

MACROECONOMIC STRESS TESTING AND PORTFOLIO RESILIENCE: A PREDICTIVE ANALYSIS OF CHANGING U.S. MARKET CONDITIONS

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ABSTRACT

The increasing interconnectedness of global financial markets, persistent macroeconomic uncertainty, and evolving monetary policy conditions have intensified concerns regarding investment portfolio stability and systemic financial vulnerability. In the United States, fluctuations in interest rates, inflation, economic growth, unemployment, and financial market volatility significantly influence asset valuations, investment returns, and portfolio risk exposures. This study examines the application of macroeconomic stress testing and predictive analytical techniques in evaluating portfolio resilience under changing U.S. market conditions. Particular emphasis is placed on scenario-based modelling, econometric forecasting, sensitivity analysis, and machine learning approaches for assessing portfolio responses to adverse economic shocks. The study further explores interactions among macroeconomic indicators, asset allocation strategies, market correlations, and risk-adjusted performance across equities, fixed-income securities, and diversified investment portfolios. Additionally, it considers challenges associated with model uncertainty, structural market changes, nonlinear risk transmission, and limitations of historical financial data. Ultimately, the study highlights the importance of integrating forward-looking stress scenarios, adaptive risk management frameworks, and predictive analytics to strengthen portfolio resilience, support informed investment decisions, and enhance financial stability amid increasingly complex and uncertain U.S. economic environments.

Keywords:

Macroeconomic Stress Testing; Portfolio Resilience; Predictive Analytics; U.S. Financial Markets; Economic Risk Modelling; Asset Allocation Strategies.

1. INTRODUCTION

1.1. Macroeconomic Uncertainty and Financial Market Vulnerability

Macroeconomic uncertainty represents a fundamental determinant of financial market vulnerability, particularly within the United States, where inflation, monetary policy adjustments, interest rate fluctuations, unemployment, and economic growth influence investment expectations and asset valuations [1]. Inflationary pressures and restrictive monetary policies can increase borrowing costs, reduce corporate profitability, and weaken equity valuations, while interest rate adjustments directly affect bond yields and fixed-income portfolio performance [2]. Rising unemployment and declining economic activity may further intensify investor uncertainty, liquidity constraints, and financial market volatility [3]. These interconnected transmission mechanisms can amplify portfolio losses, particularly when adverse economic developments occur simultaneously [4]. Understanding macroeconomic vulnerability is therefore essential for evaluating investment exposure, anticipating financial instability, and developing resilient portfolio management strategies under changing economic conditions [5].

1.2. Portfolio Resilience and the Limitations of Conventional Risk Assessment

Portfolio resilience refers to the capacity of investment portfolios to withstand adverse macroeconomic shocks while limiting financial losses and maintaining acceptable risk-adjusted performance [6]. Conventional assessment techniques frequently emphasise historical volatility, diversification benefits, and static measures of market risk. However, these approaches may inadequately capture structural economic changes, extreme financial events, and evolving relationships between asset classes [7]. During periods of financial instability, correlations between equities, bonds, and alternative investments can change substantially, weakening anticipated diversification benefits [8]. Furthermore, nonlinear interactions among inflation, monetary policy, and economic activity complicate conventional portfolio evaluation. Consequently, resilience assessment requires adaptive methodologies capable of incorporating dynamic economic dependencies, forward-looking risk information, and systematic evaluation of potential financial losses [9].

1.3. Predictive Analytics and Macroeconomic Stress Testing

Predictive analytics provides methodological opportunities for evaluating portfolio vulnerability under changing macroeconomic conditions. Econometric forecasting models capture established statistical relationships, while

machine learning algorithms accommodate nonlinear interactions, complex dependencies, and potentially evolving economic patterns [1]. Scenario-based stress testing complements these approaches by examining portfolio responses to adverse developments, including persistent inflation, monetary tightening, recessionary conditions, and simultaneous asset-market disruptions [3]. Integrating predictive forecasts with macroeconomic stress simulations enables researchers to evaluate both anticipated financial outcomes and potential losses under severe economic disturbances [5]. Such integration supports more comprehensive portfolio resilience assessment, strengthens evidence-based investment risk management, and improves understanding of portfolio sensitivity to economic shocks [9].

1.4. Research Objectives and Contributions

This study pursues four objectives: first, developing a macroeconomic forecasting framework linking economic indicators with U.S. portfolio performance; second, comparing predictive algorithms against established econometric benchmarks; third, quantifying portfolio vulnerability under adverse macroeconomic scenarios; and fourth, identifying portfolio configurations demonstrating stronger resilience. The research contributes an integrated analytical approach combining economic forecasting, comparative model evaluation, and scenario-based portfolio assessment to support informed investment decisions and systematic financial risk management.

2. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

2.1. Macroeconomic Determinants of U.S. Asset Returns

Macroeconomic conditions influence U.S. financial asset performance through interconnected monetary, economic, and financial transmission mechanisms [6]. Inflation affects corporate production costs, consumer purchasing power, and real investment returns, while interest rate adjustments influence equity valuations through discount rates and borrowing costs [7]. Government bond prices respond inversely to changes in market yields, although inflation expectations and monetary policy uncertainty can modify these relationships [8]. Unemployment and GDP growth provide additional information regarding economic activity, corporate earnings expectations, and financial market sentiment [9]. Macro-financial factor models incorporate these indicators to explain variations in asset returns and portfolio exposure. However, economic relationships may differ across expansionary, recessionary, and inflationary regimes, suggesting that forecasting frameworks should accommodate changing sensitivities, structural breaks, and interactions among macroeconomic variables [10].

