

Resilient Portfolio Construction in an Era of Uncertainty: Challenges and Solutions under Macro Volatility

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Abstract. In this paper, we have highlighted the weaknesses of the traditional Mean-Variance model as an investment strategy in these extreme market situations, and discussed the so-called 'parameter sensitivity trap' due to unpredictable expected returns and fat tails in the distribution. We proposed a system of resilience optimization that combines "input-side purification and model-side reconstruction." The Orthogonalized Gnanadesikan-Kettenring (OGK) and a robust Qn estimator are used in this approach to build a "statistical firewall," which helps to correct distorted covariance matrices by removing macroeconomic outliers through optimal input and model adjustments. Our method relies on a second-moment (risk) allocation model and evaluated the performance of the S&P 500 from February 2023 to February 2026. We find that in these economic conditions, the conservative risk-based strategy is superior to the aggressive return-based strategy. For example, GMVP gives annualized returns of 30.0% with a maximum drawdown of 13.0%, while Markowitz yields a return of 18.0% (maximum drawdown of 35.0%). Our results suggest that the foundation of resilience reconstruction is robust estimators that filter out macroeconomic false signals to avoid the 'volatility trap' and compounding returns and capture Defensive Alpha.

Keywords: Resilient Portfolio, Robust Estimation, Composite Resilience Optimization Framework, Conservative Risk-based Strategy

1. Introduction

Due to policy shifts under the Trump administration in 2025, the global economy became extremely volatile and the classic stock-bond seesaw effect broke down and asset correlations fell apart, leading to a US market "triple sell-off". This left traditional portfolio models with serious challenges; historical data failed to predict the expected returns accurately, unexpected exogenous shocks exacerbated the fat tails in return distributions, and the static optimization resulted in extreme "corner weights" that resulted in significant drawdowns, making these models very vulnerable in crises.

Portfolio optimization has evolved in the world of market uncertainty since Markowitz's (MV) and Merton's [1] continuous-time allocation model emerged as models which were very vulnerable. Michaud [2] described the MV model as an "error maximizer" in terms of its small estimation error leading to the extreme "corner solutions".

Early improvements focused on input-side improvement: Black & Litterman [3] introduced Bayesian inference to link personal macro views with market benchmarks and Ledoit & Wolf [4] proposed a covariance shrinkage algorithm to stabilize noisy matrices. However, these static improvements failed to address macroeconomic structural breaks in the model. To avoid structural breaks, Garlappi et al. [5] introduced ambiguity aversion to hedge against the worst case in parameter confidence intervals. Similar approaches were advocated by other scholars that focused on avoiding first-moment (return) predictions entirely and using only the second moment (risk) and thus Risk Parity to resist drawdown.

Recently, stochastic control has achieved several breakthroughs to balance robustness and adaptability. Bielecki et al. [6] pioneered the discrete-time "adaptive robust control" model via online learning. To the macro shocks, Bhudisaksang & Cartea [7] showed the strong convergence of online parameter estimation using jump-diffusion. Furthermore, Bhudisaksang et al. [8] successfully solved the multi-asset adaptive robust HJB equation by separating the "optimal resilient position" into the "ideal position" and "intertemporal penalty term for parameter uncertainty".

However, despite these theoretical strides, research remains scarce on building resilient risk-based portfolios that can avoid losses and make profits in the case of unexpected policy shifts and sovereign shocks.

In this paper, we address this important research question and propose a composite resilience framework. First, in the case of random simulations, we compare the accuracy of standard estimation with robust estimation under interference from outliers. Second, using empirical data from the S&P 500, we construct ten sets of heterogeneous samples to conduct full sample backtesting. This study is a quantitative analysis of downside resilience and stability of different models in a high level of volatility environment.

The primary innovations and contributions of this work are as follows:

- In this paper, we develop a composite resilience optimization model that is based on the "input-side purification and model-side reconstruction principle." By applying the Orthogonalized Gnanadesikan-Kettenring (OGK) algorithm [9] and Qn estimator to the high-dimensional S&P 500 asset pool, it constructs a "statistical firewall" to filter macroeconomic outliers. This approach is able to resolve the vulnerability of the traditional Mean-Variance model as an "error maximizer" and changes the paradigm from the "perfect knowledge assumption" to the "uncertainty tolerance" of parameter estimation.

