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Risk Control in Cross-Asset Portfolios: Portfolio Optimization from a Risk–Return Perspective

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Abstract. Recent market shocks and shifts in cross-asset correlations have complicated risk control in multi-asset portfolios. Using daily data from January 2019 to July 2026 for the CSI 300, NASDAQ-100, gold, and U.S. 10-year Treasuries, this study compares an equal-weight buy-and-hold portfolio with static risk parity (RP) and monthly and quarterly dynamic RP strategies. Matched-frequency 1/N portfolios are included to distinguish the effect of the RP weighting rule from that of rebalancing. The results indicate that cross-asset diversification substantially improves the portfolio's risk–return profile. RP further lowers annualized volatility and 95% one-day value at risk, but it also reduces returns and produces only a modest improvement in maximum drawdown. Stress tests suggest that the protection offered by RP varies across market conditions. When the stock–bond correlation shifts from negative to positive, both traditional diversification and the incremental protection provided by RP may weaken. The main findings remain broadly robust to alternative estimation windows, transaction-cost assumptions, and trading-day alignment methods.

Keywords: cross-asset allocation, risk parity, risk contribution, dynamic rebalancing, stress testing

1. Introduction

Since 2019, the COVID-19 shock, shifts in global monetary policy, and pronounced technology-sector cycles have generated substantial differences in the risk and return profiles of equities, gold, and government bonds. Although a single asset may perform well during certain periods, it can also expose investors to considerable volatility and drawdowns. This raises a practical question: once basic cross-asset diversification is in place, how much additional risk control does risk parity (RP) provide, and what return and implementation costs accompany it?

Modern portfolio theory shows that combining assets whose returns are not perfectly positively correlated can reduce portfolio risk [1]. Equal-risk-contribution methods extend this principle by allocating risk, rather than capital, more evenly across assets [2]. Subsequent studies, however, show that RP performance varies across market regimes [3] and that stock–bond correlations change with macroeconomic and inflation conditions [4, 5]. Recent research also examines how such changes affect multi-asset portfolio risk [6, 7]. Because rebalancing generates turnover and transaction costs [8], and because the choice of risk measure and dependence model can affect RP outcomes [9-11],

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comparing RP only with a buy-and-hold portfolio may conflate the effects of diversification, RP weighting, and rebalancing.

This study makes three contributions. First, it uses matched-frequency 1/N portfolios: monthly RP is compared with monthly 1/N, and quarterly RP with quarterly 1/N, using identical rebalancing dates. This design helps isolate the effect of the RP weighting rule from that of rebalancing. Second, it combines full-sample analysis with stress tests for 2020, 2022, and 2026 and examines rolling stock–bond correlations to assess RP performance across market conditions. Third, it evaluates robustness using 126-, 252-, and 504-day estimation windows, transaction-cost assumptions of 0, 5, 10, and 20 basis points, and a sample restricted to common valid trading days.

2. Literature review

Cross-asset allocation begins with the diversification argument in modern portfolio theory. In the mean–variance framework, Markowitz shows that combining assets that are not perfectly positively correlated can lower portfolio risk [1]. Equal-risk-contribution (ERC) allocation shifts the focus from how much capital is invested in each asset to how much risk each asset contributes. Maillard et al. formalize this idea by choosing weights so that risk contributions are approximately equal [2]. This change in weighting can reduce dependence on expected-return estimates, but it does not imply that ERC will always outperform a simple equal-weight portfolio in either return or risk-adjusted performance.

Whether this risk-based allocation remains effective depends partly on the market environment. Costa and Kwon show that RP allocations can change materially across market regimes [3]. For a portfolio that combines equities and government bonds, the stock–bond relationship is especially relevant. Yang et al. document substantial long-run variation in stock–bond correlations across macroeconomic conditions [4], and Pericoli identifies inflation dynamics as one factor associated with these changes [5]. Brixton et al. further note that a move from negative toward positive stock–bond correlation can reduce the diversification benefit usually expected from the two asset classes [6]. Evidence from Molenaar et al. links stock–bond correlation to inflation, real interest rates, and government creditworthiness, and shows that higher correlations can increase risk in multi-asset portfolios [7]. These findings suggest that the defensive role of RP should be evaluated across different market states rather than treated as constant over time.

