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FULL LENGTH ARTICLE

Regime-Aware Digital-Asset Allocation: Balancing Participation and Downside Risk

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ABSTRACT

The exposure of cryptocurrencies has been so easy to make a part of the digital-asset platforms, but the risk engines that come with these products are frequently based on static allocations or unconditional correlation estimates. The problem is that the states that allow participation in upside potential are different from the states that allow protection against sudden drawdowns; solving both optimization problems as a single problem can lead to a portfolio that retains too much crypto risk or to a portfolio with a zero digital asset exposure. In this paper, we introduce a participation constrained, regime aware allocation framework which allocates Bitcoin and Ether alongside gold and the S&P 500. A pre-specified volatility signal separates out the normal period from the stress period, and normal period minimum variance optimization enforces a significant crypto allocation during the normal period, whereas the stress period has an explicit ceiling on the amount of crypto invested. The design is tested without look-ahead bias over 2020–2023, assuming that there is a 10 basis points per unit of turnover charge for the design. Importance of the framework for FinTech investment platforms is that it converts a qualitative risk setting into allocation rules that are easily explainable, auditable, and repeatable. The volatility of the static crypto portfolio was 64.7%, the maximum drawdown was 72.1%, and the conditional loss at 5% monthly was 34.6% for the portfolio. A crypto-only strategy had an annualized return of 12.0% and reduced volatility to 16.3% and the 5% conditional loss to 20.1%, while a regime-aware strategy had an annualized return of 14.9% and reduced volatility to 25.9% and the 5% conditional loss to 14.5%.

Keywords: Financial technology ▪ Digital assets ▪ Cryptocurrency allocation ▪ Regime switching ▪ Portfolio risk ▪ Bitcoin ▪ Ethereum ▪ Downside risk

1. INTRODUCTION

The digital-asset investing market has evolved from specialist exchanges to integrated financial-technology platforms that encompass all facets of digital assets investment: custody, trading, reporting and automated allocation. This shift has eliminated operational friction but brought a complex design challenge for portfolio managers: how to maintain meaningful exposure to digital assets efficiently without putting your portfolio's products at risk when the underlying risk takes an unexpected turn? There is no solution in the form of a risk questionnaire, or a static, "balanced" basket. Bitcoin and Ether can show different volatility, tail behavior and co-movement across the market conditions, which means that the same allocation could have very different risk at different times [1, 2, 3].

The large literature focuses on whether cryptocurrencies are a hedge for equities or a safe haven. Intentionally mixed evidence. The protection of equity portfolios during severe stress has been documented in some particular periods [4, 5] while other periodical analyses across markets suggest that cryptocurrencies are often unsuccessful at protecting equity portfolios during severe stress events [6, 7, 8]. Also, the studies on dynamic connectedness and market-efficiency reveal that dependency shifts around major shocks [9, 10, 11]. The findings suggest that it cannot be an asset property that a FinTech platform will encode the term “safe haven.” Rather, allocation rules react to changes in observable risk conditions is the relevant operational question.

In this paper, a regime-aware framework around that operational question is proposed. It applies a return on Bitcoin and Ether, where the two currencies have weights equal to the number of bitcoins, as the signal for digital asset risk; it categorizes each month based on information that is available in advance; and solves a constrained minimum variance problem. Under normal conditions, the portfolio should be balanced with 45-65

The empirical design contributes in three ways. First, it measures a clear allocation system as opposed to ad hoc asset classification as "hedges.First, it measures a clear allocation system as opposed to an ad hoc “hedges” classification of assets. Second, it distinguishes an unrestricted diversified minimum-variance benchmark from a participation-constrained strategy, and quantifies the economic cost of staying exposed to cryptocurrencies. Third, it compares all strategies in sequence, incorporates turnover costs and avoids short-run return dependence by applying a moving-block bootstrap. This yields a feasible comparison of pure crypto, crypto-only optimization, wide defensive optimization and regime-aware participation.

The remainder of the paper is organized as follows. Section 2 develops the allocation problem and positions the framework against recent evidence. Section 3 describes the data architecture and state variable. Section 4 formalizes the portfolio rules and validation design. Section 5 reports asset dynamics, out-of-sample portfolio performance, and bootstrap evidence. Section 6 discusses implications for digital-investment platforms, Section 7 identifies limitations, and Section 8 concludes.