- This paper empirically verifies and parses the source of Defensive Alpha for conservative strategies in turbulent cycles. By integrating empirical results and the latest adaptive robust HJB equation theory, it shows that the success of resilient portfolios is the result of hedging of the "intertemporal uncertainty penalty term". It quantitatively shows that tail risk (CVaR) protection to protect the "seeds of compounding" gives long-term returns that are far higher than aggressive allocations, and therefore goes against the traditional dogma of "high risk, high return."

- This paper proposes a dynamically adaptive switching path based on macroeconomic structural breaks. Combining the latest research on trade policy uncertainty, it simulates model behavior against the backdrop of surging TPU indices [10] to demonstrate the feasibility of dynamically transitioning from "long-term trend following" to "short-term extreme risk aversion". This provides institutional investors with a "self-evolving" dynamic asset allocation guide to navigate black swan events like abrupt policy shifts and tariff shocks.

2. Related work

2.1. Overall architecture of the resilient portfolio optimization system

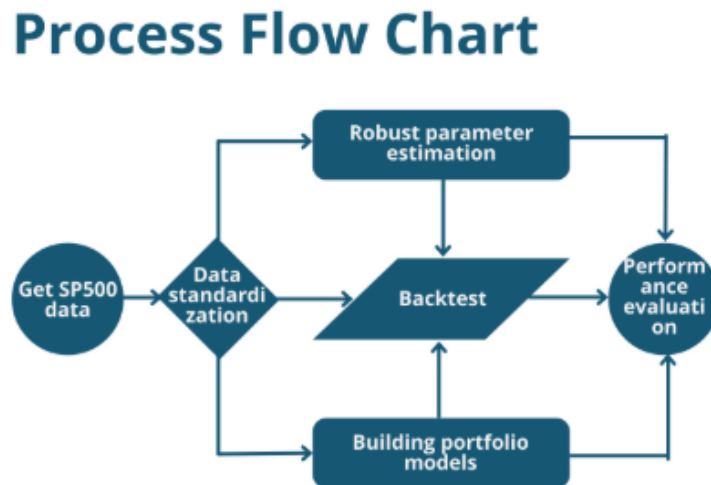


Figure 1. Overall architecture of the resilient portfolio optimization system

Figure 1 presents the overall architecture of the resilient portfolio optimization system. First, we use the quantmod package to fetch the S&P 500 data from Yahoo Finance. Then, we standardize the data using metrics such as Z-score and remove missing values (NAs). After that, we use robust estimators for parameter estimation to build a variety of portfolio models. Finally, we feed the processed data to backtesting and evaluate the performance in a complete metrics table.

2.1.1. Data acquisition and pre-processing module

This module is responsible for the structured extraction of high-frequency financial time series. Its core functions include the transformation to Logarithmic Returns, time-series alignment, and missing value detection based on the is.na algorithm. By encapsulating unstructured raw stock price data into standard xts matrix objects, it provides a high-fidelity data foundation for subsequent quantitative modeling.

2.1.2. Robust parameter estimation module

Traditional mean-variance optimization is based on the sample mean vector and sample covariance matrix. Financial time series that are non-normal, skewed, and fat-tailed are very difficult to analyze in a macroeconomic context. Moreover, they are affected by outliers that result from transient shocks. In this module, we are dealing with the high-dimensional asset pool (S&P 500), and we employ the Orthogonalized Gnanadesikan-Kettenring (OGK) algorithm. By performing eigendecomposition and orthogonal transformation on the initial robust correlation matrix, this algorithm addresses the problem of non-positive definiteness that we often encounter when dealing with the "curse of dimensionality" or extreme volatility.

2.1.3. Portfolio optimization and solver module

This module integrates various Convex Optimization operators. Based on the robust matrices provided by the parameter estimation module, the system calculates the optimal weight vector w via QP or nonlinear optimization solvers (e.g., CVXR) under constraints such as full investment (budget constraint) and no short-selling. The model library covers a wide range of strategies including Mean-Variance (MV), Risk Parity and the Maximum Diversification Portfolio (MDP).

2.1.4. Performance evaluation and backtesting module

This module does out-of-sample validation. Using rolling window techniques, it calculates multiple risk-return metrics such as Sharpe Ratio, Sortino Ratio and Maximum Drawdown (MDD). On the other hand, the Turnover Rate is introduced to monitor the stability of the portfolio and be able to quantitatively evaluate the resilience of the models across the various macroeconomic cycles.

