

Risk-adjusted performance, performance persistence, and portfolio diversification of multi-crypto exchange-traded products

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ABSTRACT

The proliferation of cryptocurrency-based exchange-traded products (ETPs) presents investors with a product-selection and portfolio-allocation challenge that the existing literature has examined only partially. This study constructs an exploratory, integrated four-stage investor-facing framework, including: risk-adjusted performance, out-of-sample persistence, cross-asset positioning, and portfolio diversification. The framework was applied to fifteen multi-crypto ETPs spanning Canada, Switzerland, the United States, and Brazil over 1 June 2022 to 31 December 2025. The performance varies; annual returns ranged from -34.68% to 46.24% and rankings shift materially when downside-risk metrics were applied. The persistence evidence is statistically insignificant; the Top-minus-Bottom spread is 0.64% per month (Newey-West $t = 0.63$), implying that historical alpha has limited predictive value. The ETPs occupy a distinct risk-return profile relative to BTC, ETH, gold, and the domestic equity index. In the portfolio stage, a 10% BTC sleeve shows the largest improvement in which the annualized return of +4.00%, Sharpe +0.253, with stable volatility and improved downside, thus combining a return effect and a diversification effect. A diversified ETP sleeve provides the most convincing ETP-based alternative, consistently outperforming a single-product sleeve on risk-adjusted metrics and turnover. The explained advantage widens once transaction costs are applied. Ultimately, the value of cryptocurrency exposure is conditional, depending on instrument form, allocation size, and investor access to spot assets.

Keywords: Cryptocurrency exchange-traded products, Performance persistence, Portfolio diversification, Risk-adjusted performance, Walk-forward backtesting

JEL Classification: G11, G23, G12, G15

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1. Introduction

Cryptocurrency has become increasingly integrated into the modern financial system with market capitalization approaching USD 3 trillion in November 2021 (Adrian et al., 2022). One indication of this integration is the cryptocurrency-based exchange-traded product (ETP), an investment vehicle

traded on a regulated exchange that provides exposure to cryptocurrency while offering operational convenience, institutional custody, and on-exchange liquidity (SIX, 2025). Such products allow investors to gain exposure to the asset class while avoiding the operational complexity of directly holding and safeguarding the underlying coins (Malhotra, 2025). Since 21Shares listed the first cryptocurrency ETP on the SIX Swiss Exchange in 2018, similar products have expanded to Canada, the United States, and Brazil, reaching 405 listed products by the end of November 2025 (SIX, 2025; ETFGI, 2025). As these products have proliferated from single-asset offerings to index, basket, and thematic structures, investors have faced an increasingly important product-selection problem: determining, on a consistent basis, which products offer the most attractive investment opportunity.

In addition, these products also defining how cryptocurrency enters the financial-reporting apparatus. By converting a directly held coin into an investment vehicle with a daily net asset value and an exchange-quoted price, the wrapper makes cryptocurrency exposure reportable through conventional investment-reporting channels while resting on underlying digital assets whose accounting treatment remains divergent: measured at a fair value through net income under US GAAP (FASB, 2023), yet generally treated as an intangible asset or inventory under IFRS (IFRS Interpretations Committee, 2019). For the record, this study does not test any accounting treatment. These standards are included because they establish the daily performance series analyzed in this study, which effectively represent fair value series. This makes the empirical results relevant to preparers and users of financial statements, with the reporting implications discussed further in Section 4.6.

Evaluating the problem requires more than a comparison of nominal returns. Cryptocurrency return distributions are defined by extreme volatility, skewness, and heavy tails, implying a greater probability of extreme outcomes than a normal distribution would assume (Muvunza, 2020), thus both total and downside risk must enter the assessment. The literature has established several relevant findings. Conlon et al. (2025) show that ranking cryptocurrency funds on historical alpha yields out-of-sample persistence in abnormal returns. Tang et al. (2025) show that the exchange-traded structure prices more efficiently and tracks underlying value better than a non-redeemable trust. Malhotra (2025) finds that digital-asset ETFs can surpass global equities on a risk-adjusted basis, and Han et al. (2024) document meaningful diversification benefits from cryptocurrency exposure relative to a stock-bond benchmark.

Two gaps remain unaddressed. First, the evidence on persistence points in opposite directions: Bianchi & Babiak (2022) show that the significance of positive fund alpha weakens once cross-sectional correlation is applied, directly contradicting the predictive value reported by Conlon et al. (2025). Whether this divergence reflects differences in instrument type, sample period, or benchmark specification remains unclear. Second, the documented advantages are narrower than they initially appear: Tang et al. (2025) establish their result exclusively for Bitcoin, Malhotra (2025) evaluates digital-asset ETFs at the aggregate group level rather than on a product-by-product basis and finds that their advantage over U.S. equities is uneven, while the diversification benefit reported by Han et al. (2024) derives from factor portfolios constructed from thousands of coins rather than from investment products directly available to investors.

Multi-crypto exchange-traded products differ from the instruments examined in this literature in three ways that are important for evaluation. First, they track an index or basket rather than being actively managed, so performance differences primarily reflect underlying-asset construction rather than manager skill. Consequently, past performance has a different informational meaning than it does for actively managed funds. Second, they are listed and directly investable at quoted market prices, unlike the factor portfolios constructed by Han et al. (2024), meaning that the returns available to

investors are observable rather than simulated or constructed. Third, they have a daily net asset value within a regulated exchange-traded structure, unlike direct spot holdings, and are therefore subject to prospectus and risk-disclosure requirements that shape the information available to investors. Evidence from actively managed cryptocurrency funds, single-asset products, or constructed factor portfolios therefore cannot be directly generalized to this class of instruments.

This study therefore addresses an emerging question: under what conditions, if any, are multi-crypto exchange-traded products worth holding? Answering this question requires four sequential steps, with each providing the basis for the next: assessing how risk-adjusted performance varies across products (RQ1); determining whether such performance persists out of sample (RQ2); comparing the products with major cryptocurrency assets and traditional alternatives (RQ3); and evaluating whether their inclusion improves a traditional portfolio (RQ4).

The integration, therefore, is not the contribution in itself; what comes after the integration is. Evaluating the same fifteen products across four consistent stages reveals that a conclusion reached at one stage does not necessarily carry over to the next. The products with the highest raw returns are not the strongest on a risk-adjusted basis, nor the most resilient to downside risk. Products selected for the Top portfolio based on historical alpha prove vulnerable to reversal, indicating that selection based on past performance does not necessarily translate into a portfolio advantage. Moreover, a diversified ETP sleeve outperforms the single best-performing product, a conclusion that cannot be reached from performance rankings alone. These findings require at least two stages to be applied sequentially to the same sample using a consistent methodology, and none would be observable if the stages were conducted separately, as in prior studies.

The framework is applied to fifteen cryptocurrency-based ETPs traded in Canada, Switzerland, the United States, and Brazil from 1 June 2022 to 31 December 2025. Because the sample spans several structures, including ETFs, ETNs, and ETCs, the evaluation is conducted at the level of exposure faced by investors rather than as a comparison of legal structures. All prices are converted to a common USD valuation base to ensure comparability across markets. Consequently, returns on non-USD products incorporate exchange-rate movements that are not separately identified in the analysis.

The analysis is exploratory, examining a selected group of fifteen products over a single period in a highly volatile and regime-dependent market. Accordingly, the results are interpreted as evidence for the sampled products rather than generalized to the global population of cryptocurrency-based ETPs. Within these boundaries, the framework demonstrates how product selection and allocation decisions can be evaluated jointly. It also shows that the value of cryptocurrency exposure in this sample is conditional on instrument structure, allocation size, and correlation with the baseline portfolio, including whether investors can hold spot cryptocurrency directly or must access the asset class through a regulated, diversified product.

2. Literature Review and Research Questions

Risk-adjusted performance and downside sensitivity (RQ1)

Modern Portfolio Theory ([Markowitz, 1952](#)) emphasizes that an asset should be evaluated not by its return in isolation, but by the return it generates relative to the risk borne. This risk–return trade-off underpins the standard risk-adjusted measures and implies that products with similar nominal returns need not be equivalent once their risk profiles are taken into account. For cryptocurrency-based products, the trade-off is particularly consequential, since both return dispersion and tail behavior vary widely across underlying-asset structures.

Evaluating cryptocurrency-based ETP performance requires metrics beyond nominal return. [Baur et al. \(2018\)](#) find that cryptocurrency exhibits substantially higher volatility than traditional assets alongside negative skewness and high kurtosis, elevating the probability of extreme negative outcomes. Metrics treating upside and downside variability symmetrically risk understating tail exposure for such distributions, while [Eling & Schuhmacher \(2007\)](#) show that Sharpe ratio rankings can shift materially for assets with pronounced tail risk, making downside-oriented metrics a necessary check.

A comprehensive evaluation therefore combines total-risk metrics, including: annual return, annual volatility, and the Sharpe, Sortino, and Omega ratios, with downside and tail-risk metrics, including: Maximum Drawdown, Value at Risk at 95% (VaR95), and Expected Shortfall at 95% (ES95) ([Jorion, 2001](#); [Keating & Shadwick, 2002](#); [Rockafellar & Uryasev, 2002](#); [Sortino & van der Meer, 1991](#)). The Treynor ratio and Information Ratio are excluded because their benchmark-relative standardization is reserved for the persistence stage. Consequently, this stage evaluates standalone exposure from the investor's perspective. The full set of metrics is used rather than a single summary ratio because no single ratio can capture both symmetric and downside risk. Given the heterogeneity in index construction, basket composition, and thematic focus across the fifteen products, dispersion in risk-adjusted outcomes is expected. The ordering of products is also expected to be sensitive to whether risk is measured symmetrically or on the downside only. This leads to the first research question:

RQ1: How does risk-adjusted performance vary across multi-crypto exchange-traded products?

