

Stylized cryptocurrency portfolios: A diversification analysis

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Abstract

While studies have exhaustively examined the diversification utility of individual cryptocurrencies, few studies investigate the diversification benefits of stylized cryptocurrency portfolios. We construct equal-, capitalization-, and volume-weighted cryptocurrency portfolios using diverse combinations of 50 major cryptocurrencies, examining their diversification benefits for G7 equity indices. We find that cryptocurrency portfolios outperform their constituents (individual cryptocurrencies) in reducing the downside risk and the expected shortfall of equities, which we measure through the four-moment modified value at risk (VaR) and conditional VaR (CVaR) using Cornish-Fisher expansion. Additionally, we introduce a novel composite cryptocurrency index (CC40) comprising the 40 most liquid, stable, and high market-cap cryptocurrencies. CC40 substantially reduces the downside risk and expected shortfall of the G7 equity indices across various weight allocations during the sample period (February 1, 2018–December 1, 2025). Our analysis of 13,825 crypto-equity mixed portfolios, constructed using different bivariate combinations and weights, supports the inclusion of stylized cryptocurrency.

Keywords: Cryptocurrency portfolios; Equity indices; Portfolio diversification

1. Introduction

Previous studies assess the utility of cryptocurrencies in optimizing traditional portfolios, with these studies typically assessing individual or small groups of cryptocurrencies (Leong et al., 2025; Wu et al., 2025). In contrast, we assess the diversification benefits of stylized cryptocurrency portfolios. Such investigation provides a more accurate and comprehensive view of the cryptocurrency market's diversification benefits. We construct several equal-, capitalization-, and volume-weighted portfolios using different combinations of 50 major cryptocurrencies with the highest capitalization and complete trading data between February 1, 2018, and December 1, 2025.

Given the importance of four moments in the context of cryptocurrencies (Ali et al., 2022; Apergis, 2023), we employ four-moment modified value at risk (VaR) and conditional value at risk (CVaR) models to examine the reduction in the downside and expected shortfall of investors holding well-diversified equity indices, respectively. We examine the G7 equity markets (US, Canada, UK, Germany, France, Italy, and Japan), observing changes in their VaR and CVaR once a certain proportion of wealth is invested in a cryptocurrency or a crypto-portfolio.

Analysis indicates that crypto portfolios generally provide greater diversification utility for equity than their individual cryptocurrency constituents, as measured by mean return, volatility, skewness, kurtosis, downside risk, and expected shortfall. However, there is heterogeneity of diversification utility across equal-, capitalization-, and volume-weighted portfolios. Our analysis suggests that pairing G7 equity indices with crypto-portfolios produces a greater reduction in both downside risk and expected shortfall than pairing them with any of the individual cryptocurrencies within that portfolio. We examine different wealth allocations ranging from 5% of the wealth in a cryptocurrency (or a crypto-portfolio) and the remaining 95% in an equity index to 95% of the wealth in a cryptocurrency (or a crypto-portfolio) and the remaining 5% in an equity index. Our comprehensive empirical exercise involves 13,825 portfolios with different wealth allocations between the two asset classes. The results show that the equity-crypto (mixed) portfolios that allocate 30% or lower wealth in a crypto-portfolio and the remaining wealth (70% or more) in an equity index achieve significant diversification benefits during the sample period. These diversification benefits are superior to equity-only portfolios, crypto-only portfolios, and equity-crypto mixed portfolios that pair equities with individual cryptocurrencies.

We find that a proportion of wealth exceeding 35% in cryptocurrency portfolios is found to be relatively riskier in most cases. However, in some markets, a wide allocation to a crypto portfolio (up to 70%) is found capable of reducing both the downside risk and the expected shortfall of equity indices, with crypto-portfolios being comparatively more effective at reducing downside risk and expected shortfall in the Canadian and Italian stock markets than their counterparts.

Additionally, given the initial empirical evidence in support of crypto portfolios, we construct a novel composite cryptocurrency index (CC40) and use it as the benchmark index to understand the cryptocurrency market. The constituents of CC40 are the 40 major cryptocurrencies that are relatively stable (in terms of price), have high capitalization, and are actively traded throughout the sample period (liquid with significant trading volume).