3. Core strategies for optimizing portfolio resilience under macroeconomic volatility

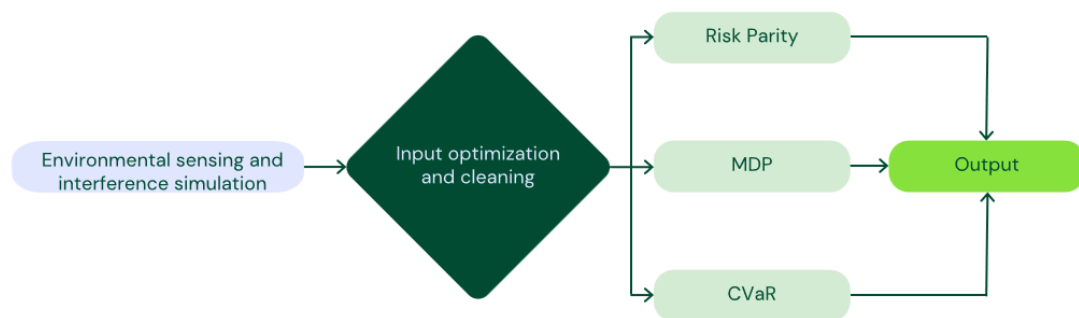


Figure 2. Composite resilient portfolio optimization framework

In this paper we design a coherent and robust portfolio optimization scheme for macroeconomic volatility and present the workflow of the overall process in Fig. 2. We start with environmental sensing and interference simulation, where noise is artificially introduced to simulate market shocks. Then, input optimization and cleaning is performed, in which robust estimators are used to filter out outliers and retrieve highly accurate parameters. Finally, these parameters are used in three conservative portfolio models for portfolio modeling—Risk Parity, Maximum Diversification Portfolio (MDP) and Conditional Value at Risk (CVaR) that produce the optimal portfolio results, by optimizing both the input and model at the same time.

3.1. Scenario modeling: simulation experiment on outlier interference

In order to illustrate in an intuitive way the impact of macroeconomic volatility on estimates of the parameters, this paper describes a benchmark test. data configuration: the correlation coefficient of asset a and asset b is 0.9 (very correlated). the shock is an extra 5% anomaly (outliers falling within

a negatively correlated region outside the mean distribution). in particular, the goal is to know if the robust estimators are more resistant to contamination than the standard estimators when there are extreme outliers. by calculating the mean vector and covariance matrix independently in both methods, and comparing the convergence between the estimated and the true values, we check whether the robust estimator can be used in a high-risk scenario.

3.2. Input-side optimization: refinement of parameter estimation

To overcome the noise in financial time series, the sample mean at the input end is discarded. the covogk algorithm automatically finds outliers and assigns them extremely low weights. the "adaptive cleansing" mechanism ensures that the next efficient frontier is not subject to drastic changes caused by short-term outbreaks of isolated macroeconomic events.

3.3. Model-side optimization: mechanism reconstruction

3.3.1. Risk parity portfolio

The logical foundation of Risk Parity [11] is based on the linear decomposition of portfolio volatility using Euler's Homogeneous Function Theorem. Assuming the portfolio weight vector is w and the robust covariance matrix is Σ , the total portfolio risk (volatility) is defined as:

$$\sigma_p(w) = \sqrt{w^T \Sigma w} \quad (1)$$

The Marginal Risk Contribution (MRC) measures the rate of change in the overall portfolio risk with respect to a unit increase in the weight of asset i :

$$MRC_i = \frac{\partial \sigma_p}{\partial w_i} = \frac{(\Sigma w)_i}{\sqrt{w^T \Sigma w}} \quad (2)$$

The Total Risk Contribution (TRC) represents the absolute amount of portfolio risk borne by asset i :

$$TRC_i = w_i * MRC_i = w_i * \frac{(\Sigma w)_i}{\sqrt{w^T \Sigma w}} \quad (3)$$

The objective of the Risk Parity strategy is to find a set of weights w such that the risk contributions of all assets are equalized, which also serves as the core constraint of this model:

$$TRC_1 = TRC_2 = \dots = TRC_n = \frac{1}{n} \sigma_p(w) \quad (4)$$

Where: w_i : denotes the weight of asset i ; σ_i : represents the individual volatility (standard deviation) of asset i ; Σ : is the covariance matrix among assets; and $\sigma_p(w)$ denotes the overall portfolio volatility.