Out-of-sample persistence (RQ2)

Persistence in this study refers to the tendency of products with relatively superior historical performance to maintain superior performance in subsequent periods, representing an out-of-sample test rather than a retrospective description ([Elton et al., 1996](#)). The concept is economically important because investors make forward-looking assumption: if past performance is merely a historical artifact, allocating capital to past winners provides no predictive value.

The assumption connects directly to market efficiency. Under the semi-strong form of the efficient market hypothesis, publicly observable past performance should not predict future abnormal returns, thus the evidence of persistence would suggest that the pricing of these products does not fully impound available information. The same question underlies the active-versus-passive management debate: if past winners cannot be identified reliably ex ante, selection effort adds cost without adding expected value ([Elton et al., 1996](#)).

The evidence for persistence in cryptocurrency-based instruments remains unsettled. [Conlon et al. \(2025\)](#) find that ranking cryptocurrency funds based on 12-month historical alpha yields out-of-sample persistence in abnormal returns, supporting the view that past performance has predictive value. In contrast, [Bianchi & Babiak \(2022\)](#) find that positive alpha among cryptocurrency funds weakens once cross-sectional correlation is accounted for, suggesting that past performance may not be robust. Whether this divergence reflects differences in instrument type, such as funds versus investable exchange-traded products, sample period, or benchmark choice remains unresolved. This study addresses the issue directly using rolling 12-month CAPM alpha against the BDA Index as the formation signal, following [Conlon et al. \(2025\)](#). Because the BDA Index is a broad cryptocurrency market proxy rather than a multifactor model, the resulting alpha represents performance relative to the broad market rather than an isolation of all sources of risk. It is therefore used as a parsimonious and transparent ranking signal ([Liu et al., 2022](#)). Persistence is indicated if products ranked in the Top

portfolio based on historical alpha consistently outperform those ranked in the Bottom portfolio during the subsequent holding month. This leads to the second research question:

RQ2: Do multi-crypto exchange-traded products exhibit out-of-sample performance persistence across consecutive evaluation windows?

Positioning against alternative assets (RQ3)

Asset pricing implies that instruments carrying different risk exposures should exhibit systematically different risk–return characteristics. Comparing ETPs with the assets an investor already holds beforehand is therefore the natural way to establish where they sit within the available opportunity set. Placing ETPs in investor context requires comparison within the viable alternatives in investors’ perspectives. [Tang et al. \(2025\)](#) show that exchange-traded structures exhibit more efficient pricing and track underlying values more accurately than non-redeemable trusts for Bitcoin-based products, suggesting structural advantages associated with the ETP form. [Malhotra \(2025\)](#) finds that digital-asset ETFs can outperform global equities on a risk-adjusted basis but do not consistently outperform U.S. equities. Their returns also exhibit a strong correlation with the BDA Index, at approximately 0.90, indicating that the group broadly tracks the overall cryptocurrency market. [Han et al. \(2024\)](#) document meaningful diversification benefits from cryptocurrency factor portfolios relative to a stock-bond benchmark, though their portfolios are constructed from thousands of coins rather than listed investable products.

The comparison also draws on the safe-haven and alternative-asset literature. Gold is the recognized safe-haven asset ([Baur & Lucey, 2010](#)), valued for retaining or gaining value when equity markets decline, while a domestic equity index (IHSG) represents the investor’s core growth exposure. Whether cryptocurrency-based products behave as an alternative asset class in their own right, or as a high-beta extension of the cryptocurrency market, is precisely the comparative question at issue.

Because ETPs vary in underlying-asset breadth and concentration, their risk–return profile, both individually and as an equally weighted aggregate, is expected to sit between direct spot cryptocurrency exposure and conventional assets. This leads to the third research question:

RQ3: How do multi-crypto exchange-traded products compare with major cryptocurrency assets and traditional assets in terms of risk–return characteristics?

Portfolio diversification and value-add (RQ4)

Taken together, the preceding contexts give rise to a question: does adding cryptocurrency exposure improve an investor’s portfolio? [Markowitz \(1952\)](#) establishes that portfolio value is not determined by an asset’s standalone return, but by its contribution to the overall return–risk combination, including the joint effect of its expected return, its own risk, and its correlation with existing holdings. A low-correlation asset can improve portfolio efficiency even with moderate standalone performance if it reduces co-movement with the baseline; conversely, a high-return asset with high correlation may provide little diversification benefit. What matters formally is the asset’s marginal contribution to portfolio risk, specifically the change in portfolio variance produced by a small increase in its weight. This depends on the asset’s covariance with existing holdings rather than on its own volatility alone. An allocation is therefore justified only when the marginal return it adds exceeds the marginal risk it contributes.

[DeMiguel et al. \(2009\)](#) demonstrate that naive (1/N) diversification benchmarks are difficult to outperform out-of-sample when estimation error is present, making them an appropriate baseline for

evaluating cryptocurrency additions. Because cryptocurrency assets generally exhibit low correlation with equities and gold (Krückeberg & Scholz, 2019), they offer a potential diversification benefit. However, low correlation alone is not sufficient, as whether this benefit translates into portfolio improvement depends on the form and size of the exposure. This motivates a comparison between a diversified ETP sleeve (P1a), a single-product sleeve (P1b), and direct spot-crypto additions (P2, P3) at measured allocations, evaluated out of sample so that the results reflect decision-relevant information. Since the marginal risk contribution depends on both the size and form of the exposure, any improvement is expected to be conditional rather than uniform. This leads to the fourth research question:

RQ4: Does adding multi-crypto exchange-traded product exposure improve the risk-adjusted performance and diversification benefits of a traditional portfolio?

The four research questions form a sequential chain. RQ1 establishes which products merit consideration; RQ2 examines whether historical performance is a reliable guide to future performance; RQ3 locates the ETPs within the broader investment universe; and RQ4 converts those findings into an allocation decision. Since each stage supplies the input for the next, they are addressed sequentially rather than independently.

3. Methodology

Sample and comparison assets

The study evaluates fifteen multi-crypto exchange-traded products (ETPs), which refers to instruments that provide on-exchange exposure to more than one cryptocurrency, spanning ETF, ETN, and ETC legal structures. The sample is drawn by purposive sampling on three criteria: 1. multi-crypto characteristics in which consist of exposure to a cryptocurrency index, basket, thematic index, or other multi-asset structure, 2. availability of historical price data on Yahoo Finance, and 3. data coverage sufficient for consistent use across all four analytical stages. The multi-crypto focus is deliberate: it aligns with the portfolio logic of the study, which means the assets are judged by their contribution to diversification rather than by a single exposure, and it targets a segment that, unlike single-asset Bitcoin funds, remains under-examined. Applying these criteria yielded fifteen products. The products trade across four markets, including Canada, Switzerland, the United States, and Brazil, and are listed in Table 1.

Purposive selection from a single data source introduces two acknowledged limitations: selection bias, because products absent from Yahoo Finance or with insufficient coverage are excluded; and survivorship bias, because inactive or data-deficient products may be omitted. The sample is therefore treated as a consistently analyzed selected group rather than a statistical population, and structural heterogeneity across ETF, ETN, and ETC formats means performance is evaluated at the investor-facing exposure level, not as a comparison of legal structure or issuer risk. The study is accordingly characterized as an exploratory, investor-focused empirical analysis of selected multi-crypto exchange-traded products. Its findings describe the fifteen products examined over the observation window and are not presented as evidence applicable to the global ETP market.

Four comparison assets relevant to an investor's decision are added: Bitcoin (BTC), Ethereum (ETH), gold, and IHSG (Indonesia Stock Exchange: IDX Composite). For the cross-asset stage, an equal-weight portfolio of the fifteen ETPs serves as a collective aggregate. For the portfolio stage, BTC and ETH are the candidate additions, while gold and IHSG form the baseline portfolio.

Table 1. Sample of cryptocurrency-based exchange-traded products

Product Name	Country	Ticker	Issuer	Product Type	Main Cryptocurrency Assets
Evolve Cryptocurrencies ETF	Canada	ETC-U.TO	Evolve Funds Group Inc.	ETF	Bitcoin, Ether, Solana, XRP (market-cap weighted)
21Shares Bitwise Select 10 Large Cap Crypto Index Grayscale	Switzerland	KEYS.SW	21Shares	ETP	Top 10 market-cap cryptocurrencies
CoinDesk Crypto 5 ETF	US	GDLC	Grayscale Investments	ETF	5 largest cryptocurrencies (CoinDesk 5 Index, ~90% market cap)
Bitwise 10 Crypto Index Fund	US	BITW	Bitwise Asset Management	ETF	10 large cryptocurrency assets (BTC ~73%, ETH ~15.9%, XRP ~5%)
21Shares Crypto Basket 10 Core ETP	Switzerland	HODLX.SW	21Shares	ETP	Top 10 market-cap cryptocurrencies
21Shares Crypto Basket Equal Weight ETP	Switzerland	HODLV.SW	21Shares	ETP	Top 5 market-cap cryptocurrencies (equally weighted)
21Shares Crypto Basket Index ETP	Switzerland	HODL.SW	21Shares	ETP	Top 5 market-cap cryptocurrencies
21Shares Bitcoin Ethereum Core ETP	Switzerland	ABBA.SW	21Shares	ETP	Bitcoin and Ethereum
WisdomTree Physical Crypto Altcoins	Switzerland	WALT.SW	WisdomTree	ETP	Large-cap altcoins
21Shares Crypto Mid-Cap Index ETP	Switzerland	ALTS.SW	21Shares	ETP	8 large cryptocurrency assets excluding BTC and ETH
Hashdex Nasdaq Crypto Index Fundo De Indice (ETF)	Brazil	HASH11.SA	Hashdex	ETF	Replicates the Nasdaq Crypto Index (NCI)
Hashdex Defi Index Fundo De Indice (ETF)	Brazil	DEFI11.SA	Hashdex	ETF	Replicates the CF DeFi Composite Index
Hashdex Smart Contract Platforms Fundo De Indice (ETF)	Brazil	WEB311.SA	Hashdex	ETF	Replicates the CF Web 3.0 Smart Contract Platforms Index
Empiricus Teva Cryptocurrencies Top 20 Index Fund Investment Abroad (CRIPTO20 EMPC)	Brazil	CRPT11.SA	Empiricus	ETF	Replicates the Teva Cryptocurrency Top 20 Index
Hashdex Crypto Metaverse Fundo De Indice (ETF)	Brazil	META11.SA	Hashdex	ETF	Replicates the CF Digital Culture Index

Source: compiled by the author from issuer documentation and Yahoo Finance. Products are listed across four markets (Canada, Switzerland, the United States, and Brazil). ETF = exchange-traded fund; ETP = exchange-traded product.