2. THE DIGITAL-ASSET ALLOCATION CHALLENGE

2.1 From safe-haven labels to conditional allocation

Safe-haven research has established that the role of cryptocurrency is contingent on the comparison asset, event, horizon, and estimation method. During the COVID-19 shock, gold generally offered more reliable protection than Bitcoin across oil and equity markets [12, 13, 14]. Bitcoin and Ether nevertheless delivered diversification or short-lived protection in some settings [15, 4, 16]. Studies using dynamic correlations, smooth transitions, wavelets, and connectedness models therefore converge on a practical conclusion: dependence is state dependent even when their classifications differ [17, 18, 11].

This conditionality creates a platform-design dilemma. Unconstrained minimum-variance optimization may assign virtually no weight to cryptocurrency because its variance dominates the covariance matrix. A fixed crypto allocation preserves access to upside but ignores changing risk. A useful intermediate design must therefore include both a statistical risk objective and explicit product constraints. Such constraints are not defects in optimization; they encode the portfolio mandate that a digital-asset product must remain meaningfully exposed during ordinary conditions.

2.2 Positioning against related work

Table 1 summarizes representative studies. Existing research primarily evaluates whether a cryptocurrency is a hedge, diversifier, or safe haven. Portfolio applications often calculate optimal weights or hedge ratios after estimating pairwise dependence. The present study changes the unit of analysis from an asset classification to a platform allocation rule. It also contrasts unconstrained and participation-constrained solutions under the same data, covariance window, cost assumption, and out-of-sample period.

Table 1. Representative literature and the operational gap addressed in this study.

Study	Assets and setting	Method	Principal result	Gap relative to platform allocation
[6]	Cryptocurrencies and international equities; COVID-19	Downside-risk and safe-haven tests	Cryptocurrencies generally increased rather than reduced downside equity risk.	Does not translate the result into a changing multi-asset allocation rule.
[4]	Bitcoin, Ether, and S&P 500	DCC/cDCC and regression	Bitcoin and Ether acted as short-term safe havens during extreme stock declines.	Episode-specific classification; no participation constraint or chronological backtest.
[9]	Gold, oil, equities, currencies, and bonds	TVP-VAR connectedness	Cross-asset connectedness changed sharply around the pandemic outbreak.	Establishes state dependence but does not include crypto allocation constraints.
[17]	Bitcoin, gold, global equities, and currencies	Asymmetric DCC	Gold was a weak safe haven; Bitcoin was a hedge but not a reliable shelter.	Focuses on pairwise hedging rather than a platform portfolio architecture.
[14]	Gold, Bitcoin, and equities	Wavelet quantile correlation	Safe-haven properties varied across quantiles and investment horizons.	Does not test a pre-specified rule with transaction costs.
[5]	Bitcoin, Ether, and emerging equities	ADCC-GARCH; hedge ratios	Bitcoin generally protected emerging equity indices more effectively than Ether.	Portfolio weights are evaluated around event periods rather than in a unified live rule.
[8]	Bitcoin, gold, oil, and equities	TVP-VAR spillovers	Gold, but not Bitcoin, acted as a safe haven during the pandemic.	No explicit trade-off between crypto participation and downside protection.
[19]	146 cryptocurrency diversification studies	Systematic and bibliometric review	Evidence is heterogeneous across assets, horizons, and methods.	Calls for integrative portfolio evidence but does not provide an out-of-sample strategy.
This study	Bitcoin, Ether, gold, and S&P 500; 2017–2023	Lagged volatility state, constrained minimum variance, block bootstrap	Quantifies the return and downside-risk cost of preserving crypto participation.	Provides an auditable, chronological allocation architecture for FinTech platforms.

The broader evidence reinforces the need for explicit risk architecture. Herding and efficiency change during extreme events [20, 21]; investor type affects which assets function as shelters [22]; and even comparisons between the global financial crisis and COVID-19 reveal event-specific behavior [23]. Recent synthesis work concludes that portfolio benefits are real but conditional rather than universal [24, 19]. Accordingly, the framework does not assume that a risk state predicts negative cryptocurrency returns. It assumes only that a high-volatility state warrants a different exposure limit.