A second issue is how portfolio risk is measured and estimated. Ararat et al. construct RP portfolios using mean absolute deviation and report empirical risk–return outcomes that generally fall between minimum-risk and equally weighted portfolios [9]. Paolella et al. consider heavy-tailed returns and time-varying dependence, drawing attention to the behavior of RP when correlations and tail risks change during stressed markets [10]. Sheng et al. use conditional value at risk together with machine learning in a dynamic RP setting, placing greater emphasis on downside risk and adaptive rebalancing [11]. Although these approaches differ from the variance-based specification used here, they point to the same practical concern: RP results are sensitive to the chosen risk measure, the estimation procedure, and the dependence structure among assets.

Implementation provides another reason to separate the sources of portfolio performance. El Bernoussi and Rockinger examine rebalancing with transaction costs using theoretical, simulated, and empirical evidence and show that increasing rebalancing frequency does not necessarily improve net performance [8]. This matters for the comparison in this study because an RP strategy can differ from a simple benchmark in both its weighting rule and its rebalancing schedule. To distinguish these effects, the empirical analysis introduces matched-frequency 1/N benchmarks: monthly RP is compared with monthly 1/N, and quarterly RP with quarterly 1/N on the same

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rebalancing dates. The analysis then combines these comparisons with stress-period evidence and rolling stock–bond correlations to examine how much additional risk control the RP weighting rule provides beyond basic cross-asset diversification and whether that benefit remains similar across market conditions.

3. Research design

3.1. Data and processing

The asset universe comprises the CSI 300, NASDAQ-100, gold, and U.S. 10-year Treasuries. The main sample spans January 2019 to July 2026, with 2017–2018 serving as a warm-up period for rolling risk estimation. The study uses daily data. The CSI 300 price index is converted into U.S. dollars, the NASDAQ-100 is represented by its price index, and gold is represented by a continuous XAU/USD spot series. The Treasury return series is constructed from the FRED 10-Year Treasury Constant Maturity Rate (DGS10) using the duration–convexity approximation described by Swinkels [12]. It is therefore a simulated constant-maturity total-return series rather than a commercial bond total-return index.

The baseline sample is constructed on a Monday-to-Friday calendar, with prices forward-filled on local market holidays. As a robustness check, the analysis is repeated using only dates on which all required assets have actual observations. The analysis adopts the perspective of a U.S. dollar investor and assumes that foreign-exchange exposure is unhedged. The FRED 3-Month Treasury Bill Secondary Market Rate (DTB3) serves as the risk-free-rate proxy in the Sharpe ratio. Daily simple returns are defined as follows:

$$r_t = \frac{P_t}{P_{t-1}} - 1 \tag{1}$$

where r_t denotes the simple return on day t and P_t denotes the asset price on day t. Annualized volatility is calculated as the standard deviation of daily returns multiplied by $\sqrt{252}$. CSI 300 data are obtained from the China Securities Index historical database; NASDAQ-100, DGS10, and DTB3 data are obtained from FRED; and gold is represented by daily XAU/USD spot quotes.

3.2. Portfolio construction and evaluation

Individual assets and the equal-weight (1/N) portfolio serve as benchmarks. The primary model is an equal-risk-contribution RP portfolio. Let w denote the vector of portfolio weights and Σ the covariance matrix. Portfolio volatility is defined as:

$$\sigma_p = \sqrt{w' \Sigma w} \tag{2}$$

The contribution of asset i to total portfolio risk is defined as:

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$$RC_i = \frac{w_i(\Sigma w)_i}{\sigma_p} \tag{3}$$

where σ_p denotes portfolio volatility and RC_i denotes the risk contribution of asset i. RP selects capital weights such that the four assets contribute approximately equally to total portfolio risk. Thus, it equalizes risk budgets rather than capital allocations.