Data, sources, and currency base

The study uses secondary daily data for 1 June 2022–31 December 2025. This window is set by consistent historical-data availability, the limited listing age of several multi-crypto ETPs, and the need to analyze all products over an identical horizon; it is also long enough to form the rolling 12-month signal for the persistence stage while leaving an adequate out-of-sample holding period for the walk-forward backtest. Daily prices for the fifteen ETPs and for BTC, ETH, gold, and IHSG are obtained from Yahoo Finance, as are the exchange rates used for currency conversion (BRLUSD=X, CHFUSD=X, and IDR=X).

All prices are denominated in USD as a single common valuation base so that products and assets from several markets are comparable within one framework; non-USD instruments are converted to USD before returns are calculated. A consequence is that returns on non-USD instruments embed both local-currency price change and the exchange-rate movement against USD; the study does not decompose these two components. Results are therefore read as a USD-based investor evaluation.

The risk-free rate is DGS1, the one-year U.S. Treasury yield, obtained from Federal Reserve Economic Data (FRED). DGS1 is recorded daily but as an annualized yield; it is converted to a daily rate (Section 3.3) before excess returns are formed. The one-year tenor is chosen to match the twelve-month evaluation and signal-formation window used in the persistence stage.

A single USD risk-free proxy is applied to all instruments, while the four considerations support this. First, listing jurisdiction does not necessarily define the denomination currency. Although the fifteen products are listed in four different markets, they trade in only three currencies, and four of them are already USD-denominated, including the sole Canadian product, which trades as a USD unit class rather than in Canadian dollars, and one Swiss-listed product. Second, under fully hedged conditions the Sharpe ratio of an asset is invariant to the investor's base currency: a CHF-based investor buying a USD asset and hedging the currency earns approximately $r_{\text{USD}} + (r_{\text{f_CHF}} - r_{\text{f_USD}})$ through the forward premium, so that subtracting $r_{\text{f_CHF}}$ returns exactly the USD excess return, with volatility unchanged. The USD-based figures reported therefore represent the asset's risk premium for any hedged investor. Third, because all prices are converted to USD before returns are computed, applying a local risk-free rate to a USD-denominated return would create a currency mismatch: the interest-rate differential is already embedded in the exchange-rate movement, and subtracting it again would double-count it. Fourth, a single proxy keeps the Sharpe ratio, the Sortino ratio, and CAPM alpha defined on a common basis across fifteen products and four comparison assets, which is the purpose of the single valuation base.

A sensitivity analysis is nevertheless conducted in which each product is evaluated in its own trading currency using the corresponding local risk-free rate: the Swiss Confederation one-year spot rate for CHF-denominated products (Swiss National Bank), the Selic policy target rate for BRL-denominated products (Bank for International Settlements, CBPOL dataset), and DGS1 for USD-denominated products. The Spearman rank correlation between the USD-based and local-currency Sharpe rankings is 0.97; five of fifteen products change rank, and the ordering within each currency group is preserved without exception, so every rank change is a cross-currency effect rather than a change in the assessment of any product. The four highest-ranked and three lowest-ranked products are unchanged. The cryptocurrency-market benchmark, used only in the persistence stage, is the S&P Cryptocurrency Broad Digital Asset (BDA) Index, obtained from [S&P Dow Jones Indices \(2025\)](#). Data are processed in Microsoft Excel and Python (Google Colab), aligned to a uniform trading calendar; the data are daily throughout and the persistence stage is evaluated at monthly frequency.

Returns and excess returns

Two return forms are used. Log returns serve the performance, persistence-signal, and cross-asset stages; simple returns serve the portfolio stage. For asset i on day t with price $P(i,t)$:

$$r_{\log}(i, t) = \ln \left[\frac{P(i,t)}{P(i,t-1)} \right] \quad (1)$$

$$r_{\text{simple}}(i, t) = \frac{P(i,t)}{P(i,t-1)} - 1 \quad (2)$$

Log returns are additive over time and suit the risk-adjusted measures; simple returns suit portfolio simulation, since portfolio simple return is the weighted average of constituent simple returns (Tsay, 2010). The annualized DGS1 yield $y(t)$ is converted to a daily rate (252 trading days assumed):

$$r_{f,\log}(t) = \frac{\ln(1+y_t)}{252} \quad (3)$$

$$r_{f,\text{simple}}(t) = (1 + y_t)^{1/252} - 1 \quad (4)$$

Excess returns are then $er_{\log}(i,t) = r_{\log}(i,t) - rf_{\log}(t)$ and $er_{\text{simple}}(i,t) = r_{\text{simple}}(i,t) - rf_{\text{simple}}(t)$.

Performance metrics (RQ1)

Each ETP is evaluated on eight metrics computed from daily log returns and annualized at 252 trading days: annual return, annual volatility, the Sharpe, Sortino, and Omega ratios, Maximum Drawdown, ES95, and VaR95. Annual return is computed in log form and converted to a simple annual return for interpretability:

$$AR_{\log}(i) = \bar{r}_{\log}(i) \times 252 \quad (5)$$

$$AR_{\text{simple}}(i) = \exp(AR_{\log}(i)) - 1 \quad (6)$$

Annual volatility is $\sigma_{\text{annual}}(i) = SD(r_{\log}(i)) \times \sqrt{252}$. The Sharpe ratio standardizes mean excess return by total risk; the Sortino ratio replaces total risk with downside deviation $DD(i)$ computed against a zero target; the Omega ratio compares total gains to total losses about a zero threshold across the full return distribution (Keating & Shadwick, 2002; Sharpe, 1994; Sortino & van der Meer, 1991):

$$\text{Sharpe}(i) = \frac{\bar{er}_{\log}(i)}{SD(r_{\log}(i))} \times \sqrt{252} \quad (7)$$

$$DD(i) = \sqrt{\frac{1}{T} \sum_t \min(0, er_{\log}(i, t))^2} \quad (8)$$

$$\text{Sortino}(i) = \frac{\bar{er}_{\log}(i)}{DD(i)} \times \sqrt{252} \quad (9)$$

$$\Omega(i) = \frac{\sum_t \max(er_{\log}(i, t), 0)}{\sum_t \max(-er_{\log}(i, t), 0)} \quad (10)$$

Maximum Drawdown is the worst peak-to-trough decline of the wealth index $W(i,t) = \exp(\sum_{\tau \leq t} r_{\log}(i, \tau))$: $MDD(i) = \min_t [W(i,t) / \max_{s \leq t} W(i,s) - 1]$ (Magdon-Ismail et al., 2004). VaR95 is the

5% quantile of daily log returns, $\text{VaR}(i, 95) = Q_{\{0.05\}}(r_{\log}(i))$, and ES95 is the conditional mean below that quantile, $\text{ES}(i, 95) = E[r_{\log}(i) \mid r_{\log}(i) \leq \text{VaR}(i, 95)]$ (Jorion, 2001; Rockafellar & Uryasev, 2002). The Treynor ratio and Information Ratio are deliberately excluded because they standardize against beta or a benchmark, a role already filled by CAPM alpha in the persistence stage (Eling & Schuhmacher, 2007). A rank-sensitivity check re-ranks products once Maximum Drawdown and ES95 are included alongside the standard ratios. Differences across products at this stage are evaluative comparisons, not tests of statistical significance.

Persistence procedure (RQ2)

Persistence is tested on a risk-adjusted basis. At each month-end, a one-factor CAPM is estimated for each product over the trailing twelve months of daily excess log returns, with the BDA Index as the cryptocurrency-market proxy:

$$er_{\log}(i, t) = \alpha(i, \tau) + \beta(i, \tau) \cdot er_{\log}(m, t) + \varepsilon(i, t) \quad (11)$$

The rolling 12-month window is applied because cryptocurrency markets are non-stationary; re-estimating at each month-end keeps the signal point-in-time and responsive to regime shifts, consistent with the persistence literature including Conlon et al. (2025). The daily intercept is annualized ($\alpha_{\text{annual}}(i, \tau) = \alpha_{\text{daily}}(i, \tau) \times 252$) and used as the formation signal. Products are sorted by annualized alpha and split equally into Top, Mid, and Bottom portfolios of five products each. Each formation month t is paired with holding month $t+1$, evaluated on monthly simple excess returns. Each portfolio's holding-period return is the simple average of its five members' monthly simple excess returns, and the Top-Bottom spread is $er_{\text{simple}}(\text{Top}, t+1) - er_{\text{simple}}(\text{Bottom}, t+1)$.

Two inferential tests follow, both estimated with HAC Newey-West standard errors at lag 6 (Newey & West, 1987): (i) a mean-excess-return test ($er_{\text{simple}}(p, t) = \mu_p + u_{\{p, t\}}$), and (ii) a holding-period CAPM-alpha regression ($er_{\text{simple}}(p, t) = \alpha_p + \beta_p \cdot er_{\text{simple}}(m, t) + \varepsilon_{\{p, t\}}$). Persistence would be indicated if the Top portfolio consistently outperforms Bottom and the spread is positive and statistically significant. This stage is the study's sole inferential test.