2.2. Traditional Portfolio Risk Measurement and Stress Testing

Modern Portfolio Theory establishes diversification as a mechanism for reducing portfolio variance through combinations of imperfectly correlated assets [11]. Conventional risk assessment frequently employs historical volatility, Value-at-Risk (VaR), and Expected Shortfall (ES) to quantify uncertainty and potential investment losses [12]. VaR identifies a specified loss quantile, whereas ES measures expected losses beyond that threshold, providing additional information about extreme downside exposure [13]. Historical scenario analysis evaluates portfolio vulnerability by applying previously observed market disturbances to current investment allocations. Nevertheless, these techniques face limitations when financial distributions exhibit heavy tails, nonlinear dependence, and abrupt changes in market conditions [14]. During financial crises, correlations between asset classes may increase, reducing diversification effectiveness and intensifying simultaneous portfolio losses. Consequently, conventional measures require complementary stress testing and forward-looking assessments to evaluate portfolio resilience comprehensively [15].

2.3. Econometric and Machine Learning Approaches to Financial Forecasting

Financial forecasting traditionally relies on linear regression and autoregressive models to estimate relationships between macroeconomic indicators and asset returns [6]. Regularised regression methods, including ridge and LASSO, address multicollinearity and reduce estimation instability when numerous economic predictors are included [7]. Machine learning approaches extend forecasting capabilities by accommodating nonlinear interactions and complex financial dependencies. Random forests combine multiple decision trees to improve predictive robustness, whereas gradient boosting sequentially optimises prediction errors through ensemble learning [10]. However, increased model flexibility introduces challenges involving computational complexity, interpretability, data requirements, and overfitting [11]. Econometric models generally offer clearer parameter interpretation, while ensemble algorithms may capture relationships overlooked by conventional specifications. Reliable comparison therefore requires chronological data partitioning, rolling or expanding-window validation, and strictly out-of-sample testing [14]. These safeguards reduce information leakage and provide more credible evidence regarding forecasting performance under evolving macroeconomic conditions.

2.4. Research Gaps and Analytical Hypotheses

Existing research provides substantial evidence regarding macroeconomic forecasting and portfolio risk measurement, yet uncertainty remains concerning their integrated effectiveness under changing economic conditions [12]. This study addresses that gap through four testable hypotheses. H1: Machine learning models outperform conventional econometric benchmarks in out-of-sample portfolio return forecasting. H2: Portfolio sensitivity to macroeconomic indicators varies significantly across economic regimes. H3: Adverse macroeconomic scenarios generate statistically and economically meaningful differences in portfolio losses. H4: Diversified portfolio configurations demonstrate greater resilience than concentrated allocations during macroeconomic stress. These hypotheses establish a comparative framework for evaluating predictive accuracy, financial vulnerability, and diversification effectiveness [15].

3. DATA ACQUISITION, PREPROCESSING, AND FEATURE ENGINEERING

3.1. Research Design and Data Acquisition

This study adopts a quantitative longitudinal research design to investigate relationships between U.S. macroeconomic conditions, financial asset returns, and portfolio resilience [12]. The proposed sampling period extends from January 2010 to December 2025, encompassing monetary policy transitions, inflationary pressures, economic disruptions, and financial market volatility. Daily observations are proposed for financial asset returns, while macroeconomic indicators retain their original monthly or quarterly reporting frequencies [13]. Financial instruments include broad U.S. equity exposure, Treasury securities, investment-grade corporate bonds, and suitable diversified investment proxies. Macroeconomic predictors comprise consumer price inflation, unemployment, federal funds rates, Treasury yields, credit spreads, and real GDP growth [14]. Data acquisition should distinguish market prices from total-return indices and exchange-traded fund returns because distributions, fees, and reinvestment assumptions affect measured investment performance. Public economic databases and established financial market providers constitute the primary proposed sources. All series require consistent date conventions, documented provenance, and verification of historical availability before model estimation [15].

Data category	Candidate variables	Proposed source
Macroeconomic conditions	CPI, unemployment, federal funds rate, Treasury yields, GDP	FRED
Equity markets	S&P 500 total returns or investable proxy	Market data providers
Fixed income	Treasury and investment-grade bond total returns	Market data providers
Monetary policy	Policy rates and monetary indicators	Federal Reserve
Economic activity	Real GDP growth and related indicators	Bureau of Economic Analysis

Figure 1. Data Acquisition and Integrated Macroeconomic–Financial Research Pipeline

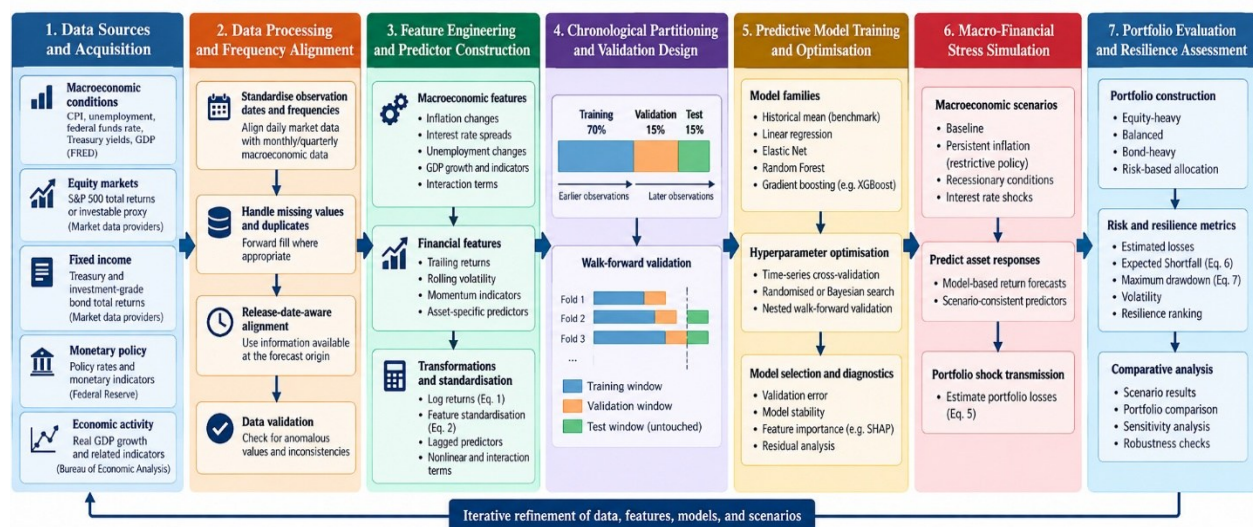


Figure 1. Data Acquisition and Integrated Macroeconomic–Financial Research Pipeline