3. EVIDENCE ARCHITECTURE

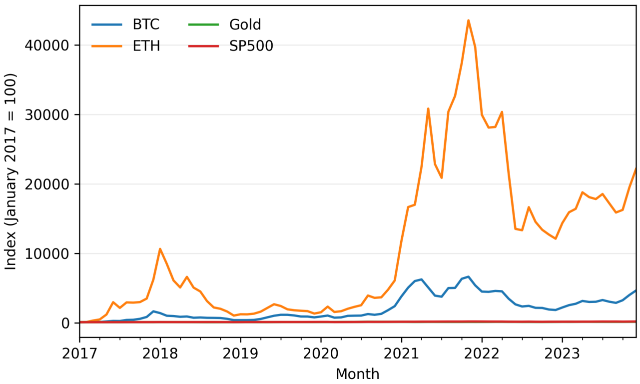
3.1 Asset panel

The study aligns monthly observations for Bitcoin (BTC), Ether (ETH), gold, and the S&P 500 price index from January 2017 through December 2023. Daily USD prices for BTC and ETH are converted to monthly arithmetic averages using the Coin Metrics community archive. Gold is represented by the monthly USD price per troy ounce sourced from the World Bank Commodity Markets Pink Sheet, and the equity series is the monthly average S&P 500 price index. The packaged analytical file contains only observations through 2023. Monthly log returns are

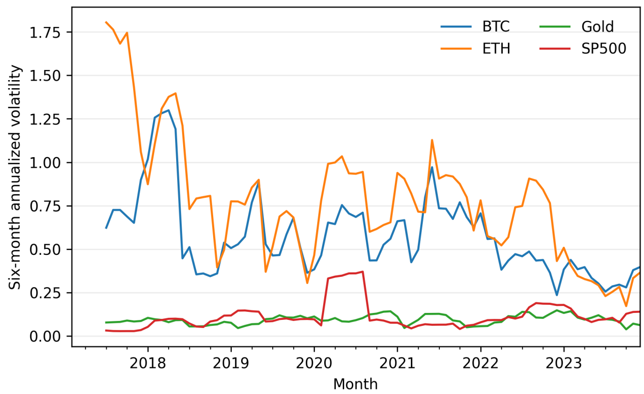
$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}), \tag{1}$$

where $P_{i,t}$ is the monthly average price of asset i. The S&P 500 measure is a price index rather than a total-return index; the comparison therefore concerns market-price exposure and does not include dividends.

The common sample contains 84 monthly price observations and 83 return observations. January 2017–December 2019 is used to calibrate the state threshold and initialize covariance estimation. January 2020–December 2023 forms a 48-month out-of-sample evaluation. This division places the pandemic shock, the subsequent digital-asset expansion, the 2022 contraction, and the 2023 recovery entirely within the test period without using their realized outcomes to set the initial threshold.



(a) Indexed monthly prices.



(b) Six-month annualized volatility.

Figure 1. Price expansion and time variation in asset risk, January 2017–December 2023.

3.2 Lagged risk state

The crypto factor is the equal-weight return

$$r_t^C = \frac{1}{2}(r_{BTC,t} + r_{ETH,t}). \tag{2}$$

At the beginning of month t, the platform observes only the preceding six returns and computes

$$\widehat{\sigma}_{t-1}^C = \sqrt{12}\,\mathrm{sd}(r_{t-6}^C, \ldots, r_{t-1}^C). \tag{3}$$

The threshold $q_{0.50}$ is the median of this statistic in the pre-2020 calibration period. The state variable is

$$S_t = \mathbb{I}\left(\widehat{\sigma}_{t-1}^C > q_{0.50}\right). \tag{4}$$

Thus $S_t = 1$ denotes stress and $S_t = 0$ denotes normal conditions. The threshold equals 65.4% annualized volatility. Seventeen of the 48 out-of-sample months are classified as stress. Because the signal is lagged, no contemporaneous return enters the state assigned to that return.