The one-factor specification is a deliberate design choice rather than an oversight, and five considerations support it. First, alpha functions here as a ranking signal, not as an estimate of skill: what the design requires is a stable, transparent, point-in-time ordering of products, not a complete decomposition of risk. Second, the procedure deliberately replicates the formation-and-holding design of Conlon et al. (2025), whose divergence from Bianchi & Babiak (2022) motivates RQ2; adding factors would break the direct comparability that makes this replication informative. Third, the signal is re-estimated on rolling twelve-month windows of daily data for fifteen products, and a multi-factor model over so short a window raises estimation noise that enters the ranking signal directly. Fourth, the cryptocurrency factors of Liu et al. (2022) are constructed from coin-level data covering hundreds of assets and are not available as public series adjustable with the trading calendar of listed products. Fifth, the direction of the resulting bias is known: because the BDA Index is a broad market proxy, part of what is measured as alpha may be compensation for unmodelled factor exposure. This works against finding persistence rather than in favor of it, meaning a looser benchmark should make persistence easier to detect, not harder, so the specification does not account for the weak persistence reported in Section 4.2.

To confirm that the finding does not depend on this specification, the persistence procedure is repeated with two alternative formation signals that require no factor model: the raw twelve-month

mean excess return and the twelve-month Sharpe ratio, both computed on the same window and the same observations as the CAPM regression. The three signals differ materially in the products they select, agreeing on 68.8% to 69.9% of group assignments with a mean within-month Spearman rank correlation of 0.76 to 0.78, so the comparison is a genuine test rather than a restatement. The Top-minus-Bottom spread nonetheless remains statistically insignificant under all three: 0.64% per month ($t = 0.63$) for CAPM alpha, 0.26% ($t = 0.17$) for raw excess return, and 0.42% ($t = 0.31$) for the Sharpe signal. The alternative signals in fact produce smaller spreads than the baseline, indicating that the one-factor choice is not what suppresses evidence of persistence.

Cross-asset comparison (RQ3)

The fifteen ETPs, their equal-weight aggregate, and the four comparison assets (BTC, ETH, gold, IHSG) are evaluated on the same eight metrics in a USD-common framework. Each asset is ranked for each metric, with higher values considered preferable for return and the three ratios, while lower values, particularly those closer to zero, are preferred for volatility, Maximum Drawdown, and ES95. The results are then summarized using the average standard rank and average downside rank. As a robustness check, all metrics are recomputed using only trading dates shared by every compared asset to assess whether the conclusions depend on differences in sample length. Differences at this stage represent evaluative comparisons rather than statistical significance tests.

Walk-forward portfolio backtest (RQ4)

The baseline portfolio, P0, consists of 50% IHSG and 50% gold, representing a naive ($1/N$) diversification benchmark rather than an optimized allocation (DeMiguel et al., 2009). Its daily return is calculated as $r(P0,t) = 0.5 \cdot r(IHSG,t) + 0.5 \cdot r(GOLD,t)$. Four addition strategies are tested: P1a, the Winner ETP Portfolio, consisting of the five Top products from the persistence stage with equal weighting; P1b, the Best Single ETP, consisting of the product with the highest formation-window Sharpe ratio selected dynamically; P2, BTC; and P3, ETH. Each strategy is tested at crypto sleeve sizes of 10%, 15%, and 20%, with the remaining allocation, $(1-s)$, divided equally between IHSG and gold.

Evaluation is conducted using a walk-forward, out-of-sample, monthly rebalanced backtest. Target weights are determined using signals available at the end of the preceding month, applied at the beginning of each holding month, and allowed to drift with daily returns until the next rebalancing date. Thus, each allocation decision relies only on information available before the holding period. Strategies are evaluated based on cumulative return, annualized return, annualized volatility, Sharpe, Sortino, and Calmar ratios, Maximum Drawdown, VaR95, ES95, and average one-way turnover as a proxy for implementability. Results represent gross performance before market frictions, as transaction costs, bid-ask spreads, slippage, and liquidity constraints are not modeled.

Each strategy is also expressed as a delta versus P0, and daily correlations between each crypto exposure and IHSG, gold, and P0 identify the source of any improvement. A return effect denotes a higher annualized return; a diversification effect denotes a return gain with low correlation to P0, unchanged volatility, and stable or improved downside risk; a return effect with risk trade-off denotes a return gain with higher volatility, a lower Sharpe or Sortino ratio, or worse Maximum Drawdown or ES95. Robustness comprises (i) a return-form check recomputing portfolio returns in log form from daily NAV changes, and (ii) a baseline-composition sensitivity check using 60% IHSG + 40% gold and 40% IHSG + 60% gold, with weight sensitivity captured across the three sleeve sizes. Portfolio comparisons are evaluative assessments of allocation strategies; they are not joint significance tests of metric differences.

4. Results and Discussion

Risk-adjusted performance and downside sensitivity

Across the fifteen ETPs, performance over the observation period is highly heterogeneous (Table 2). Annual returns range from “34.68% to 46.24%, while annual volatility ranges from 47.34% to 75.81%, indicating substantial differences in product profiles. The highest annual returns are recorded by GDLC (46.24%) and BITW (46.09%), followed by HODLV.SW (42.56%) and HODLX.SW (30.98%). On a risk-adjusted basis, however, the strongest results shift toward the 21Shares basket products. HODLV.SW records the best or near-best Sharpe (0.582), Sortino (0.836), and Omega (1.119) ratios, while HODLX.SW combines the lowest annual volatility (47.34%) with the most controlled downside, including a Maximum Drawdown of “38.97%, ES95 of “6.87%, and VaR95 of “4.19%. META11.SA is the weakest product across most headline metrics, with an annual return of “34.68%, a Sharpe ratio of “0.619, and the most severe downside, including a Maximum Drawdown of “86.06%, ES95 of “11.28%, and VaR95 of “7.49%.

Table 2. Principal performance of cryptocurrency-based exchange-traded products

Ticker	Ann. Ret. (%)	Ann. Vol. (%)	Sharpe	Sortino	Omega	Max DD (%)	ES95 (%)	VaR95 (%)	R-Ret	R-Vol	R-Sh	R-So	R-Om	R-DD	R-ES
ABBA.SW	25.44	52.96	0.346	0.486	1.064	-45.65	-7.54	-5.26	7	4	6	7	6	4	4
ALTS.SW	20.27	61.32	0.230	0.312	1.043	-46.87	-9.24	-5.41	11	9	11	11	11	7	11
BITW	46.09	62.91	0.533	0.774	1.096	-68.74	-8.90	-5.51	2	10	2	2	2	14	10
CRPT11.SA	21.34	52.32	0.287	0.420	1.051	-46.51	-7.23	-5.19	9	2	9	9	9	5	2
DEFI11.SA	-9.68	73.82	-0.197	-0.268	0.967	-66.65	-10.64	-7.21	14	12	14	14	14	13	13
ETC-U.TO	26.10	54.79	0.344	0.496	1.067	-47.96	-7.76	-4.93	5	7	7	5	5	8	6
GDLC	46.24	67.14	0.501	0.751	1.090	-65.68	-8.74	-5.74	1	11	3	3	4	12	9
HASH11.SA	25.54	52.35	0.354	0.494	1.064	-49.00	-7.35	-4.80	6	3	5	6	7	9	3
HODL.SW	20.83	55.49	0.263	0.357	1.049	-46.64	-8.35	-5.18	10	8	10	10	10	6	8
HODLV.SW	42.56	53.46	0.582	0.836	1.119	-41.15	-7.66	-4.86	3	5	1	1	1	2	5
HODLX.SW	30.98	47.34	0.478	0.663	1.095	-38.97	-6.87	-4.19	4	1	4	4	3	1	1
KEYS.SW	23.52	54.74	0.307	0.422	1.058	-45.23	-8.04	-5.08	8	6	8	8	8	3	7
META11.SA	-34.68	75.81	-0.619	-0.850	0.896	-86.06	-11.28	-7.49	15	15	15	15	15	15	15
WALT.SW	18.24	75.31	0.165	0.229	1.031	-59.66	-11.05	-6.64	12	14	12	12	12	10	14
WEB311.SA	-4.67	74.79	-0.122	-0.171	0.980	-64.77	-10.12	-7.65	13	13	13	13	13	11	12

Note: Annual return and volatility are annualized from daily log returns (252 trading days). Max DD = Maximum Drawdown; ES95/ VaR95 = Expected Shortfall/Value at Risk at 95%. R- columns are within-sample ranks (1 = best) across the fifteen ETPs.

Table 3. Ranking sensitivity of cryptocurrency-based exchange-traded products

Ticker	R-Sh	R-So	R-Om	R-DD	R-ES	Avg. Std. Rank	Avg. Down. Rank	Gap (Down – Std)
ABBA.SW	6	7	6	4	4	6.333	4	-2.333
ALTS.SW	11	11	11	7	11	11	9	-2
BITW	2	2	2	14	10	2	12	10
CRPT11.SA	9	9	9	5	2	9	3.5	-5.5
DEFI11.SA	14	14	14	13	13	14	13	-1
ETC-U.TO	7	5	5	8	6	5.667	7	1.333
GDLC	3	3	4	12	9	3.333	10.5	7.167
HASH11.SA	5	6	7	9	3	6	6	0
HODL.SW	10	10	10	6	8	10	7	-3
HODLV.SW	1	1	1	2	5	1	3.5	2.5
HODLX.SW	4	4	3	1	1	3.667	1	-2.667
KEYS.SW	8	8	8	3	7	8	5	-3
META11.SA	15	15	15	15	15	15	15	0
WALT.SW	12	12	12	10	14	12	12	0
WEB311.SA	13	13	13	11	12	13	11.5	-1.5

Note: Avg. Std. Rank = mean of Sharpe, Sortino, and Omega ranks; Avg. Down. Rank = mean of Maximum Drawdown and ES95 ranks. Gap = Avg. Down. Rank – Avg. Std. Rank; a positive gap indicates a product that ranks worse on downside risk than on standard risk-adjusted metrics.