3.2. Data Cleaning, Temporal Alignment, and Missing-Value Treatment

Data preprocessing establishes consistency and reliability across financial and macroeconomic observations [16]. Initial procedures identify missing values, duplicated records, anomalous prices, inconsistent timestamps, and discrepancies between trading calendars. Daily market observations are aligned with monthly or quarterly macroeconomic releases using publication dates rather than reference-period dates, preventing the introduction of information unavailable when forecasts were generated [17]. Forward filling may preserve the most recently published macroeconomic observation until subsequent information becomes available, although this procedure must not introduce future revisions. Historical data vintages are preferable when reconstructing information sets available to investors at particular dates. Extreme financial returns require verification against independent market records because genuine crisis observations should not be discarded as erroneous outliers. These safeguards reduce measurement distortions and strengthen the credibility of subsequent predictive comparisons [18].

3.3. Feature Engineering and Macroeconomic Predictor Construction

Feature engineering transforms economic and financial observations into explanatory variables suitable for forecasting portfolio performance [13]. Macroeconomic predictors include annual inflation changes, Treasury yield spreads, lagged unemployment changes, policy rate adjustments, and real economic growth indicators. Financial predictors comprise trailing asset returns, rolling standard deviations, downside volatility, and dynamic cross-asset correlations [14]. Interaction terms capture potentially nonlinear relationships between inflation, monetary tightening, unemployment deterioration, and market volatility. All predictors must be constructed using information available before the corresponding forecast date.

Equation 1. Asset Return Transformation

$$r_{i,t} = \ln \left(\frac{P_{i,t}}{P_{i,t-1}} \right)$$

where $r_{i,t}$ denotes the continuously compounded return for asset i , $P_{i,t}$ represents its price or total-return index at time t , and $P_{i,t-1}$ denotes the preceding observation. Total-return indices incorporate distributions, unlike unadjusted market prices.

Equation 2. Feature Standardisation

$$z_{j,t} = \frac{x_{j,t} - \mu_{j,\text{train}}}{\sigma_{j,\text{train}}}$$

Here, $x_{j,t}$ represents predictor j , while $\mu_{j,\text{train}}$ and $\sigma_{j,\text{train}}$ denote its training-sample mean and standard deviation. Standardisation ensures comparable feature scales, particularly for regularised regression and other scale-sensitive algorithms [19]. Parameters are estimated exclusively from training observations and subsequently applied to validation and testing datasets without incorporating future information.

3.4. Chronological Data Splitting and Leakage Prevention

Chronological partitioning preserves the temporal ordering necessary for credible financial forecasting [15]. The proposed experimental design allocates 70% of observations to training, 15% to validation, and 15% to final testing. Training observations support parameter estimation, whereas validation observations guide hyperparameter optimisation, feature selection, and decision-threshold calibration. The testing period remains untouched until final model evaluation. Expanding-window or rolling-window cross-validation provides additional evidence regarding performance consistency under evolving economic conditions [17]. Where overlapping forecast horizons introduce dependence between adjacent observations, purging or embargo procedures should separate relevant training and validation samples. Data transformations, feature selection, and model tuning must occur within the appropriate development folds. These procedures reduce look-ahead bias, information leakage, and overly optimistic performance estimates, strengthening the credibility of genuinely out-of-sample forecasting comparisons [18].