4. PORTFOLIO CONSTRUCTION AND VALIDATION

4.1 Four allocation rules

Let $\mathbf{w}_t = (w_{BTC,t}, w_{ETH,t}, w_{G,t}, w_{E,t})'$ and let $\widehat{\Sigma}_{t-1}$ be the covariance matrix estimated from the preceding 24 monthly returns. Every optimized portfolio solves

$$\min_{\mathbf{w}_t} \mathbf{w}_t'\widehat{\Sigma}_{t-1}\mathbf{w}_t, \quad \mathbf{1}'\mathbf{w}_t = 1, \quad 0 \le w_{i,t} \le 0.70. \tag{5}$$

Four rules are evaluated. *Crypto 50/50* holds 50% BTC and 50% ETH. *Crypto MinVar* solves Equation 5 using only BTC and ETH. *Diversified MinVar* uses all four assets without additional allocation constraints. *Regime-Aware* uses all four assets and adds state-dependent restrictions:

$$S_t = 0: \quad 0.45 \le w_{BTC,t} + w_{ETH,t} \le 0.65, \quad w_{G,t} \ge 0.15, \tag{6}$$

$$S_t = 1: \quad w_{BTC,t} + w_{ETH,t} \le 0.20, \quad w_{G,t} \ge 0.45. \tag{7}$$

The normal-state lower bound ensures that the strategy remains a digital-asset product rather than collapsing into a conventional defensive portfolio. The stress rule makes the protection decision explicit rather than relying on covariance estimates alone.

Portfolio log return after trading cost is

$$r_t^p = \mathbf{w}_t'\mathbf{r}_t - c\|\mathbf{w}_t - \mathbf{w}_{t-1}\|_1, \tag{8}$$

where $c = 0.001$, equivalent to 10 basis points per unit of turnover. All weights are determined using data ending at $t-1$.

4.2 Performance and inference

Annualized geometric return is $\exp(12\bar{r}) - 1$, and annualized volatility is $\sqrt{12}s_r$. The reward-to-volatility ratio uses a zero benchmark: $SR = 12\bar{r}/(\sqrt{12}s_r)$. Maximum drawdown is the minimum of $W_t/\max_{u\le t} W_u - 1$, where $W_t = \exp(\sum_{u\le t} r_u^p)$. Monthly conditional value at risk at 5% is the mean return below the empirical fifth percentile. Sortino ratios use the annualized standard deviation of negative returns. Average turnover is the monthly mean of the L_1 weight change.

Sampling uncertainty is assessed through a moving-block bootstrap. Six-month blocks are resampled with replacement until each replicate contains 48 months, preserving local serial dependence and cross-strategy alignment. Four thousand replicates estimate 95% intervals for differences in annualized mean return and volatility relative to Crypto 50/50. This comparison is descriptive rather than a claim of population optimality; its purpose is to determine whether observed risk reductions are robust to the ordering of short return blocks.

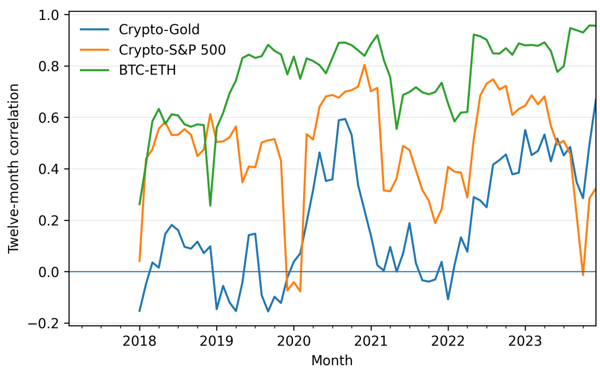
5. RESULTS

5.1 Asset behavior and changing dependence

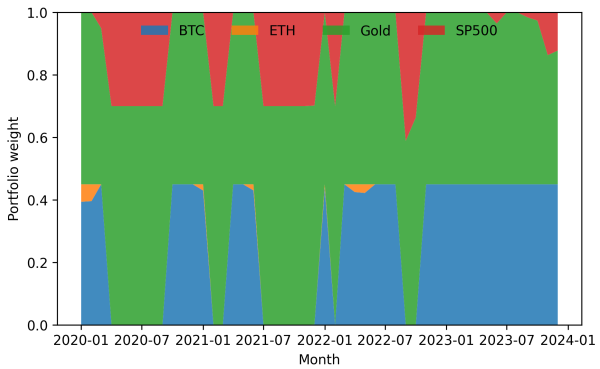
Figure 1 shows the scale asymmetry between digital and traditional assets. Over the full sample, BTC and ETH annualized volatilities were 68.3% and 100.4%, compared with 9.9% for gold and 13.6% for the S&P 500. ETH also displayed the widest monthly range, from −46.1% to 101.5%. These differences explain why unconstrained variance minimization treats digital assets as expensive risk contributors even when their correlations with gold and equities are not consistently high.