The return leaders are not the risk-adjusted leaders, reflecting a return-downside trade-off: BITW and GDLC pair their high returns with deep drawdowns of “68.74% and “65.68%. Rankings move once downside metrics are applied. A rank-sensitivity analysis (Table 3) shows BITW and GDLC falling sharply when Maximum Drawdown and ES95 enter the assessment (standard-to-downside rank gaps of +10.0 and +7.167), while HODLX.SW and CRPT11.SA improve (gaps of “2.667 and “5.5); HODLX.SW attains the best average downside rank in the sample.

Out-of-sample persistence

Evidence of out-of-sample persistence is limited and statistically weak (Table 4). The Top portfolio earns a higher mean monthly excess return than the Bottom portfolio (4.09% vs. 3.45%), resulting in a positive Top–Bottom spread of 0.64% per month. However, its Newey-West t-statistic is only 0.63, well below conventional significance levels. The pattern is also inconsistent, as the Mid portfolio, rather than the Top portfolio, records the highest mean excess return (4.87% per month). The CAPM alpha tests reinforce this finding: only the Mid portfolio exhibits a statistically significant positive alpha (1.16% per month, $t = 2.35$), whereas the Top portfolio’s alpha is small and insignificant (0.33%, $t = 0.57$), and the Top–Bottom alpha spread, although positive at 1.04%, is also insignificant ($t = 1.21$). Cumulatively (Figure 1), the Mid portfolio accumulates the highest value, while the Top–Bottom spread, although ending positive, fluctuates without developing into a stable winner-minus-loser effect. The same conclusion holds under two alternative formation signals that require no factor model, with the Top–Bottom spread remaining insignificant in every case.

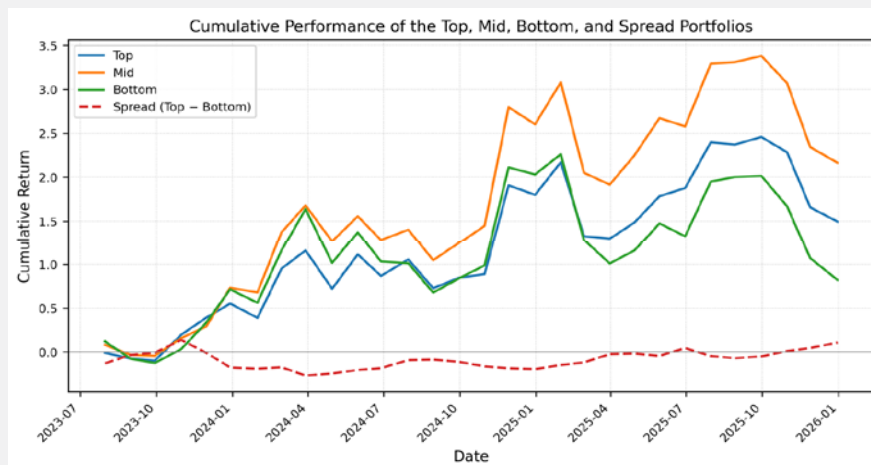


Figure 1. Cumulative performance of the top, mid, bottom, and spread portfolios

Table 4. Performance persistence of cryptocurrency-based exchange-traded products

Portfolio	Mean Excess Return	t (Mean, NW6)	Alpha	t (Alpha, NW6)	Beta
Top	4.09%	1.84	0.0033	0.57	1.0956
Mid	4.87%	1.88	0.0116	2.35	1.0812
Bottom	3.45%	1.16	-0.0071	-1.02	1.2123
Spread Top – Bottom	0.64%	0.63	0.0104	1.21	-0.1166

Note: Mean excess return is the monthly out-of-sample mean; t-statistics use Newey-West standard errors with six lags (NW6).

Alpha and Beta are from the CAPM regression of portfolio excess returns on the crypto-market benchmark.

Table 5. Comparison of cryptocurrency-based ETPs with alternative assets

Asset	Ann. Ret. (%)	Ann. Vol. (%)	Sharpe	Sortino	Omega	Max DD (%)	ES95 (%)	VaR95 (%)	R-Ret	R-Vol	R-Sh	R-So	R-Om	R-DD	R-ES	Avg. Std. Rank	Avg. Down. Rank
ABBA.SW	25.44	52.96	0.346	0.486	1.064	-45.65	-7.54	-5.26	10	8	9	10	9	7	8	9,333	7,667
ALTS.SW	20.27	61.32	0.230	0.312	1.043	-46.87	-9.24	-5.41	14	13	14	14	14	10	15	14	12,667
BITW	46.09	62.91	0.533	0.774	1.096	-68.74	-8.90	-5.51	2	14	3	3	3	19	14	3	15,667
CRPT11.SA	21.34	52.32	0.287	0.420	1.051	-46.51	-7.23	-5.19	12	6	12	12	12	8	6	12	6,667
DEFI11.SA	-9.68	73.82	-0.197	-0.268	0.967	-66.65	-10.64	-7.21	19	17	19	19	19	18	18	19	17,667
ETC-U.TO	26.10	54.79	0.344	0.496	1.067	-47.96	-7.76	-4.93	8	11	10	8	8	11	10	8,667	10,667
GDLC	46.24	67.14	0.501	0.751	1.090	-65.68	-8.74	-5.74	1	15	4	4	4	6	17	13	4,667
HASH11.SA	25.54	52.35	0.354	0.494	1.064	-49.00	-7.35	-4.80	9	7	8	9	10	12	7	9	8,667
HODL.SW	20.83	55.49	0.263	0.357	1.049	-46.64	-8.35	-5.18	13	12	13	13	13	9	12	13	11
HODLV.SW	42.56	53.46	0.582	0.836	1.119	-41.15	-7.66	-4.86	3	9	2	2	2	4	9	2	7,333
HODLX.SW	30.98	47.34	0.478	0.663	1.095	-38.97	-6.87	-4.19	5	3	6	6	4	3	4	5,333	3,333
KEYS.SW	23.52	54.74	0.307	0.422	1.058	-45.23	-8.04	-5.08	11	10	11	11	11	6	11	11	9
META11.SA	-34.68	75.81	-0.619	-0.850	0.896	-86.06	-11.28	-7.49	20	20	20	20	20	20	20	20	20
WALT.SW	18.24	75.31	0.165	0.229	1.031	-59.66	-11.05	-6.64	15	19	15	15	15	14	19	15	17,333
WEB311.SA	-4.67	74.79	-0.122	-0.171	0.980	-64.77	-10.12	-7.65	18	18	17	17	17	16	17	17	17
ETF_EW	28.83	47.55	0.441	0.614	1.080	-43.77	-6.70	-4.41	6	4	7	7	7	5	3	7	4
BTC	34.02	50.42	0.495	0.716	1.094	-49.68	-7.14	-4.63	4	5	5	5	5	13	5	5	7,667
ETH	14.15	68.24	0.130	0.184	1.024	-63.79	-9.83	-6.18	16	16	16	16	16	15	16	16	15,667
GOLD	26.94	16.35	1.194	1.710	1.227	-13.26	-2.38	-1.60	7	1	1	1	1	1	1	1	1
IHSC_USD	1.39	17.75	-0.167	-0.225	0.971	-32.26	-2.53	-1.73	17	2	18	18	18	2	2	18	2

Note: ETF_EW is the equal-weight aggregate of the fifteen ETPs. Ranks (1 = best) are computed across all twenty assets. Avg. Std. Rank = mean of Sharpe, Sortino, and Omega ranks; Avg. Down. Rank = mean of Volatility, Maximum Drawdown, and ES95 ranks.

Positioning against alternatives

Placed alongside BTC, ETH, gold, and IHSG, the ETPs occupy a distinct middle ground (Table 5; Figure 2). Gold is the strongest asset overall: without the highest return, it records the best Sharpe, Sortino, and Omega ratios and the most controlled Maximum Drawdown, ES95, and VaR95, owing to lower volatility and low co-movement with cryptocurrency, so it holds up when cryptocurrency markets are stressed. IHSG, in USD terms, is weak, with very low return and a negative Sharpe ratio. The ETPs sit between BTC and ETH: HODLV.SW exceeds BTC on the combination of return and risk-adjusted performance, while HODLX.SW stands out on downside control; BITW and GDLC again show high returns with deeper drawdowns. As a collective, the equal-weight ETP aggregate is more attractive than ETH and far stronger than IHSG, remains below gold on risk efficiency and downside resilience, and relative to BTC offers lower return with slightly more controlled downside. The strict-common-dates robustness check leaves these conclusions unchanged.