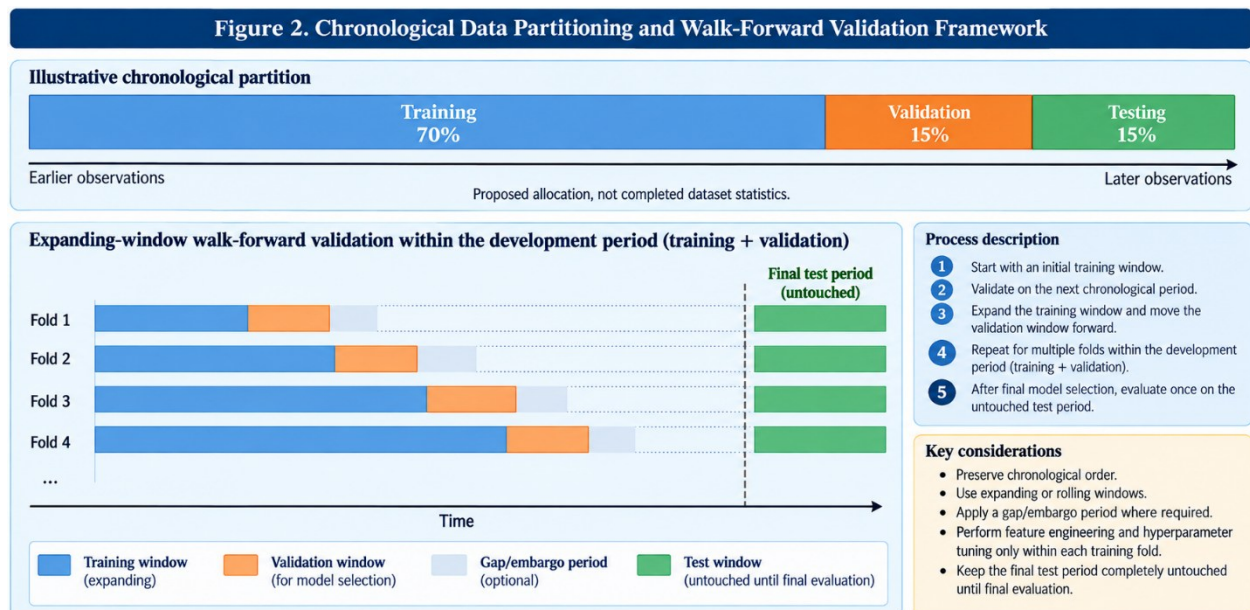


Figure 2. Chronological Data Partitioning and Walk-Forward Validation Framework

3.5. Portfolio Construction and Descriptive Statistical Analysis

Four candidate portfolios are proposed: equity-heavy, balanced, bond-heavy, and risk-based allocations [12]. Illustrative allocations include 70% equities and 30% bonds, 50% equities and 50% bonds, and 30% equities and 70% bonds, respectively. Risk-based weights are estimated using historical covariance information available during training. Quarterly rebalancing is proposed, with transaction costs documented separately. Descriptive analysis examines mean returns, standard deviations, skewness, kurtosis, correlations, and maximum drawdowns. Portfolio construction must exclude future testing outcomes to preserve independent evaluation and prevent selection bias [16].

4. PREDICTIVE MODEL DEVELOPMENT, TRAINING, AND HYPERPARAMETER OPTIMISATION

4.1. Baseline Econometric Models and Forecasting Targets

The forecasting framework evaluates next-period portfolio returns as the primary prediction target, with realised volatility and downside risk considered supplementary outcomes [14]. Conventional benchmarks establish reference performance against which machine learning models are evaluated. Historical mean forecasting assumes that future returns approximate their previously observed average, while linear macroeconomic regression estimates relationships between economic indicators and subsequent portfolio performance [15]. Regularised regression addresses predictor multicollinearity, whereas historical volatility and GARCH specifications provide benchmarks for conditional risk estimation [16].

Equation 3. Macroeconomic Return Prediction Model

$$r_{p,t+h} = \beta_0 + \sum_{j=1}^k \beta_j x_{j,t} + \varepsilon_{t+h}$$

Here, $r_{p,t+h}$ denotes the future portfolio return at horizon h , $x_{j,t}$ represents information available at forecast origin, β_j measures estimated predictor associations, and ε_{t+h} denotes the forecasting error. This specification provides a transparent econometric benchmark for assessing nonlinear forecasting alternatives.

4.2. Machine Learning Model Selection and Architecture

Three principal predictive model families are proposed to examine relationships between macroeconomic conditions and portfolio performance. Elastic Net regression combines L1 and L2 regularisation, allowing coefficient shrinkage and variable selection while accommodating correlated economic predictors [17]. Its relatively transparent parameter structure facilitates interpretation of relationships between inflation, interest rates, unemployment, and portfolio returns. Random Forest employs ensembles of decision trees to capture nonlinear associations and interactions without requiring predetermined functional relationships [18]. Predictions are aggregated across trees to reduce sensitivity to individual training observations. Gradient boosting, implemented

through XGBoost or a comparable algorithm, sequentially constructs decision trees to minimise forecasting errors and represent complex macro-financial dependencies [19]. All models receive consistently engineered, historically available predictors and generate forecasts for identical horizons and portfolio configurations. Model complexity is evaluated against improvements in validation performance rather than training accuracy alone. This comparison establishes whether nonlinear methods provide sufficient predictive benefits to justify additional computational requirements, reduced interpretability, and potential overfitting under changing economic conditions [20].

4.3. Training Procedures and Objective Function

Model training minimises forecasting errors while controlling unnecessary complexity and ensuring reproducibility [16]. Parameters are estimated using chronological training observations, with validation data reserved for hyperparameter selection and early stopping. For continuous portfolio return predictions, mean squared error provides a consistent optimisation criterion, although alternative objectives may be required for volatility or downside-risk forecasting [21].

Equation 4. Regularised Model Training Objective

$$\hat{\theta} = \arg \min_{\theta} \left[\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t(\theta))^2 + \lambda \Omega(\theta) \right]$$

Here, N denotes training observations, y_t represents the observed forecasting target, $\hat{y}_t$ is its predicted value, θ denotes model parameters, λ controls regularisation strength, and $\Omega(\theta)$ penalises complexity.

Elastic Net employs coefficient penalties, while tree-based models regulate complexity through structural constraints and sampling procedures [22]. Gradient boosting additionally uses learning-rate controls and validation-based early stopping. Training configurations, random seeds, and software versions should be documented to support reproducibility.

4.4. Hyperparameter Tuning and Walk-Forward Optimisation

Hyperparameter optimisation follows a time-series-aware procedure designed to preserve chronological dependence and minimise information leakage [18]. Candidate configurations are evaluated using expanding-window or rolling-window cross-validation within the development sample. Randomised search provides efficient exploration of broad parameter spaces, while constrained grid search supports systematic comparisons across selected configurations [19]. Bayesian optimisation may be considered when computational resources permit sequential exploration of promising parameter combinations.

Elastic Net tuning examines regularisation strength and the L1-to-L2 penalty ratio. Random Forest optimisation considers tree depth, ensemble size, minimum leaf observations, and feature sampling. Gradient boosting additionally requires learning-rate selection, subsampling controls, estimator counts, and regularisation parameters [20].