We find that CC40 substantially reduces the downside risk (expected shortfall) of all equity indices for weight allocations up to 75% (85%) in CC40. An exception is Japan, for which this benefit is only manifested when the CC40 allocation is kept below 50% (55%). For Canada and Italy, CC40 is found to lower both downside risk and expected shortfall across all allocation levels. Overall, the implications of our results are meaningful for both researchers and investors: Investors should diversify their traditional investments into a portfolio of cryptocurrencies, preferably CC40, rather than a single (or a few) randomly selected cryptocurrency. Our results confirm that CC40 provides the most pronounced shelter to equity investors. More importantly, this study focuses on opening up an important new research direction rather than giving exact statistical estimates, thus establishing a comparable playing field to assess the true potential of the crypto market.

The rest of the paper is organized as follows. Section 2 discusses the data and methodology. Section 3 presents the baseline results. Section 4 details robustness checks and highlights additional considerations. Section 5 concludes.

2. Background

The surge in cryptocurrency prices in 2017 significantly elevated investor interest in the cryptocurrency market. Corbet et al. (2019) identify that cryptocurrencies are used as investments in addition to being a currency. While early research on the cryptocurrency market primarily focused on market efficiency and price discovery (e.g., Urquhart, 2016; Kapar and Olmo, 2019), the focus has since shifted toward understanding the cryptocurrency market's role as a decentralized asset class and their connectedness with traditional financial markets and macroeconomic variables (Bouri et al., 2017; Goldstein et al., 2019; Goodell and Goutte, 2021; Dai et al., 2023).

While early evidence indicates weak interconnectedness between cryptocurrencies and traditional financial markets and potential diversification benefits of cryptocurrencies for traditional asset classes, specifically for equities (e.g., Bouri et al., 2017; Guesmi et al., 2019), such findings leave open how markets behave when access is unequal and the same signal is distributed on a proprietary basis during the trading cycle.

Other studies examine the diversification benefits, including hedging and safe haven roles, of cryptocurrencies for other assets (e.g., Ji et al., 2020; Apergis, 2023; Gambarelli, 2023; Ali et al., 2024;

Polyzos and Youssef, 2025; Vuković et al., 2025). However, these studies are limited to observing the diversification benefit of a few randomly selected individual cryptocurrencies during a specific event, as opposed to their portfolio-level and widespread diversification benefits. Bouri et al. (2017), Guesmi et al. (2019), Umar et al. (2021), and Robertson and Zhang (2025) examine Bitcoin only, whereas Ali, Khurram, and Sensoy (2025) and Leong, Alexeev, and Kwok (2025) examine Bitcoin and Ethereum. However, studies that include several cryptocurrencies also emphasize their individual diversification benefits, rather than their collective diversification benefits as an asset class and a market (Chen et al., 2022; Naeem et al., 2022; Ali et al., 2024; Apergis, 2025; Vuković et al., 2025). Pairing equities with individual or small groups of equity securities or cryptocurrencies has generally been found to provide poor diversification (Conlon and McGee, 2020; Ji, Zhang, and Zhao, 2020; Ali et al., 2022, 2023). However, the diversification utility of pairing equity portfolios with select cryptocurrency portfolios remains understudied.

Classical asset-pricing literature employs portfolios rather than individual assets (Markowitz (1952) and Black, Jensen, and Scholes (1972)). While a growing body of research criticizes the applicability of classical asset pricing assumptions to the cryptocurrency market (Fieberg et al., 2024; Ali, Du, and Majeed, 2025), a specific critique remains unaddressed: the use of individual, volatile cryptocurrencies in the analyses, which may be particularly susceptible to these flawed assumptions. While some basic transition of traditional asset pricing models in the cryptocurrency market is empirically provided by a few seminal studies (e.g., Liu and Tsyvinski, 2021; Liu, Tsyvinski, and Wu, 2022), several important and topical issues remain unaddressed, including the consensus on a standard cryptocurrency index and stylized crypto portfolios or anomalies. Zhao, Wang, and Liu (2024) and Hadhri et al. (2025) extend earlier studies by incorporating lottery-like features and music-based sentiment into the pricing models, respectively.

Ali et al. (2022, 2024) dispute the cryptocurrency market being regarded as a homogeneous asset class. Thus, assessing cryptocurrency portfolios is of likely value to market participants and likely better reflects the overall cryptocurrency market. Given the consistent surge in crypto investment and attention from both individual and institutional investors (Ozdamar, Sensoy, and Akdeniz, 2022; Wu et al., 2025), in addition to discussion on their benefits in hedging inflation and currency crises (Gambarelli, Marchi, and Muzzioli, 2023; Liu and Valcarcel, 2024), it is important to assess the roles of crypto-asset portfolios in investors portfolios.