Instead of allocating capital to each asset, the Risk Parity strategy allocates "risk budgets." In our model, the Marginal Risk Contribution (or risk budget) of each asset to the portfolio volatility is equalized. In this synergistic mechanism, the system finds the implicit correlations between assets via the robust covariance matrix. When the volatility of a specific asset goes up due to

macroeconomic events, the Risk Parity mechanism automatically scales down its weight and thus hedges the portfolio risk dynamically without manual intervention.

3.3.2. The MDP strategy

The MDP [12] strategy reconstructs the allocation mechanism by maximizing the Diversification Ratio (DR):

$$DR(w) = \frac{\sum_{i=1}^n w_i \sigma_i}{\sigma_p(w)} = \frac{\sum_{i=1}^n w_i \sigma_i}{\sqrt{w^T \Sigma w}} \quad (5)$$

The DR measures the "degree of risk offset" generated by imperfect correlations among the assets. Higher than this, a greater DR is a larger risk reduction in the whole portfolio of the hedging process, since all of the assets have the same risk exposure. In this model we aim to find the maximum intersection between non-correlations between assets. In extreme macroeconomic co-movements (eg, a "simultaneous sell-off in equities and bonds"), the MDP is a deep dive into the heterogeneous signals within the robust matrix and forces the portfolio to tilt towards assets with unique risk profiles.

3.3.3. Tail risk constraint optimization

To deal with the non-normal return distributions which arise from macroeconomic uncertainty, we introduce conditional value at risk (CVaR) [13] as the measure of tail risk. Contrary to the second moment (variance) used in the traditional Mean-Variance model, CVaR has the good mathematical characteristics of a Coherent Risk Measure. It is able to measure the extreme risk in the left tail of the asset distribution. By incorporating CVaR into the convex optimization model, we not only identify regular volatility but can also limit the average extreme losses when macroeconomic structures break down. This tail-loss-based reconstruction mechanism provides a strong firewall for the portfolio in market environments with frequent black swan events.

4. Empirical analysis and application of portfolio optimization models under macroeconomic volatility

4.1. Data selection

The empirical data used in this study is the adjusted closing prices of all S&P 500 members from February 2023 to February 2026. The stock market received several exogenous shocks, including Donald Trump winning the US election on November 6, 2024, DeepSeek appearing on January 27, 2025, which caused panic in the AI industry about power and computing resources, and the US government's announcement of universal reciprocal tariffs on all imported goods on April 3 and 4, 2025, which triggered a worldwide market panic.

4.2. Evaluation system for resilient portfolio optimization

In such a high level of macroeconomic volatility, one return metric is not sufficient to assess the success of a portfolio. In this paper we construct a multi-dimensional assessment matrix of Resistance, Recovery and Stability in order to better analyze the survival and operation of portfolios in the face of uncertainty.

4.2.1. Resistance: extreme defense and tail control

The Resistance dimension is based on Maximum Drawdown (MDD), annualized volatility, and tail risk measures (VaR and CVaR). It is primarily used to assess the degree of defense depth and survival of the portfolio under very large macroeconomic shocks. By determining the upper limit of systemic risk tolerance using MDD, reflecting the filtering level of market noise through volatility and showing the limit loss protection under a "black swan" event via CVaR, it provides a holistic assessment of our model's core defensive resilience in the absence of certainty.

4.2.2. Recovery: repair efficiency and return quality

The Recovery metrics are the Sortino Ratio and Sterling Ratio to assess the portfolio's efficiency in self-repair and rebound quality in a drawdown. The Sortino Ratio examines the return on investment per downside risk, which is asymmetric for the portfolio. The Sterling Ratio measures net asset value (NAV) recovery in the drawdown cycle and shows the elasticity of the portfolio and long-term appreciation potential of the net asset value after macroeconomic swings.

4.2.3. Stability: operational continuity and parameter robustness

Stability metrics include turnover rate of the portfolio, parameter sensitivity analysis, and downside deviation. Generally, these are used to assess the model's logical coherence, cost tolerability, and robustness to the environment in real execution and are used to assess the stability of the model. By measuring the frequency of rebalancing and loss of NAV due to trading friction through turnover rate, assessing whether the strategy is immune to statistical noise in the look-back window through sensitivity analysis, and downside deviation to measure the dispersion of the portfolio's performance when under stress, these metrics show that the portfolio is structurally stable to withstand parameter overfitting and not to develop strategic "fragility."