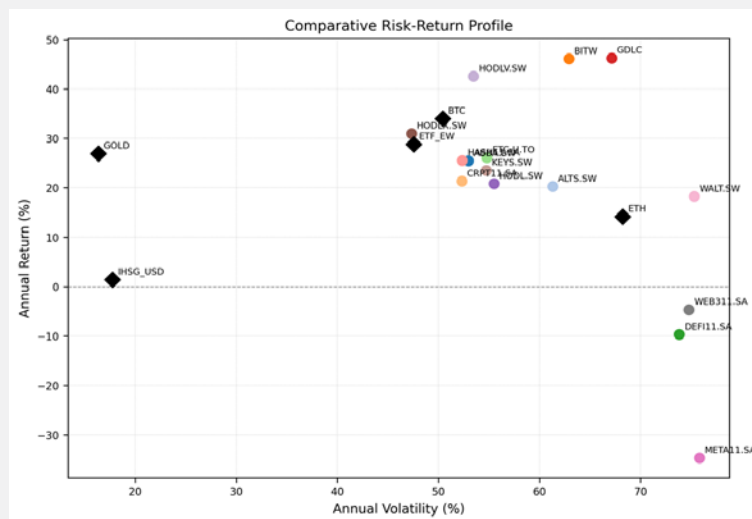


Figure 2. Risk-return distribution of cryptocurrency-based ETPs and alternative assets

Portfolio role and the source of improvement

The portfolio stage translates the preceding evidence into an allocation decision. The baseline portfolio, P0, consisting of 50% IHSG and 50% gold, already exhibits strong risk-adjusted performance, with a cumulative return of 64.09%, annualized return of 21.31%, annualized volatility of 12.86%, Sharpe ratio of 1.225, Sortino ratio of 1.775, Calmar ratio of 1.790, Maximum Drawdown of “11.90%, and ES95 of “1.81% (Table 6). Therefore, cryptocurrency additions must be evaluated not only for their ability to increase returns but also for their ability to preserve risk efficiency and downside resilience.

All four strategies increase returns relative to P0, but the quality of these gains differs substantially. Adding BTC (P2) delivers the strongest overall results. At a 10% sleeve, P2 increases the cumulative return to 78.31% and the annualized return to 25.31% while maintaining volatility at 12.85% and improving the Sharpe (1.478), Sortino (2.173), and Calmar (2.413) ratios, as well as downside measures, with a Maximum Drawdown of “10.49% and ES95 of “1.77%. At a 20% sleeve, P2 achieves the highest cumulative return (92.47%), annualized return (29.10%), Sharpe ratio (1.53), and Sortino ratio (2.30) among all strategies. The diversified Winner ETP Portfolio (P1a) is the next strongest and the most compelling ETP-based strategy. Its cumulative return increases from 77.79% to 90.82% across the three allocation levels, with

Sharpe ratios ranging from 1.45 to 1.49 and Sortino ratios from 2.15 to 2.23, although volatility increases from 13.01% to 14.66%. P1a consistently outperforms the single-product sleeve P1b, which has lower Sharpe ratios (1.32–1.38) that decline as the allocation increases. P1b also exhibits substantially higher average one-way turnover (7.48%–13.76%) than P1a (4.30%–7.39%), indicating that concentration in a single “best” product is both less efficient and more difficult to implement. ETH (P3) is the weakest strategy. Although every P3 variant outperforms P0 in terms of return, it does not achieve comparable risk-adjusted performance. At a 20% allocation, its performance deteriorates, with an annualized return of 24.86%, volatility of 17.06%, Sharpe ratio of 1.13, Sortino ratio of 1.68, Calmar ratio of 1.12, Maximum Drawdown of “22.16%, and ES95 of “2.29%. The cumulative NAV paths (Figure 3) are consistent with these results, with P2 at 20% establishing the widest margin over P0, while P3 trails the other strategies.

Table 6. Out-of-sample performance summary of all portfolio strategies

Strategy	%	Cum. Return	Annual Return	Annual Volatility	Sharpe	Sortino	Calmar	Max Drawdown	ES95	Avg. Oneway Turnover
P0	0	64.09%	21.31%	12.86%	1.22	1.78	1.79	-11.90%	-1.81%	1.21%
P1a_10	10	77.79%	25.17%	13.01%	1.45	2.15	2.16	-11.63%	-1.78%	4.30%
P1a_15	15	84.40%	26.96%	13.67%	1.49	2.22	2.08	-12.98%	-1.88%	5.85%
P1a_20	20	90.82%	28.67%	14.66%	1.49	2.23	2.00	-14.33%	-2.01%	7.39%
P1b_10	10	75.70%	24.59%	13.43%	1.38	2.00	2.05	-11.98%	-1.90%	7.48%
P1b_15	15	81.20%	26.10%	14.53%	1.37	2.00	1.93	-13.50%	-2.05%	10.63%
P1b_20	20	86.47%	27.52%	16.05%	1.32	1.94	1.83	-15.01%	-2.27%	13.76%
P2_10	10	78.31%	25.31%	12.85%	1.48	2.17	2.41	-10.49%	-1.77%	1.73%
P2_15	15	85.41%	27.23%	13.51%	1.52	2.26	2.41	-11.29%	-1.85%	1.98%
P2_20	20	92.47%	29.10%	14.54%	1.53	2.30	2.41	-12.08%	-1.96%	2.20%
P3_10	10	71.28%	23.36%	13.64%	1.29	1.88	1.49	-15.72%	-1.88%	1.94%
P3_15	15	74.21%	24.18%	15.10%	1.22	1.80	1.27	-18.99%	-2.05%	2.35%
P3_20	20	76.68%	24.86%	17.06%	1.13	1.68	1.12	-22.16%	-2.29%	2.73%

Note: P0 is the 50% IHSG / 50% gold baseline. P1a = diversified Winner ETP Portfolio; P1b = single best ETP; P2 = Bitcoin sleeve; P3 = Ethereum sleeve. The % column is the crypto sleeve weight. Walk-forward, monthly-rebalanced, out-of-sample results.

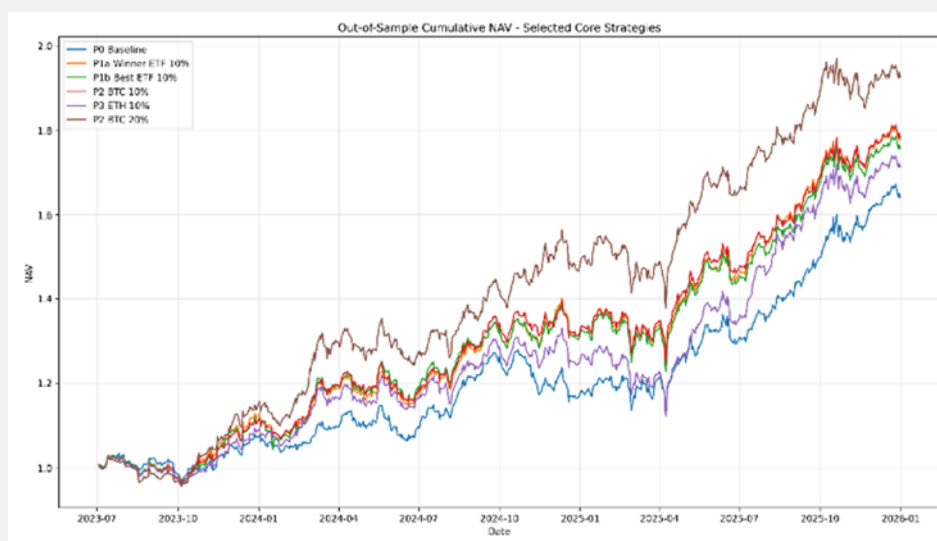


Figure 3. Out-of-sample cumulative NAV of selected core strategies

Reading the changes relative to P0 alongside the correlation structure (Tables 7 and 8) clarifies the underlying mechanism. Each cryptocurrency exposure is weakly correlated with the baseline, with correlations of 0.080 for BTC, 0.074 for ETH, 0.134 for the Winner ETP Portfolio, and 0.120 for the Best Single ETP. Thus, each provides a potential diversification channel, although low correlation alone does not guarantee a portfolio benefit. P2_10 shows the strongest pattern, combining a 4.00% increase in annualized return with essentially unchanged volatility (“0.01%), increases in the Sharpe (+0.253) and Sortino (+0.398) ratios, and improvements in both Maximum Drawdown and ES95. This represents a genuine combination of return and diversification effects. P1a_10 exhibits a similar but more modest pattern, with a 3.85% increase in annualized return, Sharpe improvement of 0.228, and Sortino improvement of 0.371, without worsening tail risk. P3 at higher allocations shows the opposite pattern. At 20%, the 3.55% increase in annualized return is accompanied by a 4.20% increase in volatility, a 0.095 decline in the Sharpe ratio, and a 10.26-percentage-point deterioration in Maximum Drawdown, indicating a return effect accompanied by a clear risk trade-off rather than a diversification gain. Three patterns therefore emerge: P2_10 and P1a_10 combine return and diversification effects; P1a at 15–20%, P1b at all allocation levels, and P2 at higher allocations retain the return effect but begin to exhibit greater risk or turnover; and P3 at 15–20% generates higher returns with limited economic benefit.

Table 7. Daily correlations of cryptocurrency exposures with IHSG, gold, and P0

Cryptocurrency Exposure	Correlation with Gold	Correlation with IHSG	Correlation with P0
Winner ETP Portfolio	0.037	0.154	0.134
Best Single ETP	0.061	0.112	0.120
BTC	0.059	0.056	0.080
ETH	0.041	0.065	0.074

Note: Pearson correlations of daily returns. P0 is the 50% IHSG / 50% gold baseline portfolio. Winner ETP Portfolio and Best Single ETP are the crypto sleeves used in strategies P1a and P1b.

The results reported so far consist of gross of transaction costs. Since the strategies differ substantially in turnover, a cost sensitivity is run in which a one-way cost of 25, 50, or 100 basis points is charged on gross turnover at each monthly rebalance, with the baseline portfolio charged on the same basis since it is also rebalanced monthly. The cost is absorbed into the daily return series rather than deducted from the terminal value alone, so all reported measures, including the Sharpe and Sortino ratios, are net of costs.

Costs do not overturn the ranking, in contrast, they sharpen it. At 100 basis points the annualized return drag is 3.00 percentage points for P1b against 1.67 for P1a, 0.56 for P2, and 0.32 for P0, following the turnover ordering directly. The advantage of the diversified sleeve over the single-product sleeve therefore widens rather than narrows: at a 20% allocation on the 50/50 baseline, the P1a-P1b Sharpe gap grows from 0.172 gross to 0.252 at 100 basis points, and P1a outperforms P1b in all thirty-six combinations of baseline, sleeve size, and cost level. Nine of thirty-six strategy-baseline combinations fail to beat P0 once costs reach 100 basis points, and all nine are high-turnover variants: P1b and P3 at 15% and 20% allocations. P1b at 20% on the 40/60 baseline already falls below P0 at 25 basis points.