3. Data and methodology

3.1. Data

We follow a stepwise procedure to select the sample of cryptocurrencies (Ali et al., 2024): First, we examine the 650 cryptocurrencies with the highest market capitalization. We consider that the remaining cryptocurrencies are illiquid, thinly traded, and have inconsequential market capitalization, with limited

trading histories. Further, we exclude cryptocurrencies with missing price, volume, or capitalization data. We follow Ali, Du, and Majeed (2025) and match trading days of each equity market—an asset that we aim to diversify—with those of cryptocurrencies, thereby excluding non-trading days of the respective equity index to form a uniform trading and investing horizon.

Our final sample includes the 50 cryptocurrencies with the highest capitalization that remain actively traded and cover all recent important macroeconomic, geopolitical, and financial market events. The starting date of the sample is February 1, 2018, driven by the availability of complete data for all assets under study. Our sample period ends on December 1, 2025, and accounts for approximately 99% of the total market capitalization, including cryptocurrencies across all major types and classes. Table 1 provides the details of the sample, including tickers, full names, and market capitalization in US dollars.

Our equity market sample includes those of the G7 countries. We reason that the economies of these countries account for a large share of both global GDP and stock market capitalization. Specifically, we study Morgan Stanley Capital International (MSCI) equity indices that represent the US, Canada, the UK, Germany, France, Italy, and Japan. Data for cryptocurrencies are obtained from Coingecko (<https://www.coingecko.com/>), a reliable data source for the cryptocurrency market, whereas equity indices are obtained from MSCI (<https://www.msci.com/>).

(Please insert Table 1 about here)

3.2. Portfolio formation strategy

We construct cryptocurrency portfolios using three different methods, equal-weighted (EW), capitalization-weighted (CW), and volume-weighted (VW). Dividing 50 cryptocurrencies into deciles gives us five cryptocurrencies in each group. A portfolio with fewer than five cryptocurrencies is not considered sufficiently diversified to be assessed. Further, managing a portfolio of more than five cryptocurrencies may require greater capital and effort, which could be challenging for small retail investors.

However, constructing crypto-portfolios with five different cryptocurrencies is not straightforward either, as it produces over two million portfolios (2,118,760) following the well-established formula to calculate possible combinations, $nCr = n! / (r! (n - r)!)$, where n is the number of total assets (50 in our case) and r is the number of assets taken at a time (5 in our case) without exact overlapping. Therefore, for brevity and to form an overall understanding of the benefits associated with constructing cryptocurrency portfolios, we adopt a simple portfolio formation strategy. We begin by selecting five cryptocurrencies with the highest market capitalization, then the next five, and so on [1-5, 6-10, 11-15, ..., 45-50]. In doing so, the 50 individual cryptocurrencies are divided into 10 different decile groups, where we construct EW, CW, and VW portfolios for each group. Note that while the sample period ends on December 1, 2025, the market-

cap used to form the ten groups is as of July 16, 2024, the day we conceptualized and began the empirical work. Table 2 presents descriptive statistics of the selected 50 cryptocurrencies and 30 crypto-portfolios: 10 EW, 10 CW, and 10 VW.

Additionally, we extend our analysis to robustness checks, constructing portfolios of 10 cryptocurrencies. We then sort all assets into quintile portfolios based on market capitalization [1-10, 11-20, ..., 40-50] and construct 15 crypto-portfolios in total: 5 EW, 5 CW, and 5 VW. Ultimately, we also construct a novel composite cryptocurrency index, CC40, that includes 40 major cryptocurrencies. In addition to the already-defined sample selection criteria, we emphasize three criteria for constructing CC40: active daily trading, high market capitalization, and stable price movements.

3.3. Descriptive statistics

Group-1 contains two of the most popular and highly traded cryptocurrencies, Bitcoin and Ethereum, as well as stablecoin (USDT). The corresponding three portfolios, P1-EW, P1-CW, and P1-VW, that combine these five cryptocurrencies with three different weighting schemes, reveal that constructed portfolios offer superior performance regarding most of the metrics we study: mean, volatility, skewness, kurtosis, and Sharpe ratio. However, while the standard deviation of USDT is stable, as expected for a stablecoin, the skewness and kurtosis are high, and the mean return is low. This suggests the necessity of a higher-moment framework, as a mean-variance analysis may fail to capture significant tail risks.