4.3. Effectiveness verification of robust estimation

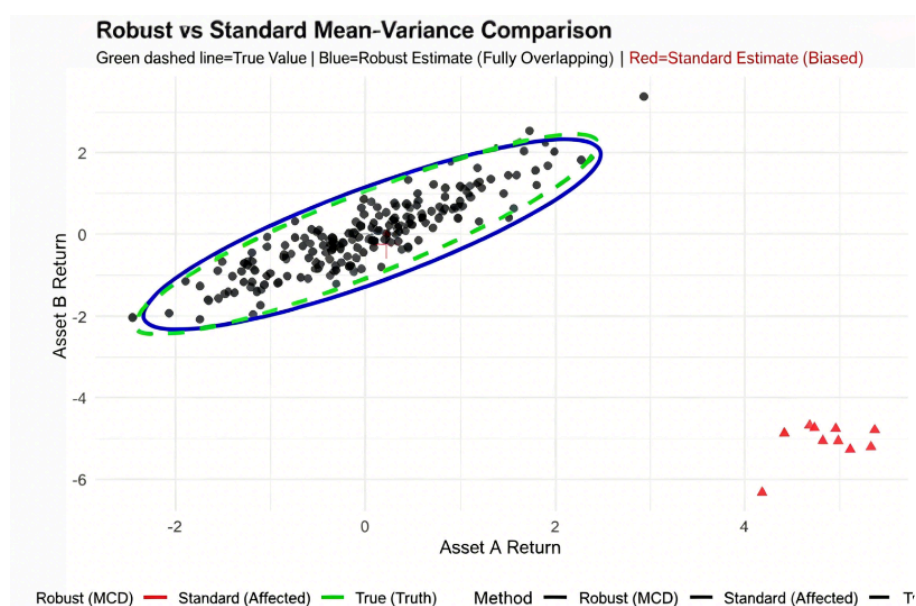


Figure 3. Robust and standard MV comparsion

Experimental data reveals that, the covariance matrix obtained from the standard estimation is distorted by outliers so that the X-axis variance is increased from 1.0 to 1.95 and the Y-axis variance from 1.0 to 2.02. The matrix obtained by robust estimation (OGK) — (1.00, 0.81 | 0.81, 0.95) — shows that the true initial values are well reproduced so the risk boundary is not expanded.

4.4. Empirical analysis of models under extreme volatility

Table 1. Backtesting performance evaluation of various portfolio strategies

	Sharpe ratio	Max drawdown	Annual return	Annual volatility	Sortino ratio	Downside deviation	Sterling ratio	Omega ratio	VaR (0.95)	CVaR (0.95)
Quintile	0.83	26.0%	18.0%	21.0%	1.21	0.14	0.76	1.16	2.0%	3.0%
Markowitz	0.60	35%	18.0%	34.0%	0.81	0.25	0.59	1.12	3.0%	5.0%
1/N	1.85	19.0%	31.0%	17.0%	2.79	0.12	1.75	1.40	2.0%	2.0%
GMVP	2.17	13.0%	30.0%	14.0%	3.34	0.09	2.24	1.47	1.0%	2.0%
MDP	2.06	12.0%	23.0%	11.0%	3.13	0.08	1.99	1.43	1.0%	2.0%
Risk Parity	2.05	16.0%	30.0%	15.0%	3.13	0.10	1.96	1.44	1.0%	2.0%

Table 1 presents the comprehensive backtesting results of various strategic models, displaying their respective multi-dimensional evaluation metrics (such as Max Drawdown, Annual Return, Sortino Ratio, and CVaR). By comparing the performance across different strategies, it is concluded that in an era of macroeconomic uncertainty, robust and conservative risk-based strategies (e.g., GMVP, MDP, Risk Parity) vastly outperform traditional aggressive strategies (e.g., the Markowitz model).