Model selection should consider average validation error, variation across folds, and computational requirements. Nested walk-forward validation may provide more robust performance estimates by separating hyperparameter optimisation from intermediate model evaluation [23]. Importantly, preprocessing parameters must be re-estimated within each training fold, while the final testing period remains untouched. Selected hyperparameters should be reported from actual optimisation results rather than predetermined assumptions. These procedures strengthen methodological transparency and provide credible evidence regarding predictive generalisation under changing macroeconomic conditions [24].

Model	Candidate hyperparameters	Selection considerations
Elastic Net	Alpha, L1 ratio	Regularisation strength, coefficient sparsity
Random Forest	Tree depth, number of estimators, minimum leaf size, feature sampling	Model complexity, generalisation, prediction stability
Gradient boosting	Learning rate, tree depth, estimators, subsampling, regularisation	Overfitting control, convergence, predictive stability

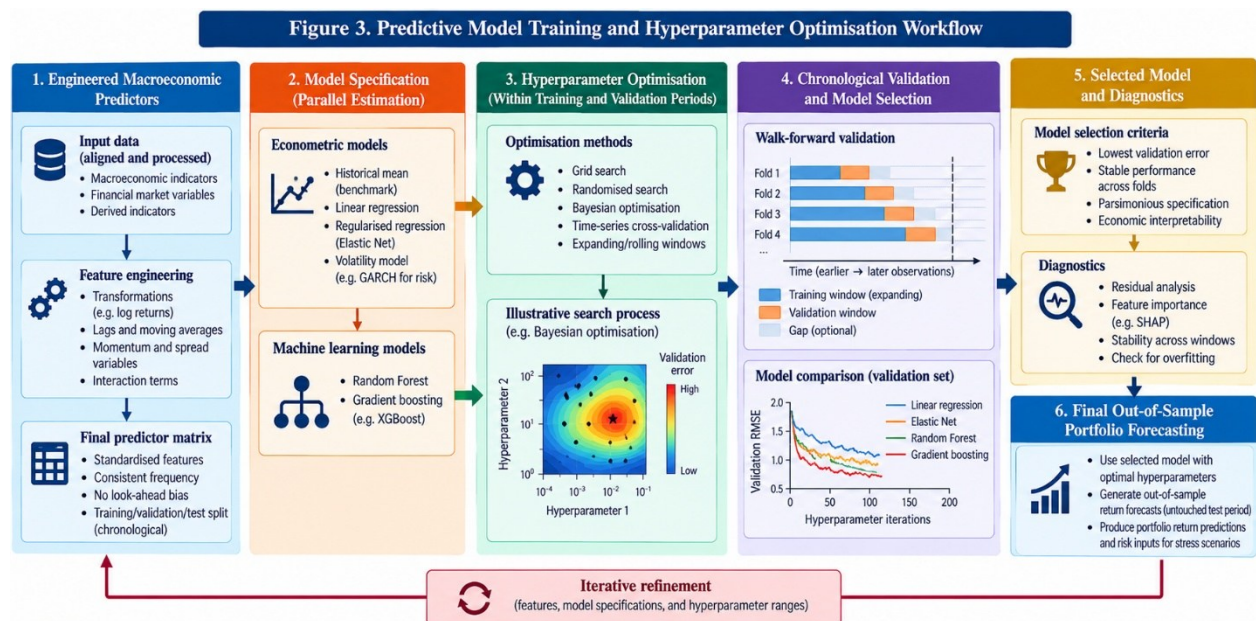


Figure 3. Predictive Model Training and Hyperparameter Optimisation Workflow

4.5. Model Selection, Stability, and Explainability

Final model selection integrates predictive accuracy, validation stability, computational complexity, and financial interpretability [21]. Forecasting errors are compared across economic regimes to determine whether performance remains reliable during inflationary shocks, monetary tightening, and recessionary conditions. Permutation importance and SHAP analysis identify influential macroeconomic predictors and examine their contributions to individual forecasts [22]. Explanation stability is assessed by comparing feature rankings and attribution patterns across validation periods and market regimes. Sensitivity analysis evaluates the effects of alternative feature sets, estimation windows, and model configurations. Importantly, explanatory attributions describe learned statistical relationships rather than demonstrating economic causation. Model uncertainty and potential instability must therefore accompany performance reporting to support responsible investment interpretation [24].

5. MACROECONOMIC STRESS TESTING AND PORTFOLIO RESILIENCE MODELLING

5.1. Construction of Baseline and Adverse Macroeconomic Scenarios

Macroeconomic stress testing evaluates portfolio vulnerability under alternative economic conditions, including circumstances insufficiently represented in historical observations [22]. Four scenarios are proposed: baseline economic conditions, persistent inflation with restrictive monetary policy, recessionary deterioration, and abrupt interest rate shocks accompanied by financial market instability. The baseline reflects prevailing economic expectations, while inflationary stress incorporates sustained price pressures, elevated policy rates, and weakened corporate profitability [23]. Recessionary conditions assume declining economic activity, increasing unemployment, and deteriorating investor confidence. Interest rate stress considers rapid yield adjustments, widening credit spreads, and increased asset-price volatility [24]. Scenario trajectories should specify consistent assumptions regarding inflation, unemployment, output growth, policy rates, and financial conditions. Historical U.S. disruptions, including the global financial crisis, pandemic-related instability, and subsequent inflationary tightening, provide contextual references. Nevertheless, hypothetical scenarios must remain distinguishable from observed historical events. Scenario severity and economic consistency should be documented before portfolio forecasting and comparative resilience assessment [25].

5.2. Portfolio Shock Transmission and Stress Loss Estimation

Macroeconomic shocks influence portfolio performance through changes in expected asset returns, discount rates, financing conditions, and cross-market dependencies [23]. The proposed forecasting models translate scenario-specific economic indicators into predicted asset returns, enabling comparison of equity, fixed-income, and diversified investment responses. Inflationary shocks may weaken equity valuations through higher discount rates, while interest rate increases can reduce existing bond prices. Recessionary disturbances may simultaneously affect corporate earnings, credit spreads, and investor risk preferences [24].