The argument for a four-moment framework is further strengthened by the extreme values of standard deviation, skewness, or kurtosis observed in many other cryptocurrencies, such as BNB, DOGE, XLM, KCS, MANA, ELF, ANT, NTRN, RLC, PRO, REQ, and NMR. Volatile and noisy estimates at the individual cryptocurrency level contrast sharply with the more stable and reliable estimates derived from portfolios in all groups. Consequently, results affirm that portfolio formation not only enhances financial performance but also mitigates estimation statistical noise, providing a more robust basis for analysis. Moreover, the heterogeneity in results also suggests that the cryptocurrency market is not a homogeneous asset class, as documented by Ali et al. (2022, 2024), and that it offers both inter- and intra-market diversification opportunities to investors.

(Please insert Table 2 about here)

The results, presented in Table 2, indicate that the portfolios across all groups exhibit superior performance than their constituents on at least three of the five performance metrics. Exceptions are Group 1 and Group 8, where the outperformance is confined to the Sharpe ratio. It is conceivable as the former includes three of the most popular and high market-cap cryptocurrencies, including a well-known stablecoin,

whereas the latter includes a very volatile cryptocurrency (NTRN) that reduces the performance of the respective portfolios. The best performer of each measure, presented in each row, is marked with ‘b.’ In contrast, the poorest performer is denoted with a ‘p.’ A higher value of mean return and Sharpe ratio (standard deviation, skewness, and kurtosis) indicates a better (poorer) performance and vice versa. None of the poorest performers belong to the crypto portfolios, suggesting that forming portfolios reduces noise.

3.4. Methodology

Relevant studies employ various models, including vector autoregression, conditional heteroskedasticity, value at risk, wavelet, and regression to assess the diversification benefit of an asset from different standpoints, where each of them has some advantages over the others (Apergis, 2023; Ali et al., 2024; Ali, Khurram, and Sensoy, 2025; Wu et al., 2025). For example, while vector autoregressive and wavelet coherence models offer useful information about co-movement between two assets, they cannot pinpoint whether one asset lowers the financial risk (e.g., downside risk) of the other or improves the financial performance (e.g., Sharpe ratio). More precisely, if BTC and S&P500 co-move in different (or the same) directions during a specific period, it is not yet clear which asset and to what extent it shelters the other asset during that period (Ali, Khurram, and Sensoy, 2025).

The four-moment modified VaR offers several advantages over dynamic correlation- and co-movement-based models for identifying diversification benefits. It provides a consistent metric that captures potential losses and diversification benefits across portfolios of heterogeneous assets without the need for questionable co-movement (GARCH or vector autoregressive) modeling, which often leads to misspecifications. Specifically, VaR captures the maximum expected loss within a specified confidence level and time frame, providing a clear picture to investors regarding the diversification effects in loss mitigation (Conlon and McGee, 2020; Ali et al., 2022). From an application and regulatory perspective, VaR is a widely used metric in the finance industry, underscoring its broad applicability (Basel Committee on Banking Supervision, 2019; Hertrich, 2023). Therefore, we employ the four-moment modified VaR model that uses the Cornish-Fisher expansion to estimate the downside risk of an asset.

VaR, however, has the limitation of failing to capture downside risk beyond the specified confidence level. To mitigate this issue, we employ the CVaR model to understand the extent of the loss beyond the estimated threshold level, the expected shortfall. Basel Committee on Banking Supervision (2019) recently suggested incorporating expected shortfall as a primary risk measure for assessing market risk. Related empirical studies similarly show that two-moment VaR and CVaR estimators yield misleading results, particularly for assets with higher skewness, kurtosis, and bubble-like dynamics. However, the four-moment modified VaR and CVaR models, specifically those employing Cornish-Fisher expansion and incorporating skewness and kurtosis, accurately adjust quantiles of distributions and best explain the higher-

order moments (Bredin et al., 2017; Conlon and McGee, 2020; Ali et al., 2024). The four-moment modified VaR and CVaR models following the Cornish-Fisher expansion are as follows (Favre and Galeano, 2002):

$$[VaR]_p(\alpha) = - \left[\mu_p + \sigma_p \left(z_\alpha + (z_\alpha^2 - 1) \frac{S_p}{6} + z_\alpha (z_\alpha^2 - 3) \frac{K_p}{24} - z_\alpha (2z_\alpha^2 - 5) \frac{S_p^2}{36} \right) \right] \quad (1)$$

where μ_p , σ_p , S_p , and K_p are the mean, standard deviation, skewness, and excess kurtosis of portfolio p , respectively. $z(\alpha)$ is the α quantile of the standard normal distribution.

