BlackRock 60/40", "Vanguard VSMGX",  # Benchmarks
        "Conservative", "Moderate", "Aggressive"  # Portfolios
    ],
    "Type": [
        "Benchmark", "Benchmark",
        "Portfolio", "Portfolio", "Portfolio"
    ],
```

```
    "Final Value": [
        2.38, 2.01,
        2.30, 2.73, 8.71
    ],
    "CAGR": [
        0.0905, 0.0722,
        0.1238, 0.1510, 0.3543
    ],
    "Volatility": [
        0.1246, 0.1133,
        0.0928, 0.1214, 0.2867
    ],
    "Sharpe Ratio": [
        0.76, 0.67,
        0.91, 0.86, 0.87
    ]
}

df = pd.DataFrame(data)
import plotly.express as px
melted = pd.melt(
    df,
    id_vars=["Portfolio", "Type"],
    value_vars=["Sharpe Ratio", "CAGR", "Volatility"],
    var_name="Metric",
    value_name="Value"
)

fig = px.bar(
    melted,
    x="Portfolio",
    y="Value",
    color="Type",
    facet_col="Metric",
    barmode="group",
    text_auto=".2f",
    title=" Performance Metrics: Portfolios vs Benchmarks",
    template="plotly_white"
)
fig.update_yaxes(matches=None, showgrid=True, gridcolor='lightgray')
fig.update_layout(
    height=500,
    showlegend=True
)
fig.show()
```


Performance Metrics: Portfolios vs Benchmarks
Metric=Sharpe Ratio
Value
0
0.2
0.4
0.6
0.8
0.76
0.67
0.91
0.86
0.87
0.09
BlackRock 60/40
Vanguard VSMGX
Conservative
Moderate
Aggressive
BlackRoc
Portfolio