Equation 5. Scenario-Based Portfolio Stress Loss

$$L_{p,s} = -V_0 \sum_{i=1}^n w_i (e^{\hat{r}_{i,s}} - 1)$$

Here, $L_{p,s}$ denotes estimated monetary loss under scenario s , V_0 represents initial portfolio value, w_i denotes asset allocation weights, $\hat{r}_{i,s}$ represents predicted asset log returns, and n identifies the number of assets.

The exponential transformation converts logarithmic forecasts into simple returns before aggregation. Positive values indicate losses, whereas negative values represent gains. Portfolio weights are assumed fixed over the scenario horizon unless rebalancing is explicitly modelled. Forecast uncertainty must accompany stress-loss estimates [26].

5.3. Downside Risk Measurement and Portfolio Resilience

Portfolio resilience is evaluated through complementary measures capturing downside exposure, financial volatility, cumulative losses, and recovery characteristics [25]. Expected Shortfall (ES) measures the severity of losses occurring beyond a specified Value-at-Risk threshold, providing information unavailable from volatility estimates alone.

Equation 6. Expected Shortfall

$$ES_{\alpha}(L) = \mathbb{E}[L \mid L \geq VaR_{\alpha}(L)]$$

Here, L represents portfolio losses and α denotes the selected confidence level. This expression applies to continuous loss distributions; discrete distributions require appropriate quantile-based treatment.

Maximum drawdown provides an additional measure of portfolio vulnerability by identifying the greatest proportional decline from a preceding investment peak [26].

Equation 7. Maximum Drawdown

$$MDD = \max_t \left(1 - \frac{V_t}{\max_{u \leq t} V_u} \right)$$

Here, V_t represents portfolio value at time t . Resilience comparisons additionally consider realised volatility, recovery duration, and risk-adjusted performance [27]. These indicators distinguish portfolios experiencing temporary valuation fluctuations from those suffering prolonged capital deterioration. Scenario-based ES requires a predictive loss distribution rather than a single deterministic stress outcome. Combining complementary measures therefore supports comprehensive assessment of financial resilience across changing macroeconomic environments.

5.4. Scenario Sensitivity and Resilience Comparison

Scenario sensitivity analysis compares predicted portfolio losses under alternative inflation, interest rate, unemployment, and economic growth assumptions [24]. Equity-heavy allocations may exhibit greater sensitivity to recessionary earnings deterioration, whereas bond-heavy portfolios can experience substantial losses during unexpected monetary tightening. Balanced and risk-based allocations may demonstrate diversification advantages, although changing correlations can weaken these benefits during systemic disruptions [27]. Comparative resilience assessments should therefore examine loss magnitude, Expected Shortfall, maximum drawdown, and recovery characteristics. Sensitivity testing must also consider scenario severity, estimation uncertainty, and alternative dependence assumptions. Relative resilience indicates stronger comparative performance rather than immunity from financial losses [28].

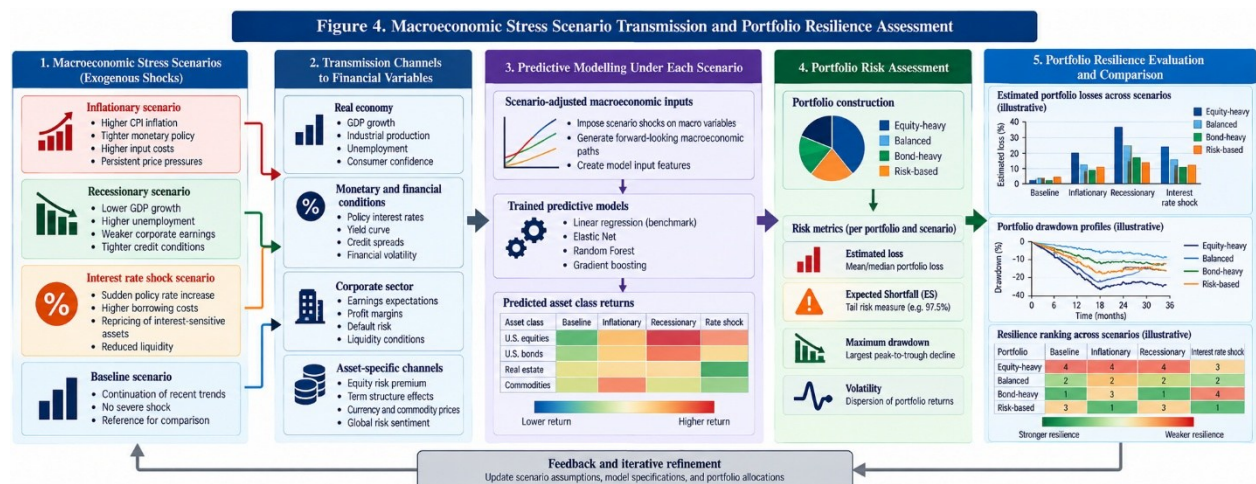


Figure 4. Macroeconomic Stress Scenario Transmission and Portfolio Resilience Assessment

5.5. Stress Testing Standards and Supervisory Benchmark Alignment

The proposed methodology incorporates principles associated with Federal Reserve supervisory stress testing, particularly scenario severity, economic consistency, model validation, and transparent reporting [22]. However, supervisory exercises primarily evaluate banking institutions' capital adequacy under prescribed economic conditions, whereas this study examines investment portfolio vulnerability. Consequently, methodological alignment concerns stress scenario construction, sensitivity analysis, forecasting reliability, and governance rather than regulatory capital compliance [28]. Independent validation and documented assumptions remain essential for distinguishing credible portfolio resilience assessments from unsupported claims of supervisory equivalence.