As the VaR framework does not estimate the extent of the loss beyond the estimated threshold level, we calculate CVaR to estimate the loss expectation if the loss is larger than the VaR. This is estimated as follows:

$$[CVaR]_p = E(R_p | R_p > VaR_p) \quad (2)$$

where $[CVaR]_p$ is calculated by taking an average of $[VaR]_p$ across quantiles greater than 1. R_p signifies the negative return of portfolio p . Returns are calculated as the difference of two consecutive closing prices scaled by the preceding price: $((P_t - P_{t-1})/P_{t-1}) \times 100$, where P_{t-1} and P_t represent the prices on trading days $t-1$ and t , respectively.

To obtain relative portfolio risk, we calculate the VaR and CVaR of an equity-cryptocurrency mixed portfolio scaled by the VaR and CVaR of the corresponding equity-only portfolio. Relative VaR and CVaR precisely indicate whether diversifying equity portfolios with individual cryptocurrencies or cryptocurrency portfolios reduces the downside risk and expected shortfall an investor is exposed to relative to holding equity-only portfolios. Relative VaR (RVaR) and relative CVaR (RCVaR) of a portfolio is presented as follows:

$$[RVaR]_p = \frac{VaR_{E-C}}{VaR_{EO}} \quad (3)$$

$$[RCVaR]_p = \frac{CVaR_{E-C}}{CVaR_{EO}} \quad (4)$$

where VaR_{E-C} and $CVaR_{E-C}$ indicate the downside risk and expected shortfall of an equity-cryptocurrency mixed portfolio, and VaR_{EO} and $CVaR_{EO}$ indicate the downside risk and expected shortfall of an equity-only unmixed portfolio, respectively.

Note that if RVaR or RCVaR of a mixed-portfolio is lower than 1.00 for a specific proportion of wealth, for example, 90% in S&P500 and 10% in Bitcoin or a portfolio of cryptocurrencies, it represents

an effective diversification as it decreases the downside risk or expected shortfall of the portfolio p . Such diversification benefits are often denoted as safe havens (Conlon and McGee, 2020).¹

We test a wide range of proportional wealth allocations [0.05, 0.10, 0.15, ..., 1.00] across seven equity indices and 50 individual cryptocurrencies, as well as several crypto portfolios. Specifically, we examine the diversification benefits of 50 individual cryptocurrencies, 30 crypto-portfolios of decile groups, 15 crypto-portfolios of quintile groups, and the crypto-index CC40 relative to G7 equity indices. Thus, we assess 13,720 equity-cryptocurrency mixed portfolios, estimating their VaR, CVaR, RVaR, and RCVaR.

Among these portfolios, 7000 involve equity indices and individual cryptocurrencies (7 equity indices $\times$ 50 individual cryptocurrencies $\times$ 20 proportional wealth allocations), 4200 involve equity indices and decile crypto-portfolios (7 equity indices $\times$ 30 decile crypto-portfolios $\times$ 20 proportional wealth allocations), 2100 involve equity indices and quintile crypto-portfolios (7 equity indices $\times$ 15 quintile crypto-portfolios $\times$ 20 proportional wealth allocations), and 420 involve equity indices and CC40 (7 equity indices $\times$ 3 CC40 crypto indices $\times$ 20 proportional wealth allocations). In addition to these equity-cryptocurrency mixed portfolios, we examine 105 unmixed portfolios that allocate 100% of wealth to an equity index, an individual cryptocurrency, or a crypto-portfolio: 7 equity indices, 50 individual cryptocurrencies, 30 decile crypto-portfolios, 15 quintile crypto-portfolios, and 3 CC40 indices.

Given the large number of portfolios and their financial performance comparisons, we develop a framework to carefully examine portfolio performance relative to their constituents, as presented in Figure 1. We first determine whether the portfolio weighting scheme matters. In other words, do equal-, capitalization-, and volume-weighted portfolios offer different benefits? We then select the best-performing crypto-portfolio in each group based on VaR, CVaR, RVaR, and RCVaR, denoted with ‘b’ in the tables. Then we compare the best-performing crypto portfolios with their constituent assets in each group, with poorer performers denoted with ‘p.’

(Insert Figure 1 about here)

4. Results and discussion

4.1. Cryptocurrency portfolios

Table 3 presents the VaR and CVaR values of both individual cryptocurrencies and crypto portfolios, as well as examines their relative performance. As illustrated in Fig. 1, we first compare EW, CW, and VW crypto portfolios and select the best performer in each group, which we mark with ‘b.’ Given that the sample is divided into 10 groups, each consisting of two metrics (VaR and CVaR) at two confidence

¹ We do not specifically investigate safe-haven relationships as its definition is loosely defined. We rather focus on diversification benefits that we examine using the four-moment VaR and CVaR models.

levels (1% and 5%), we have 40 best-performing crypto portfolios. Among them, fifteen are EW, thirteen are VW, and twelve are CW portfolios, indicating their competing performance. Subsequently, we compare these best-performing crypto portfolios with their constituents and examine whether the portfolios neutralize their constituents' noise.