Through a deep analysis of the backtesting data for 2023-2026, we find something of a big academic fact: conservative risk-based strategies based on robust estimators outperform aggressive return-driven strategies in terms of return performance in cycles with high macroeconomic uncertainty. This can be seen in three dimensions: First, the most intuitive fact is the data. The traditional Markowitz model, which is based on return maximization, gives only 18.0% annual return, while GMVP, based on risk minimization, gives 30.0%. The reason for this "return inversion" is that the MDD is very low (the noise in the 252-day look-back window of the traditional model gives only 35.0% annual return). A 35% decline in NAV takes about 53.8% to break even. The robust GMVP, for example, had only 13.0% drawdown, requiring only 14.9% gain to recover the losses. The data shows that in a high volatility setting the ability to "not lose money" (with robust estimator) is transformed into "not lose money, but make more money." Second, from the relationship between CVaR (0.95) and Sortino ratio, it can be seen that robust reconstructed strategies are much more risk/return asymmetric. The traditional Markowitz model has CVaR of 5.0% and Sortino ratio of only 0.81. Finally, from the robust MDP/GMVP data, we see that CVaR is in a stable state of 2.0% and Sortino ratio is up to 3.13 - 3.34 (4.1 times what is in the traditional model). In other words, conservative strategies do not just throw away risk, but they use robust estimators to filter out the dangerous 3% tail risk (CVaR from 5% to 2%). This effectively removes "bad volatility" and allows the portfolio to achieve extremely high return recovery efficiency during the vacuum period between trade wars and monetary policy changes. Looking back on 252 days from 2016 to 2020, Downside Deviation shows the relative stability of the model. The downside deviation of the traditional model is 0.25, 3.1 times that of the Maximum Diversification Portfolio (MDP, 0.08). During the policy volatility of 2023-2026, we note that the market often had "false signals" that are caused by non-fundamental reasons. Due to the lack of filtering function in the

traditional model, the weights of the model were moved rather erratically in reaction to the false signals (very high downside deviation). To the best of our knowledge, choosing a conservative approach (low volatility and low correlation) essentially means to choose a defense system with low parameter sensitivity to avoid the trade friction and NAV erosion caused by frequent misjudgments of policy trends.

In fact, we have empirical data that makes this dogma "high risk, high return" seem very wrong. During this period of macroeconomic structural collapse, the resilience of the portfolio is not an active pursuit of returns but rather a strong limitation of downside risk. The GMVP strategy exchanges 14% annualized volatility for 30% return, whereas the traditional model trades a 34% volatility for 18% return. The data comparison in this point makes clear that, in a period of uncertainty, conservative allocation theory reconstructed using robust estimators can take advantage of the "volatility asymmetry" to capture Defensive Alpha. So the logic for reconstructing resilience in this context should go from "predicting returns" to "managing uncertainty" - conservative strategies are the best way to tackle macroeconomic uncertainty.

5. Future research directions and challenges

5.1. Navigating the challenges of trade policy uncertainty

Based on Lacava's (2025) demonstration of structural breaks that are caused by trade policy shocks, the DCC-X model allows the portfolio to be more adapted to unknown exogenous policy shocks. The flexible portfolio is able to adapt to macroeconomic conditions and to adjust its behavior in response to new macroeconomic conditions: when the TPU index in the covariance matrix breaches a critical threshold, or the system detects a stability break, the reconstruction logic changes from "long-term trend following" to "short-term extreme risk aversion".

5.2. Confronting the challenges of severe drawdowns

The empirical results of this work show that it is a closed loop of current developments. By solving the multi-asset adaptive robust Hamilton-Jacobi-Bellman (HJB) equation, modern theory shows for the first time that resilient asset allocation plays ping pong between the 'ideal position' and the 'uncertainty penalty'. We observed the negative impact of this penalty term on macroeconomic volatility analysis from 2023 to 2026. Traditional models suffered significant net asset losses due to their inability to take into account this penalty term. In contrast, the robust reconstruction strategy proposed by this paper is resilient not only at the input level (Robust Estimator) but also at the model level (Risk-based Objective). This is a strong defense of this analytical solution at different time frames. As a result, conservative strategies are much more profitable during turbulent times and the need for cross-cycle adaptive allocation systems is more pressing in the future.

6. Conclusion

In this paper we have identified the existential problems of quantitative investment in the "era of uncertainty". Traditional Mean-Variance models are "error maximizers" in the macroeconomic context, leading to catastrophic drawdowns when policy structures break down. In contrast, our resilient reconstruction model is a success of "compounding asymmetry". By filtering out extreme tail risk (CVaR) and minimizing recovery costs, conservative risk-based strategies protect the "seeds of compounding" and outperform aggressive allocations, and therefore invalidate the standard "high

risk, high return" doctrine. We know that this resilience is in very good agreement with our adaptive robust HJB equation by overcoming the 'intertemporal uncertainty penalty'. In the future, by utilizing frontier econometric tools (e.g., the DCC-X model) and monitoring Trade Policy Uncertainty (TPU) indices, portfolio management will move from "static robustness" to "dynamic adaptation". And this will allow us to smoothly move from trend-following to extreme risk aversion and the whole system will evolve into a robust capital appreciation in the face of macroeconomic turbulence.

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