Two qualifications follow. First, the low-turnover strategies gain relative ground: because P2 trades least, its margin over every ETP-based route widens once costs are applied, which reinforces rather than softens the finding that direct Bitcoin exposure is the strongest single addition in this sample. Second, the model charges a proportional cost on traded value and does not represent bid-ask spreads or market impact explicitly, so the figures are a sensitivity band rather than a realized cost estimate.

Table 8. Summary of performance changes relative to baseline portfolio P0

Strategy	Δ Annual Return	Δ Annual Volatility	Δ Sharpe	Δ Sortino	Δ Calmar	Δ Max Drawdown	Δ ES95	Δ Oneway Turnover	Tradeoff Flag
P0	0.00%	0.00%	0.00	0.00	0.00	0.00%	0.00%	0.00%	Baseline
P1a_10	3.85%	0.15%	0.23	0.37	0.37	0.28%	0.03%	3.08%	Improved without worsening tail risk
P1a_15	5.65%	0.81%	0.27	0.44	0.29	-1.08%	-0.07%	4.64%	Improved, but tail risk worsens
P1a_20	7.36%	1.80%	0.27	0.45	0.21	-2.43%	-0.20%	6.18%	Improving, but tail risk worsens
P1b_10	3.28%	0.57%	0.15	0.23	0.26	-0.08%	-0.09%	6.27%	Improved, but tail risk worsens
P1b_15	4.79%	1.68%	0.14	0.22	0.14	-1.60%	-0.24%	9.42%	Improved, but tail risk worsens
P1b_20	6.20%	3.19%	0.10	0.17	0.04	-3.10%	-0.46%	12.54%	Improved, but tail risk worsens
P2_10	4.00%	-0.01%	0.25	0.40	0.62	1.41%	0.04%	0.52%	Improved without worsening tail risk
P2_15	5.92%	0.65%	0.30	0.49	0.62	0.62%	-0.04%	0.77%	Improved, but tail risk worsens
P2_20	7.79%	1.69%	0.30	0.52	0.62	-0.18%	-0.15%	0.99%	Improved, but tail risk worsens
P3_10	2.05%	0.78%	0.06	0.10	-0.30	-3.82%	-0.07%	0.73%	Improved, but tail risk worsens
P3_15	2.87%	2.24%	-0.01	0.02	-0.52	-7.09%	-0.24%	1.14%	Improved, but tail risk worsens
P3_20	3.55%	4.20%	-0.10	-0.09	-0.67	-10.26%	-0.48%	1.52%	Worse performance and worse tail risk

Note: Each row reports the change in the metric relative to baseline P0. Δ Sharpe, Δ Sortino, and Δ Calmar are level differences; all other columns are differences expressed in the original units of Table 6.

Robustness

The portfolio conclusions are stable across specifications (detailed exhibits in the appendices). Recomputing portfolio returns in log rather than simple form leaves the direction of the return and Sharpe-ratio deltas and the annualized-return rankings unchanged. Under baseline-composition sensitivity (Table 9), P2_10 remains a combined return-and-diversification strategy across all three baselines, lifting annualized return by +4.00% at 50/50, +4.23% at 60/40, and +3.76% at 40/60, with correlation to P0 near 0.08 throughout; P1a_10 holds this character at the 50/50 and defensive baselines but shifts to a return-with-trade-off classification under the equity-heavy 60/40 baseline as ES95 marginally worsens, while P3 stays weak across all baselines. The core ordering, with P2 as the strongest strategy, P1a as the most compelling ETP route and superior to P1b, and P3 as the weakest, is not an artifact of a particular return measure, allocation level, or baseline specification.

Table 9. Summary of sensitivity analysis to baseline composition

Baseline Composition	Strategy	Corr. with P0	Δ Annual Return	Δ Volatility	Δ Max Drawdown	Δ ES95	Classification
50% IHSG + 50% Gold	P2_10	0.080	4.00%	-0.01%	1.41%	0.04%	Return effect and diversification effect
50% IHSG + 50% Gold	P1a_10	0.134	3.85%	0.15%	0.28%	0.03%	Return effect and diversification effect
50% IHSG + 50% Gold	P3_20	0.074	3.55%	4.20%	-10.26%	-0.48%	Weak risk-adjusted improvement
60% IHSG + 40% Gold	P2_10	0.078	4.23%	-0.09%	2.21%	0.02%	Return effect and diversification effect
60% IHSG + 40% Gold	P1a_10	0.146	4.08%	0.14%	1.10%	-0.03%	Return effect with risk trade-off
60% IHSG + 40% Gold	P3_20	0.075	4.02%	4.03%	-8.88%	-0.51%	Weak risk-adjusted improvement
40% IHSG + 60% Gold	P2_10	0.080	3.76%	-0.02%	1.28%	0.06%	Return effect and diversification effect
40% IHSG + 60% Gold	P1a_10	0.116	3.62%	0.08%	0.12%	0.06%	Return effect and diversification effect
40% IHSG + 60% Gold	P3_20	0.070	3.07%	4.15%	-10.99%	-0.41%	Weak risk-adjusted improvement

Note: Sensitivity of the 10% crypto-sleeve strategies (and P3 at 20%) to the baseline IHSG/gold split. Corr. with P0 is the correlation of the cryptocurrency exposure with the corresponding baseline. Δ columns are changes relative to that baseline.

5. Discussion

Return, downside risk, and the form of exposure

The rank reversals in Section 4.1 imply that ETP selection cannot rest on return or the Sharpe ratio alone: the most attractive products are those that balance return against drawdown, not those with the highest headline return. The positioning against alternative assets in Section 4.3 follows from the form of exposure. BTC and ETH are single spot assets whose performance reflects one coin directly, whereas the ETPs deliver index-, basket-, or theme-based exposure; products blending large-cap exposure with cross-coin diversification look more balanced than ETH or approach BTC on some metrics, while more thematic or concentrated products lag when their segment diverges from the majors. The ETPs are therefore a separate digital-asset exposure with their own risk-return profile, not a substitute for gold, IHSG, BTC, or ETH.

Why historical alpha is not a reliable selection signal

The composition of the sorted groups is consistent with the weak persistence reported in Section 4.2. The Top group, formed on the highest historical alpha, holds the most aggressive large-cap exposures, including products such as GDLC and BITW that earned formation-period alpha through sharp rallies and fall hardest when the market corrects. The Mid group's more balanced constituents are less dragged down by those reversals, so its edge is associated with the Top group's vulnerability to reversal rather than with predictive power of its own. High historical alpha thus behaves as a record of past performance, not a reliable forward signal.

Interpreted against the debate the study set out to resolve, this finding sits closer to [Bianchi & Babiak \(2022\)](#), whose highlight positive cryptocurrency-fund alphas weaken once cross-sectional structure is applied, compared to the persistence documented by [Conlon et al. \(2025\)](#). Several design differences may help account for the divergence. The object of study differs: [Conlon et al. \(2025\)](#) evaluate actively managed cryptocurrency funds, whereas this study evaluates investable, listed multi-crypto ETPs that are largely index-, basket-, or theme-tracking and therefore offer less scope for the manager-driven outperformance an alpha sort is designed to capture. The persistence design also differs: while both sort on a 12-month historical alpha and evaluate the next holding month, this study measures alpha against a single broad benchmark (the BDA Index) under a one-factor CAPM, so the signal reflects relative performance above the market rather than skill isolated from multiple risk factors. Finally, the evaluation horizon is confined to a single, volatile, regime-dependent period (June 2022–December 2025); because cryptocurrency markets are non-stationary, the predictive content of historical alpha may itself be period-specific. These differences are offered as cautious explanations rather than tested propositions.

The results provide limited evidence of exploitable performance persistence within the sample and observation period. However, establishing a claim about market efficiency would require a broader set of instruments, a longer observation horizon, and a richer benchmark specification than the one-factor model used in this study. Accordingly, no such claim is made. The practical lesson is that historical alpha should inform, not dictate, product selection, which reframes the portfolio question from “pick the best product” toward “add measured, diversified exposure”.

Diversification mechanism and investor access

The portfolio results in Section 4.4 connect directly to portfolio theory. Consistent with [Markowitz \(1952\)](#), an asset improves a portfolio through its contribution to the overall return–risk combination rather than through its standalone return. This mechanism is evident in P2_10 and P1a_10, where low correlation allows additional return without a proportional increase in risk. The benefit is conditional, however, as it does not appear uniformly across assets or allocation levels. Diversification within the cryptocurrency sleeve also matters, as the diversified P1a outperforms the concentrated P1b. This provides investable-product evidence relevant to the diversification question examined by Han et al. (2024) using factor portfolios constructed from thousands of cryptocurrencies, but here demonstrated using instruments that investors can directly hold.

The headline finding that BTC dominates must also be interpreted in light of investor access. P2's superiority assumes that investors can hold and custody spot cryptocurrency, whereas many investors, particularly institutions subject to mandate, regulatory, or custody constraints, cannot. For these investors, the diversified ETP sleeve is not merely an inferior substitute for Bitcoin but a rational, regulated route to cryptocurrency exposure. P1a still adds meaningful value relative to P0 by

increasing both return and risk-adjusted performance at moderate allocations without worsening tail risk at the 10% level. The economically strongest strategies are therefore those in which return gains are accompanied by controlled risk and manageable turnover, namely P2_10 and P1a_10. P2_20 delivers the largest return gain but begins to involve a clearer risk trade-off, while the higher turnover of P1b would erode its gross advantage once transaction costs are considered, as the cost analysis in Section 4.4 confirms. These results reinforce that the value of cryptocurrency exposure depends not merely on whether an investor holds “crypto,” but on how that exposure is constructed and implemented.