The results in Table 3 show that crypto-portfolios outperform their constituents in most cases. Group-6 and Group-8, however, are exceptions due to ANT and NTRN, respectively. Both ANT and NTRN have exceptionally high VaR and CVaR, which elevate the overall VaR and CVaR of the crypto portfolios in Group-6 and Group-8. In additional tests (untabulated), we reconstruct Group-6 and Group-8 by replacing ANT and NTRN with several other cryptocurrencies, finding that the reconstructed crypto-portfolios are able to offer lower VaR and CVaR than their constituents, including DCR, ICX, and STORJ. Thus, while results indicate the benefits of constructing crypto portfolios, they also reveal the importance of the constituents of crypto portfolios.

(Insert Table 3 here)

In addition to comparing the best-performing portfolio to its individual constituents, we evaluate the VaR and CVaR for all portfolios within each group. For instance, while our earlier discussion compares P3-EW (or P3-VW) against their constituents (LTC, ETC, XMR, XLM, and MKR), as they are the best-performing crypto portfolios in Group 3, we also simultaneously compare all the assets in Group 3: LTC, ETC, XMR, XLM, MKR, P3-EW, P3-CW, and P3-VW. The results demonstrate that crypto portfolios consistently yield the lowest VaR and CVaR values across several groups, notably in Group 3, Group 7, and Group 9. In no instance does any portfolio exhibit the highest risk metrics, highlighting the case for a portfolio-based approach to crypto asset allocation.

4.2. Equity portfolios

We present descriptive statistics, VaR, and CVaR for the G7 equity markets in Table 4. The US index yields the highest mean return and Sharpe ratio, the UK index offers the lowest standard deviation, and the Japanese index holds the lowest skewness and kurtosis values. Regarding the comparison between equity and crypto portfolios, all crypto portfolios, as reported in Table 2, have higher mean returns and standard deviations than the equity portfolios, indicating crypto portfolios' ability to increase both returns and risk. However, the skewness and kurtosis values are comparable. We examine Sharpe ratios to assess whether a higher risk-adjusted return compensates for additional risk. The highest Sharpe ratio among equity indices is 0.04 for the US index. If we compare it with crypto portfolios, at least one crypto-portfolio in each group provides a 0.06 or higher Sharpe ratio. These results reveal that crypto portfolios are important

for mean-variance investors searching for higher Sharpe ratios. In line with Conlon and McGee (2020) and Ali et al. (2022), results show that equity indices are more stable than cryptocurrencies, offering lower values of modified four-moment VaR and CVaR.

(Please insert Table 4 about here)

4.3. Equity-cryptocurrency mixed portfolios: Downside risk

We examine whether adding a proportion of wealth to cryptocurrencies reduces the downside risk and expected shortfall of equity-only portfolios. Following Conlon and McGee (2020) and Ali et al. (2022, 2024), we allocate 10% of the wealth to an individual cryptocurrency or a crypto-portfolio and the remaining 90% to an equity index. Results are reported in Table 5.

We identify crypto-portfolios that provide the lowest VaR and then compare these with corresponding portfolios involving individual cryptocurrencies. Thus, in each row, we have one best-performing crypto portfolio (5% and 1% confidence levels), denoting the lowest VaR with ‘b.’ We then compare these crypto portfolios to their constituent assets. If the VaR of an individual cryptocurrency is higher than the VaR of the best-performing crypto-portfolio in the group (denoted with ‘p’), we infer that the crypto-portfolio provides superior diversification benefits than that individual cryptocurrency, which supports our conjecture.

(Please insert Table 5 about here)

The results, reported in Table 5, show that crypto-portfolios are exposed to lower downside risk than their constituents, specifically for the 5% confidence level. Exceptions to this are USDT, XMR, and BAT, where crypto portfolios have lower downside risk than them against two equity markets only. Crypto portfolios in other groups outperform their constituents against most equity markets, at least in one of the confidence levels. Among the equity indices, the Japanese market receives the highest diversification benefit from crypto portfolios relative to individual cryptocurrencies, followed by the US and Canadian markets.² However, these results are based on a specific proportion of wealth allocation between cryptocurrencies and equities: 10% to a cryptocurrency or crypto portfolio, and the remaining 90% to an equity index.