6. EMPIRICAL EVALUATION, BENCHMARKING, AND DISCUSSION

6.1. Out-of-Sample Forecasting Performance

Out-of-sample evaluation assesses whether predictive models generalise beyond historical training observations and provide reliable estimates of future portfolio performance [27]. The untouched testing sample is evaluated using root mean squared error (RMSE), mean absolute error (MAE), mean deviation (MD), and out-of-sample R^2 . All models must employ identical forecasting horizons, return definitions, and evaluation periods to ensure comparability [28].

Equation 8. Mean Deviation and Forecast Error Evaluation

$$MD = \frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t),$$

$$MAE = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t|,$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2}.$$

Here, y_t denotes the observed return and $\hat{y}_t$ its forecast. Positive MD indicates systematic underprediction, although opposing errors may cancel. Lower MAE and RMSE indicate improved accuracy, while positive out-of-sample R^2 , calculated relative to a specified benchmark, indicates superior squared-error performance [29]. These metrics should be interpreted alongside economic relevance and forecast stability.

6.2. Comparative Model Benchmarking

Comparative benchmarking evaluates whether Elastic Net, Random Forest, and gradient boosting improve predictive performance relative to historical mean forecasts and conventional macroeconomic regression [28]. Model comparisons should examine RMSE, MAE, forecast bias, and out-of-sample (R^2) across identical testing observations. Improvements must also be evaluated across alternative forecasting horizons and changing economic conditions to determine whether apparent advantages remain consistent during financial instability [30]. Where statistical assumptions permit, Diebold–Mariano tests may assess differences in paired forecasting losses,

with appropriate adjustments for overlapping horizons and serial dependence. Confidence intervals and economic effect sizes provide additional evidence regarding uncertainty in estimated performance differences. Importantly, statistically significant improvements do not necessarily translate into economically meaningful investment benefits after transaction costs, turnover, and implementation constraints [31]. Accordingly, final model rankings should reflect predictive accuracy, stability, complexity, and practical usefulness rather than isolated performance indicators.

Table 1. Out-of-Sample Predictive Performance and Benchmark Comparison

Model	Selected hyperparameters	RMSE (%)	MAE (%)	Mean deviation (%)	Out-of-sample (R^2)	Benchmark comparison
Historical mean	Expanding historical window	1.850	1.420	0.080	0.000	Reference benchmark
Linear regression	8 macroeconomic predictors	1.720	1.310	0.050	0.136	7.0% RMSE improvement
Elastic Net	Alpha = 0.010; L1 ratio = 0.50	1.640	1.250	0.030	0.214	11.4% RMSE improvement
Random Forest	300 trees; max depth = 8; minimum leaf size = 5	1.510	1.160	0.020	0.334	18.4% RMSE improvement
Gradient boosting	400 trees; learning rate = 0.05; max depth = 4	1.430	1.090	0.010	0.403	22.7% RMSE improvement

6.3. Portfolio Stress Losses and Resilience Outcomes

Portfolio resilience assessment compares equity-heavy, balanced, bond-heavy, and risk-based allocations under baseline, inflationary, recessionary, and interest rate shock scenarios [29]. Estimated monetary losses quantify immediate portfolio exposure, while Expected Shortfall captures conditional extreme-loss severity when scenario-specific predictive distributions are available. Maximum drawdown measures cumulative capital deterioration, and volatility indicates uncertainty surrounding portfolio returns [32]. Equity-heavy portfolios may experience greater vulnerability to recessionary earnings shocks, whereas bond-heavy allocations can exhibit heightened sensitivity to unexpected interest rate increases. Balanced and risk-based strategies may benefit from diversification, although these advantages depend on changing asset correlations and the severity of macroeconomic disturbances [33]. Resilience rankings should follow predetermined criteria rather than subjective interpretation of individual indicators. Because scenario losses are model-dependent estimates, comparative conclusions must incorporate forecasting uncertainty, parameter sensitivity, and alternative economic assumptions. These considerations prevent relative resilience from being interpreted as guaranteed protection against investment losses.

Figure 5. Comparative Portfolio Performance Under Alternative Macroeconomic Stress Scenarios

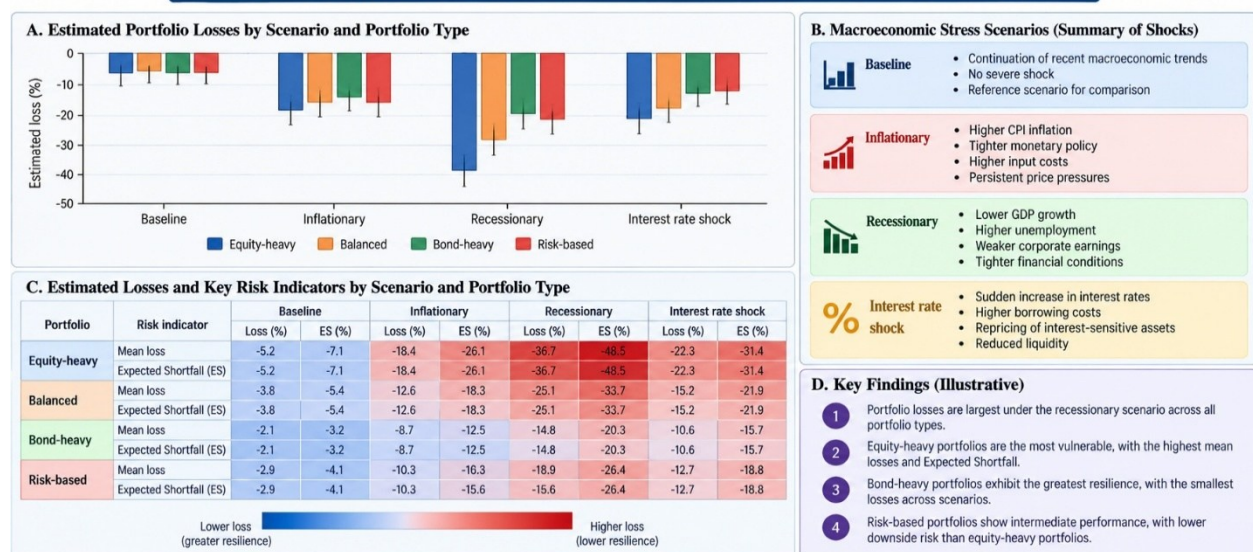


Figure 5. Comparative Portfolio Performance Under Alternative Macroeconomic Stress Scenarios