Reporting, disclosure, and valuation implications

The exchange-traded wrapper is what makes cryptocurrency exposure reportable within conventional portfolio infrastructure. Held directly, a cryptocurrency position falls outside standard investment-reporting workflows and requires bespoke custody and valuation treatment. When held through an ETP, however, the exposure has a daily net asset value and an exchange-quoted price and enters an investor’s statements as an ordinary marked-to-market line item. This is the concrete implication of the access argument in Section 4.4: for investors subject to mandate, custody, or regulatory constraints, an ETP is not merely a convenient route to cryptocurrency exposure but a structure that makes such exposure reportable within conventional investment systems. The heterogeneity documented in Section 4.1, however, shows that this reporting convenience does not neutralize differences in product design. The reporting layer standardizes the form in which the exposure is recorded without equalizing its economic substance, and the reported portfolio outcome still depends heavily on the wrapper selected. Five implications for financial reporting follow. None is directly tested in this study, but all arise from the empirical results.

Valuation of the underlying cryptocurrency assets. Annualized returns across the fifteen products range from “34.68% to 46.24% within a single observation window and a single asset class. Wrapper choice therefore determines the reported outcome to a degree that is unusual for products marketed as exposure to the same underlying phenomenon. From a reporting standpoint this heterogeneity is a valuation question rather than a performance question: two entities holding nominally similar cryptocurrency exposure through different vehicles may report materially different results, and the difference originates in the composition and construction of the underlying basket rather than in the holding decision itself. The comparison in Section 4.3 sharpens this, since the ETPs as a group sit between direct spot exposure and conventional assets rather than replicating either, so the wrapper does not simply pass through the value of the assets it holds.

Fair-value measurement and the reported performance series. The daily marked-to-market returns underlying every metric in Sections 4.1 to 4.4 are, in effect, a continuous fair-value series, which places the entire analysis within a fair-value measurement framework. For products whose underlying assets are large-capitalization cryptocurrencies with deep and continuous markets, those marks correspond closely to an observable market price. For products whose baskets extend into thinner segments, the correspondence is weaker: the two Brazilian thematic products, META11.SA and WEB311.SA, post the weakest annualized returns in the sample and track narrow segments where the depth of the underlying market is materially lower than for the broad-index products. The measurement question is not whether a price exists but how far the quoted price of the wrapper corresponds to a realizable value for the assets behind it. The common-USD valuation base adopted in Section 3 is itself a reporting choice of the same kind: it embeds exchange-rate movement in the returns of non-USD products, a reminder that the reported performance of a digital-asset ETP is inseparable from the valuation and currency conventions applied to it.

Disclosure of underlying assets, costs, and turnover. As the sample spans Canada, Switzerland, the United States, and Brazil, it also spans heterogeneous disclosure regimes governing prospectus content, risk-factor reporting, custody arrangements, tracking error, and fee structure. The wide performance dispersion documented in Sections 4.1 and 4.3, from the 21Shares basket products at one end to the weakest Brazilian products at the other, is precisely the dispersion that adequate disclosure should enable investors to anticipate rather than discover after the fact. Two findings sharpen this point. First, implementation costs are not visible without turnover disclosure. The concentrated sleeve P1b has one-way monthly turnover of 7.48% to 13.76%, compared with 4.30% to 7.39% for P1a, and Section 4.4 shows that this difference translates into a 1.33-percentage-point difference in annualized return under a 100-basis-point cost assumption. An investor comparing the two strategies based solely on gross performance would not observe this difference. Second, the downside metrics that alter the rankings, particularly Maximum Drawdown, ES95, and VaR95, capture the tail exposure that investors most need to assess, whereas headline return alone does not convey this risk. The results therefore support disclosure centered on downside and implementation risk rather than headline returns, without implying that regime differences explain the observed dispersion, as this study does not test that mechanism.

Liquidity risk and its reporting. Liquidity risk enters these results through two observable channels. The first is drawdown depth: Maximum Drawdown ranges from “38.97% for HODLX.SW to “86.06% for META11.SA, and the products at the severe end are those tracking narrower and thinner underlying segments, consistent with liquidity conditions amplifying price declines rather than merely reflecting them. Maximum Drawdown therefore carries an indirect signal of the conditions under which a product can be exited. The second channel is implementability: turnover measures how much of a strategy must actually be traded, and the cost analysis in Section 4.4 shows that strategies requiring more trading lose proportionally more, with nine of thirty-six strategy-baseline combinations failing to beat the baseline portfolio once costs reach 100 basis points, all of them high-turnover variants. Neither channel is visible from a return series alone. Both indicate that the liquidity characteristics of the underlying basket, not only of the listed wrapper, are material to users of financial statements assessing the risk of a cryptocurrency position.

IFRS and US GAAP divergence and cross-jurisdiction comparability. Each product sits atop underlying digital assets whose valuation and reporting treatment is itself unsettled and divergent across standards. Under US GAAP, ASU 2023-08 now requires in-scope cryptocurrency assets to be measured at fair value with changes recognized in net income, effective for fiscal years beginning after 15 December 2024 and therefore binding within this study’s observation window (FASB, 2023). Under IFRS there is no dedicated standard, and holdings are generally treated as intangible assets under IAS 38, or as inventory under IAS 2 for broker-traders, so fair-value gains do not consistently reach reported income (IFRS Interpretations Committee, 2019). The consequence is a comparability problem: two entities holding an economically identical position may report different amounts and different volatility of reported earnings depending on the framework they apply. This is particularly consequential for a sample spanning four jurisdictions, since the products examined here are directly comparable as investments, all being evaluated on a single valuation base, yet the accounting treatment of a holding in them is not comparable across the reporting frameworks their investors are subject to. The GAAP move toward fair-value-through-income also makes the daily marks analyzed here more representative of what will now flow to reported performance for US holders than for holders under regimes that defer or divert such gains.

These five implications are conceptual rather than tested. The study evaluates investment performance, not accounting treatment, and the connections drawn here follow from the empirical

findings without themselves constituting evidence about the standards. The valuation and reporting of the underlying digital assets, in short, is not a backdrop to these performance results but shapes the numbers investors ultimately report.

6. Conclusion and Recommendations

This study evaluates fifteen cryptocurrency-based ETPs through four sequential stages: risk-adjusted performance, out-of-sample persistence, comparative positioning, and portfolio diversification. The framework is applied consistently to a sample spanning Canada, Switzerland, the United States, and Brazil over the period from 1 June 2022 to 31 December 2025. The central finding across all four stages is that these products can serve as relevant investment instruments, but their value is conditional rather than universal. It depends on the product selected, the form of exposure, the allocation size, and the investor's access to spot cryptocurrency.

Four findings emerge. The products are sharply heterogeneous, with annualized returns ranging from “34.68% to 46.24%, and rankings shift materially when downside measures replace symmetric ones, so return leaders are not risk-adjusted leaders and evaluation cannot rest on return or the Sharpe ratio alone. Evidence of performance persistence is limited: the Top-minus-Bottom spread of 0.64% per month carries a Newey-West t-statistic of 0.63, the Mid portfolio rather than the Top records the only statistically meaningful CAPM alpha, and the same pattern holds under two alternative formation signals that require no factor model, indicating that historical alpha is not a reliable selection signal in this sample. Compared to BTC, ETH, gold, and the domestic equity index, the ETPs occupy a distinct middle ground, sitting between the major cryptocurrency assets and conventional alternatives without fully replicating either, while gold dominates on risk-efficiency and downside resilience. Portfolio improvement is conditional rather than uniform: direct Bitcoin exposure at a 10% sleeve is the strongest single addition, combining a return effect with a diversification effect, and among ETP routes the diversified sleeve is consistently superior to the single-product sleeve, an advantage that widens once transaction costs are applied. For investors who cannot custody spot cryptocurrency, the diversified ETP sleeve remains a rational and value-adding regulated alternative.

Taken together, the contribution is empirical rather than methodological. Applying four stages consistently to one sample shows that a conclusion reached at one stage does not carry over the next: the highest-return products are neither the strongest on a risk-adjusted basis nor the most resilient to downside risk; products selected on historical alpha prove vulnerable to reversal, so selection based on past performance does not translate into a portfolio advantage; and a diversified sleeve outperforms the single best-performing product. None of these is visible when the stages are conducted separately. The study also supplies evidence from investable products on questions previously examined through actively managed funds (Conlon et al., 2025) or through factor portfolios constructed from thousands of coins (Han et al., 2024). Theoretically, the findings are consistent with Markowitz (1952): an asset improves a portfolio through its return-risk contribution rather than its standalone return, and this mechanism materializes selectively rather than uniformly. The reporting, valuation, and disclosure implications that follow are set out in Section 4.6.

Several limitations are observed among these conclusions. The sample is a purposive and exploratory selection of fifteen products subject to selection and survivorship bias, the findings, therefore, is not generalizable to the global ETP population. The observation period covers a single market regime without bull and bear decomposition. USD conversion conflates price and exchange-rate movement, although the result shows that the risk-adjusted ordering is largely unaffected by the choice of currency base. The one-factor specification omits size, momentum, and other cryptocurrency-

factor exposures, although the result shows that the persistence result is not an artefact of that choice. Ultimately, only the persistence stage employs a formal inferential test; comparisons at the performance, cross-asset, and portfolio stages are evaluative rather than statistical. Future research could extend the sample and horizon, apply formal significance tests to cross-product performance differences, estimate multi-factor persistence models where cryptocurrency factor series become available for listed products, separate sub-period analyses by market regime, and decompose returns across underlying assets, fees, and product design features.

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