Next, we extend our analysis and examine two alternative wealth allocation proportions: (i) 85% in an equity index and 15% in a cryptocurrency (or crypto-portfolio), marked as 85~15; (ii) 50% in an

² Among the 100 combinations between an equity index and individual cryptocurrencies (50 cryptocurrencies at 1% and 5% confidence levels), crypto-portfolios outperform their constituents 63 (57 and 54) times for the Japanese (US and Canadian) stock market.

equity index and 50% in a cryptocurrency (or crypto-portfolio), marked as 50~50. Table 6 reports the results. We find that VW portfolios outperform CW and EW portfolios in both the 85~15 and 50~50 wealth allocation proportions. Among EW and CW portfolios, the former outperforms the latter in the 85~15 wealth allocation proportion and vice versa in the 50~50 wealth allocation proportion. These findings indicate the intricate nature of inter-class asset (crypto-equity) diversification and highlight the importance of wealth allocation proportions and portfolio weighting systems.

(Please insert Table 6 about here)

In the 85~15 wealth allocation, crypto-portfolios outperform their constituents, except for USDT (Group-1), XLM (Group-3), KCS (Group-4), ENJ (Group-7), TEL (Group-7), RLC (Group-8), and PRO (Group-9). In contrast, crypto portfolio performance under a 50~50 wealth allocation is diverse. For example, crypto-portfolios outperform XLM (Group-3), KCS (Group-4), and RLC (Group-8) but underperform BNB and XRP (Group-1), TRX (Group-2), DASH (Group-6), WAXP (Group-8), and XNO (Group-10). For ENJ and TEL, the underperformance of the respective crypto-portfolios in Group 7 is consistent across both 85~15 and 50~50 wealth allocation proportions. These results indicate that an increase (or decrease) in cryptocurrency weights alters the diversification benefit of cryptocurrencies for equities, consistent with Ali et al. (2024, 2022). However, the results, reported in Table 6, are based on VaR, which does not estimate the extent of loss beyond the threshold. To measure the loss expectation when the loss exceeds the VaR, a relatively more popular risk measure recently (Basel Committee on Banking Supervision, 2019), we employ CVaR to calculate the expected shortfall in the following section.

4.4. Equity and cryptocurrency mixed portfolios: Expected shortfall

We follow the same exposition, reporting the expected shortfall of equity-cryptocurrency mixed portfolios in Tables 7-8. Table 7 extends Table 5 and reports the CVaR for portfolios allocating 90% of wealth to an equity index and 10% to a cryptocurrency portfolio. While there are no major changes, a few differences between VaR and CVaR are observed in some groups. The differences between VaR and CVaR are in both directions: some favor crypto portfolios, while others favor individual cryptocurrencies. Overall, results for VaR and CVaR are comparable, with crypto portfolios generally offering superior performance.

(Please insert Table 7 about here)

Next, we extend the results of Table 6, reporting CVaR at the 5% confidence level for 85~15 and 50~50 wealth allocation proportions reported in Table 8. We seek to compare the results between VaR and CVaR, i.e., when loss expectation is larger than the VaR, whether it affects the performance of crypto-

portfolios. We also wish to compare the changes in the CVaRs when wealth allocation proportions differ. The results, reported in Table 8, show that the CVaRs of 85~15 and 50~50 wealth allocation proportions differ from the VaRs of 85~15 and 50~50 wealth allocation proportions, respectively. These results align with our previous findings comparing VaR and CVaR for mixed portfolios that allocate 90% of wealth to an equity index and 10% to a cryptocurrency, presented in Table 7.

Therefore, if loss expectations exceed the VaR, crypto portfolios' performance changes only mildly. Second, our results reveal that changes in the wealth allocations (i.e., 10%, 15%, or 50% in a cryptocurrency, with the remaining in an equity index) do not significantly affect the CVaRs of the equity-cryptocurrency mixed portfolios we study. The results show that both VaRs and CVaRs are mildly sensitive to wealth allocation proportions.

4.5. Relative downside risk and expected shortfall

Given crypto-portfolios' largely superior performance compared to individual cryptocurrencies, we now focus on crypto-portfolios from two different aspects: (i) relative VaR (RVaR) and (ii) wide-ranging weight allocation proportions.

First, we calculate RVaR as the VaR of a mixed equity-cryptocurrency portfolio relative to the VaR of the corresponding equity-only portfolio, thereby determining relative downside risk. RVaR is an exact measure indicating whether pairing an equity portfolio with a crypto portfolio reduces the downside risk for investors holding the equity portfolio: RVaR values below 1.00 indicate meaningful diversification benefits (also known as safe-haven effects). Second, we examine a comprehensive range of weight allocations between equity indices and crypto portfolios, from allocating 5% of wealth to a crypto portfolio and 95% to an equity-only portfolio, to allocating 95% to a crypto portfolio and 5% to an equity-only portfolio.