Table 2. Full-sample monthly return characteristics, 2017–2023.

Statistic	BTC	ETH	Gold	S&P 500
Mean return	0.046	0.065	0.006	0.009
Annualized volatility	0.683	1.004	0.099	0.136
Skewness	0.395	0.885	0.162	−2.488
Excess kurtosis	0.413	1.541	−0.505	11.355
Minimum	−0.377	−0.461	−0.058	−0.212
Maximum	0.669	1.015	0.064	0.061



(a) Twelve-month rolling correlations.



(b) Out-of-sample regime-aware weights.

Figure 2. Time-varying dependence and the resulting allocation path.

Rolling correlations in Figure 2 reinforce the limitation of fixed asset labels. BTC and ETH remained strongly connected, while the crypto factor's relationship with gold and equities varied around zero and changed direction over time. During the full set of classified months, BTC–ETH correlation was 0.78 in normal states and 0.68 in stress states; crypto–gold correlation remained modest at approximately 0.21–0.22. The state is therefore not a correlation regime. It is a risk-capacity regime that changes permissible exposure when recent crypto volatility exceeds a pre-specified level.

The regime-aware optimizer maintained an average crypto weight of 45.0% in normal months, almost entirely in BTC because its trailing covariance contribution was lower than ETH's. In stress months, average crypto exposure was effectively zero, gold rose to 69.1%, and the S&P 500 averaged 30.9%. This outcome demonstrates that the 20% stress ceiling is a maximum rather than a target: when covariance estimates made crypto unattractive, the risk objective selected a more defensive allocation.

5.2 Out-of-sample strategy performance

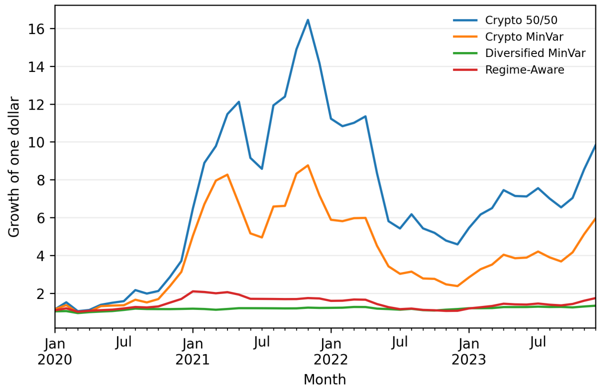
Table 3 reports the primary results. Crypto 50/50 generated the largest wealth increase and the highest reward-to-volatility ratio because the test period includes the strong 2020–2021 expansion and 2023 recovery. Its risk, however, was severe: annualized volatility reached 64.7%, maximum drawdown was 72.1%, and the average return in the worst 5% of months was −34.6%. Crypto-only minimum variance reduced volatility only modestly, because diversification between two highly related assets cannot remove the common crypto factor.

Table 3. Out-of-sample portfolio performance, January 2020–December 2023.

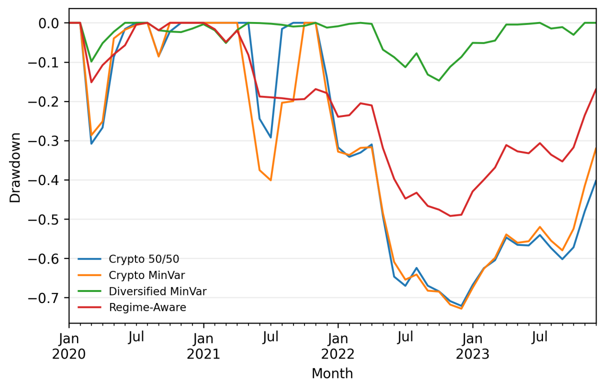
Strategy	Ann. return	Ann. vol.	Sharpe	Sortino	Max DD	CVaR 5%	Turnover
Crypto 50/50	0.770	0.647	0.883	1.384	−0.721	−0.346	0.000
Crypto MinVar	0.562	0.610	0.731	1.243	−0.728	−0.299	0.054
Diversified MinVar	0.076	0.112	0.656	0.783	−0.147	−0.078	0.048
Regime-Aware	0.149	0.259	0.536	0.803	−0.492	−0.145	0.208