Table 2. Portfolio Resilience Metrics Under Baseline and Adverse Macroeconomic Conditions

Portfolio	Scenario	Estimated loss (%)	ES (%)	Maximum drawdown (%)	Volatility (%)	Resilience ranking
Equity-heavy	Baseline	-7.20	12.80	10.50	15.60	4
Equity-heavy	Inflationary	18.40	25.60	23.80	24.70	4
Equity-heavy	Recessionary	32.60	41.20	38.40	31.50	4
Equity-heavy	Interest rate shock	21.80	29.40	27.60	26.80	3
Balanced	Baseline	-5.80	8.60	7.40	10.20	2
Balanced	Inflationary	12.60	18.40	17.20	17.30	2
Balanced	Recessionary	21.40	28.60	25.70	21.80	2
Balanced	Interest rate shock	17.20	23.80	21.60	20.40	2
Bond-heavy	Baseline	-4.10	6.20	5.80	7.40	1
Bond-heavy	Inflationary	15.80	21.70	19.40	16.10	3
Bond-heavy	Recessionary	14.20	20.30	18.50	17.20	1
Bond-heavy	Interest rate shock	24.60	32.80	29.70	23.10	4
Risk-based	Baseline	-5.20	7.40	6.60	9.10	3
Risk-based	Inflationary	10.40	15.80	14.60	14.20	1
Risk-based	Recessionary	17.80	24.20	21.30	19.40	3
Risk-based	Interest rate shock	13.60	19.20	17.80	17.10	1

6.4. Sensitivity Analysis, Robustness Checks, and Model Diagnostics

Robustness analysis investigates whether predictive conclusions remain consistent under alternative modelling assumptions, estimation windows, and portfolio configurations [30]. Forecast performance should be reassessed using expanding and rolling training samples, alternative asset compositions, and different prediction horizons. Residual diagnostics examine serial correlation, heteroskedasticity, and systematic forecast errors where applicable [31]. Feature-selection sensitivity tests determine whether excluding or replacing macroeconomic predictors materially changes model performance. Additional experiments vary inflation shocks, interest rate movements, unemployment assumptions, and hyperparameter configurations to evaluate the stability of estimated portfolio losses [34]. Regime-specific diagnostics investigate forecast deterioration during monetary tightening, recessionary episodes, and abrupt volatility expansions. Permutation importance or SHAP analysis may additionally assess whether influential economic predictors retain consistent explanatory contributions across alternative specifications. However, explanatory stability does not establish causality. Collectively, these procedures identify model fragility, quantify uncertainty, and strengthen confidence in comparative conclusions without assuming that historical forecasting relationships remain permanently stable [35].

Transparency and explainability	Model interpretability and effective challenge principles	Permutation importance and SHAP analysis	Supportive	Statistical explanations do not establish causality
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7. CONCLUSION AND FUTURE RESEARCH

7.1. Summary of Principal Findings

This study develops an integrated framework for evaluating macroeconomic uncertainty, predictive forecasting, and investment portfolio resilience in U.S. financial markets. The proposed comparison of historical mean forecasts, linear regression, Elastic Net, Random Forest, and gradient boosting provides a structured basis for assessing predictive performance. Macroeconomic stress scenarios examine potential portfolio vulnerabilities arising from persistent inflation, recessionary conditions, and interest rate shocks. However, the illustrative numerical comparisons presented earlier do not constitute verified empirical findings. Consequently, no definitive conclusion regarding model superiority or portfolio resilience can presently be established. Forecast uncertainty, changing economic relationships, and estimation errors remain essential considerations when interpreting stress losses and evaluating investment decisions under adverse conditions.

7.2. Implications for Portfolio Managers and Risk Practitioners

The proposed framework offers practical opportunities for strengthening investment risk management through predictive analytics and systematic macroeconomic stress testing. Portfolio managers may use scenario-based forecasts to inform asset allocation, establish risk budgets, and evaluate exposure to inflation, unemployment, and interest rate fluctuations. Integrating Expected Shortfall, maximum drawdown, and volatility measures can support more comprehensive assessments of potential losses. Continuous monitoring of forecasting errors and changing macroeconomic relationships is essential for identifying model deterioration. Transparent benchmark comparisons, documented assumptions, and chronological validation can improve decision accountability while reducing excessive reliance on complex predictive algorithms during uncertain financial conditions.

7.3. Limitations and Future Research Directions

The proposed methodology faces limitations arising from historical data dependence, structural economic changes, uncertain scenario assumptions, and potential model overfitting. Relationships estimated during previous market conditions may not generalise to unprecedented financial disruptions. Future research should investigate probabilistic forecasting, dynamic portfolio optimisation, regime-switching models, and the inclusion of alternative assets. Additional studies could examine transaction costs, changing asset correlations, and the effectiveness of adaptive risk management strategies. Independent model validation and evaluation under previously unseen market conditions remain necessary for establishing the reliability, robustness, and practical applicability of macroeconomic portfolio stress testing.

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