To distinguish the effect of the weighting rule from that of the rebalancing mechanism, the study compares an equal-weight buy-and-hold portfolio, static RP, monthly dynamic RP, and quarterly dynamic RP. Monthly and quarterly 1/N portfolios serve as matched-frequency controls. In the baseline specification, the covariance matrix is estimated from the preceding 252 observations; 126- and 504-day windows are used for robustness checks. All portfolios are long-only, fully invested, and unleveraged, and the dynamic strategies use only information available before each rebalancing date. Performance is assessed using annualized return, annualized volatility, maximum drawdown, the Sharpe ratio, and 95% one-day historical-simulation value at risk (VaR). Turnover is defined as half the sum of the absolute differences between target and pre-trade weights. The analysis considers transaction costs of 0, 5, 10, and 20 basis points per unit of one-way turnover. Stress tests cover 19 February–23 March 2020, 3 January–12 October 2022, and 2 June–29 July 2026. Stock–bond dependence is measured primarily using a 60-day rolling correlation, with 120- and 252-day windows used for robustness checks.

4. Empirical results

4.1. Full-sample risk and return

The full-sample results first show why diversification is important before the RP weighting rule is considered. Individual assets display markedly different risk profiles: the NASDAQ-100 has the highest annualized return at 21.84% but also high volatility, while the U.S.-dollar-denominated CSI 300 records the deepest maximum drawdown at −50.85%. By comparison, the equal-weight buy-and-hold portfolio earns 13.22% annually with 11.92% volatility, a −27.44% maximum drawdown, and a Sharpe ratio of 0.840. The improvement relative to the individual assets indicates that a substantial part of the portfolio benefit already comes from combining different asset classes.

Table 1. Full-sample risk and return of major assets and portfolio strategies

Asset/strategy	Ann. return	Ann. volatility	Max drawdown	Sharpe	95% 1-day VaR
CSI 300 (USD)	5.97%	19.85%	-50.85%	0.247	1.85%
NASDAQ-100	21.84%	23.87%	-35.56%	0.806	2.35%
Gold	16.38%	17.27%	-27.69%	0.780	1.65%
U.S. 10Y Treasury	0.88%	7.67%	-26.17%	-0.201	0.76%
Equal-weight B&H	13.22%	11.92%	-27.44%	0.840	1.18%
Static RP	9.09%	8.96%	-22.40%	0.710	0.85%
Monthly 1/N	11.79%	10.36%	-24.94%	0.826	1.02%
Monthly RP	8.04%	7.91%	-23.36%	0.671	0.78%

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Table 1. (continued)

Quarterly 1/N	11.91%	10.40%	-25.04%	0.834	1.02%
Quarterly RP	8.10%	7.99%	-23.59%	0.672	0.80%

The matched-frequency comparison provides a clearer view of what the RP weighting rule adds beyond rebalancing itself. Monthly RP has volatility of 7.91%, compared with 10.36% for monthly 1/N, and its VaR is 0.78% rather than 1.02%. The quarterly comparison points in the same direction. Because each RP portfolio and its 1/N benchmark rebalance on the same dates, these risk differences cannot be attributed to rebalancing frequency alone. The additional risk reduction is accompanied by lower returns: annualized return declines from 11.79% to 8.04% in the monthly comparison and from 11.91% to 8.10% in the quarterly comparison. In this sample, therefore, RP adds volatility and short-horizon tail-risk control, but the gain comes with roughly 3.7–3.8 percentage points less annualized return and only a modest improvement in maximum drawdown.