Diversified MinVar delivered the strongest loss containment. Relative to Crypto 50/50, it reduced volatility by 82.7%, maximum-drawdown magnitude by 79.6%, and monthly CVaR magnitude by 77.6%. Its annualized return was only 7.6%, because the optimizer assigned almost all capital to gold and equities. This is a valid defensive benchmark but not a meaningful cryptocurrency-participation product.

Regime-Aware occupied the intended middle ground. It returned 14.9% annually, with 25.9% volatility, a 49.2% maximum drawdown, and 14.5% monthly CVaR. Relative to Crypto 50/50, volatility fell by 59.9% and CVaR magnitude by 58.1%. The drawdown reduction was smaller, at 31.8%, because the rule retained 45% crypto exposure in normal states and the lagged signal cannot eliminate losses that initiate before volatility rises. Turnover increased to 20.8% per month, including the assumed trading cost, showing that state responsiveness is not free.



(a) Growth of one dollar.



(b) Portfolio drawdowns.

Figure 3. Out-of-sample wealth and drawdown paths after transaction costs.

Figure 3 makes the trade-off visible. The pure crypto portfolios dominate terminal wealth but expose investors to prolonged and deep losses. Diversified MinVar produces a much smoother path. Regime-Aware does not match the defensive benchmark's stability, yet it preserves materially more digital-asset participation and ends with a wealth multiple of 1.74, compared with 1.34 for Diversified MinVar.

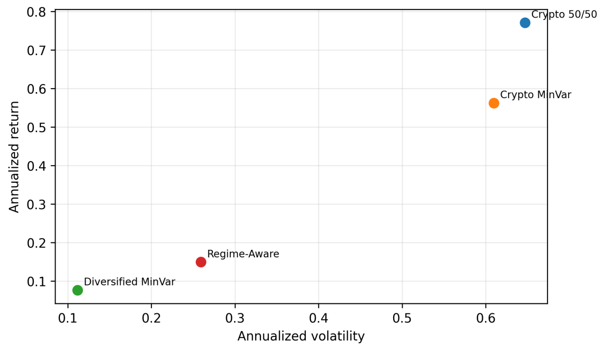
5.3 Bootstrap evidence and interpretation

The moving-block bootstrap confirms that the volatility reductions are not confined to one ordering of individual months. The 95% interval for the annualized volatility difference between Regime-Aware and Crypto 50/50 is $[-0.475, -0.276]$; for Diversified MinVar it is $[-0.667, -0.381]$. Both intervals lie below zero. The corresponding annualized mean-return intervals include zero, reflecting limited power and the extraordinary size of crypto gains in parts of the 48-month test period. The defensible conclusion is therefore about risk reduction, not return superiority.

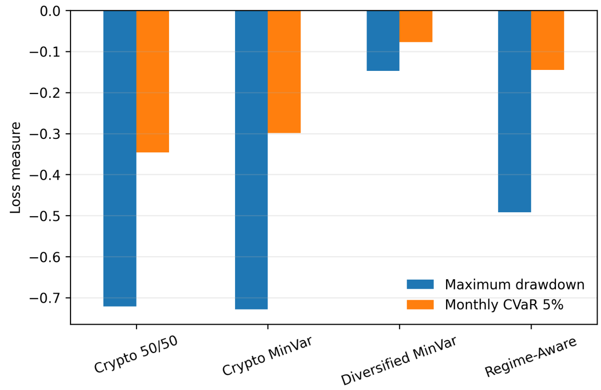
Table 4. Moving-block bootstrap differences versus Crypto 50/50.

Strategy	Δ annual vol.	Δ annual mean
Crypto MinVar	$[-0.076, 0.005]$	$[-0.344, 0.041]$
Diversified MinVar	$[-0.667, -0.381]$	$[-1.335, 0.345]$
Regime-Aware	$[-0.475, -0.276]$	$[-1.069, 0.155]$

The risk-return map in Figure 4 emphasizes three distinct products rather than one universally optimal portfolio: a high-participation crypto strategy, a low-risk conventional allocation, and a constrained hybrid. Crypto MinVar offers little structural improvement because it changes composition within the same common risk class. Regime-Aware produces a larger reduction in tail loss by changing asset classes when the risk state changes.



(a) Annualized risk and return.



(b) Maximum drawdown and monthly CVaR.

Figure 4. Performance trade-offs across the four allocation architectures.

6. IMPLICATIONS FOR FINTECH PLATFORMS

The results have direct implications for digital-investment platforms. First, risk controls should distinguish a product mandate from a statistical objective. An unconstrained optimizer minimizes variance effectively, but it can remove the digital asset that defines the product. A participation floor makes that mandate explicit and allows governance teams to see the risk cost of preserving it.

Second, platforms should disclose that regime rules reduce rather than eliminate downside exposure. A signal based on trailing volatility reacts after risk has begun to rise; it is not crash insurance. The maximum drawdown of the regime-aware strategy remained close to 50%. Suitability communication should therefore present expected allocation ranges, potential turnover, and stress behavior instead of describing the product as protected or safe.

Third, the framework supports model governance. Each component has a traceable function: a six-month lagged signal, a threshold calibrated before deployment, a 24-month covariance window, explicit weight restrictions, and a stated transaction-cost assumption. These elements can be versioned and challenged independently. Such transparency is particularly important where a platform uses automated rebalancing and must explain why exposure changed.

Fourth, results should be presented as a menu of risk architectures. The fully diversified minimum-variance portfolio is appropriate when capital preservation dominates digital-asset participation. The regime-aware solution is appropriate only when participation is an explicit objective and the investor accepts the remaining drawdown. The static crypto portfolio is a high-risk reference, not a neutral benchmark.

7. LIMITATIONS

The study uses monthly average prices, a four-asset universe, and a 48-month out-of-sample window. Monthly data reduce microstructure noise but can obscure intramonth crashes and recovery. The S&P 500 series excludes dividends, and the analysis does not include stablecoins, bonds, cash yields, or cryptocurrency-specific trading frictions. The volatility threshold and allocation limits are pre-specified for transparency rather than optimized for return; alternative windows and thresholds could produce different outcomes. Minimum-variance weights are sensitive to covariance estimation, although the long-only bounds reduce extreme solutions. Finally, the bootstrap quantifies sampling variation in the observed return sequence but does not represent structural breaks outside 2017–2023.

Future work should test the architecture with higher-frequency rebalancing, robust covariance estimators, liquidity constraints, tax effects, and multiple digital-asset sleeves. It should also examine whether platform-level behavioral controls, such as delayed re-entry or drawdown budgets, improve protection without producing excessive turnover.

8. CONCLUSION

Static diversification doesn't solve the problem in digital-assets: maintaining participation in cryptocurrency and managing risk downside are conflicting goals—with market conditions determining their respective significance. In this paper, a new transparent regime-aware allocation rule is presented which incorporates a lagged crypto-volatility state, participation and protection constraints. The results of the chronological test reveal that the primary avenue for reducing risk is through cross-asset diversification, rather than optimizing within a strictly BTC and ETH-heavy portfolio.

There was no one strategy which was superior in all criteria. Crypto 50/50 had the best return and reward to volatility ratio along with the highest tail losses. Diversified MinVar provided the best protection, with almost no exposure to crypto. In normal times, Regime-Aware kept a meaningful digital-asset mandate in place, and modestly lowered their exposure when stressed, with a reduction in volatility and conditional tail loss of approximately 60% compared to static crypto, while also taking an average hit to their returns, turnover, and even the magnitude of drawdown. The practical relevance, therefore, does not amount to better forecasting abilities. It is an actionable means for FinTech platforms to articulate and quantify the price of participation vs protection.

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