The initial static RP allocation also shows why equal risk contributions can produce very unequal capital weights. With the 252-day estimation window, 58.27% of capital is allocated to U.S. 10-year Treasuries, compared with 9.59% to the CSI 300, 11.74% to the NASDAQ-100, and 20.40% to gold, yet each asset contributes close to 25% of total portfolio risk. The large Treasury weight reflects its lower estimated volatility rather than a higher expected return. Over this sample, that defensive allocation helps lower portfolio risk but also limits the return captured from the stronger-performing assets.

4.2. Dynamic rebalancing and transaction costs

Monthly and quarterly RP are close in both return and risk, so increasing the rebalancing frequency does not produce a clear performance advantage in this sample. Monthly RP returns 8.04% annually with 7.91% volatility, while quarterly RP returns 8.10% with 7.99% volatility. The main implementation difference is turnover: approximately 24.4% for monthly RP versus 17.6% for quarterly RP. Even under the 20-basis-point transaction-cost scenario, annualized returns fall only to about 7.99% and 8.06%, respectively, leaving the relative comparison broadly unchanged. The evidence therefore favors treating rebalancing frequency as an implementation trade-off rather than assuming that more frequent adjustment is automatically better.

4.3. Stress tests and state dependence

Three episodes are used to examine whether the relative protection of RP changes with market conditions: the COVID-19 shock in 2020, the monetary-tightening period with simultaneous stock–bond losses in 2022, and the technology and semiconductor correction in 2026. The matched-frequency 1/N portfolios are retained in these tests so that differences associated with the RP weighting rule are not mixed with differences in rebalancing frequency.

The stress tests show that the size of RP's downside protection is not stable across episodes. The contrast is strongest in 2020: the equal-weight buy-and-hold portfolio loses about 10.29%, while static RP loses about 1.59%; monthly and quarterly RP also lose less than their matched 1/N benchmarks. The gap narrows substantially in 2022, when the matched 1/N portfolios lose about 22.9% and the corresponding RP portfolios about 20.8%. In the 2026 episode, the gap widens again: monthly and quarterly RP return −3.78% and −3.69%, compared with −6.25% and −5.99% for

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monthly and quarterly 1/N. Thus, the stress-period evidence supports additional downside mitigation from RP, but not a constant degree of protection.

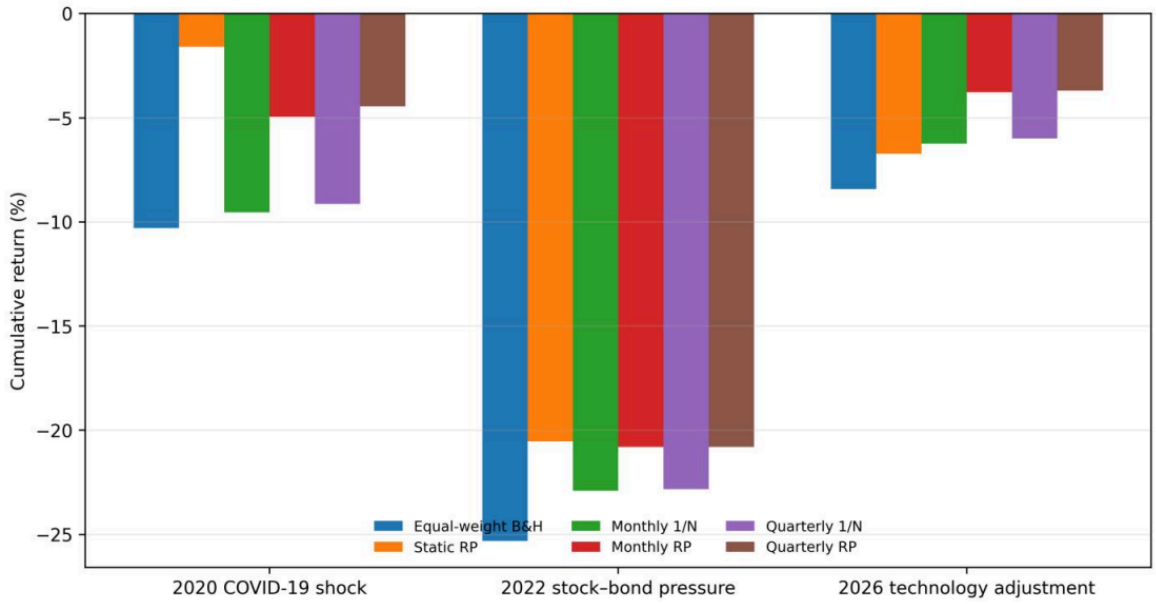

Figure 1. Cumulative returns of major portfolio strategies during stress periods

The rolling stock–bond correlations provide descriptive context for these differences. The 60-day correlation between the NASDAQ-100 and U.S. 10-year Treasuries moves from about −0.51 in March 2020 to 0.37 in October 2022 and 0.43 in July 2026; the 120- and 252-day measures move in the same general direction. The weaker RP protection in 2022 occurs alongside a positive stock–bond correlation, which is consistent with reduced diversification between the two asset classes. This evidence is descriptive rather than causal: the correlation measures help characterize changing cross-asset conditions, but they do not establish that the correlation shift caused the change in RP performance.

4.4. Robustness checks

The robustness checks do not materially alter the main interpretation. Using 126-, 252-, or 504-day estimation windows leaves RP volatility relatively low, and monthly and quarterly implementations remain close to one another while risk contributions stay near the equal-risk-budget target. Restricting the sample to common valid trading dates changes individual point estimates but preserves the broad ordering of the strategies; the rolling-correlation pattern is also directionally similar. These checks suggest that the main comparison is not driven solely by the baseline estimation window or by the calendar-alignment convention.

5. Conclusion

5.1. Main findings

(1) Cross-asset diversification accounts for a substantial share of the improvement in the portfolio's risk–return profile. In this sample, the equal-weight portfolio achieves a relatively high annualized return and Sharpe ratio while reducing the risks associated with holding a single equity asset.

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(2) RP primarily provides additional risk control rather than higher returns. Relative to matched-frequency 1/N portfolios, RP further reduces annualized volatility and 95% one-day VaR but sacrifices approximately 3.7–3.8 percentage points of annualized return. Its improvement in maximum drawdown is modest.

(3) More frequent rebalancing does not produce a clear performance advantage. Monthly and quarterly RP generate similar risk and return outcomes, while monthly RP incurs higher turnover. This conclusion remains unchanged across the transaction-cost scenarios.

(4) The protection provided by RP varies across market conditions. It is pronounced in 2020 and becomes more evident again in 2026, but it is weaker in 2022, when stocks and bonds are both under pressure. Changes in rolling stock–bond correlations are consistent with these shifts in diversification conditions.

5.2. Implications

(1) For investors who prioritize long-term returns and risk-adjusted performance, a simple cross-asset 1/N allocation may already be effective. A more complex weighting rule does not necessarily improve overall performance.

(2) For investors and institutions that prioritize volatility control and short-horizon tail-risk reduction, RP can provide an additional layer of protection. However, they must also consider the lower returns associated with that protection.

(3) Dynamic allocation does not always require more frequent rebalancing. In practice, institutions must balance timely updates to risk budgets against turnover and transaction costs.

(4) Cross-asset relationships can change over time. Risk management should therefore monitor changes in stock–bond dependence and market conditions rather than assume that historical diversification relationships will persist.

The scope of the evidence also places limits on the conclusions. The sample covers four asset classes and a finite period, so the results may not carry over unchanged to other assets or market environments. In addition, the U.S. Treasury total-return series is approximated from DGS10 with a duration–convexity method, while the transaction-cost scenarios do not represent every cost that would arise in tradable products. Finally, the rolling correlations are used to describe changes in cross-asset relationships; they are not designed to identify causal effects. Future work could test a broader asset universe and a longer sample and use more systematic procedures to distinguish market regimes.

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