Figure 2 presents the results of RVaR at the 1% confidence level.³ The 1% confidence level is a stricter measure and will help us to deeply understand the role of our stylized portfolios in diversifying equities. Among EW, CW, and VW, the RVaR of EW portfolios varies between 0.7 and 4.5, whereas the RVaR of CW (VW) portfolios varies between 0.7 (0.8) and 6 (7.5) in most cases. For Japan, the RVaR values are slightly higher than those of the other markets. In Group-8, the RVaR values of the EW and CW portfolios are divided by 100 for optical reasons, as these portfolios generate substantially high RVaR due to extremely high VaR of NTRN; plotting them at this level will be useful. However, the VW portfolio in Group-8 is depicted at the level. A careful examination reveals that the highest RVaR values are observed in the crypto-portfolios of Groups 2 and 10; the RVaR of crypto-portfolios in the remaining groups is

³ For brevity, we do not report the results of RVaR at the 5% confidence level. However, in untabulated results, we find that the results are comparable as discussed earlier.

substantially lower than that of Groups 2 and 10, depending on the portfolio weighting system. For instance, Group-6 underperforms in the EW category, whereas Group-5 underperforms in the VW category.

While assessing the constituents of Group-2 and Group-10, we find that the high standard deviation, kurtosis, and VaR of DOGE, REQ, and NMR have contributed to the comparatively high RVaR of the crypto-portfolios in the group. Overall, crypto-portfolios in Group-1 and Group-9 offer the lowest RVaR. Therefore, they considerably lower the downside risk of the equity indices ($RVaR < 1.00$) for up to 45% weight allocation proportions in most cases, whereas in some cases the RVaR values are lower than 1.00 for up to 70% weight allocation proportions in these portfolios relative to the corresponding equity portfolios. However, Japan is an exception, where these benefits are weaker, which aligns with existing studies (Ali et al., 2023).

The superiority of the crypto-portfolios of Group-1 is most likely due to their constituents: a well-known stablecoin (USDT) and four other major cryptocurrencies (BTC, ETH, BNB, and XRP). The most uneven performance of crypto-portfolios belongs to Group 8. While P8-EW and P8-CW perform poorly, P8-VW performs significantly better, at least as well as the VW portfolios in Groups 2, 5, and 10. It indicates that while market-cap-based and equal-weighting compositions resulted in placing more weight on the highly volatile cryptocurrency, NTRN, and elevated the overall RVaR values, the low trading volume of NTRN during significant price jumps neutralizes its adverse impact on the VW portfolio composition. Results, yet again, indicate the importance of constructing crypto portfolios and carefully selecting their constituents, in line with the fundamentals of modern portfolio theory.

(Please insert Table 8 about here)

(Please insert Figure 2 about here)

We further examine the diversification benefits of crypto-portfolios for G7 equity markets. As reported in Table 9, we highlight RVaR values based on their diversification benefits, those lower or higher than 1.00. For brevity, we report only the results for CW portfolios, a well-established method of constructing portfolios (Fama and French, 2017). The results are straightforward: all crypto portfolios, except those of Group-8, are found to reduce the downside risk of the G7 equity markets for wealth allocations up to 25% in a crypto portfolio relative to an equity index, as indicated by ‘L.’

Among the equity indices, the Canadian stock market provides the highest diversification benefits for crypto portfolios, with RVaR less than 1.00 for a relatively higher wealth allocations than the other equity indices, followed by Italy. For example, the diversification benefit of P3-CW for the Canadian market is limited to crypto allocations of up to 55%, whereas it is up to 50% for the Italian market. The

analysis divulges significant heterogeneity in diversification benefits across the G7 equity markets. Likewise, the ability of P1-CW to reduce downside risk of the Canadian (Italian) market is limited to crypto allocations of up to 85% (80%), whereas the ability of P5-CW is up to 30% (25%). Overall, the evidence strongly suggests that crypto portfolios effectively lower the downside risk of G7 equity portfolios, a contrast to the risk profile of their individual constituents, specifically for weight allocations of up to 35% in crypto portfolios.

(Please insert Table 9 about here)

To estimate the relative loss beyond the estimated threshold level, we present RCVaR in Fig. 3. The results show that EW portfolios in Group 6, CW portfolios in Groups 5 and 10, and VW portfolios in Groups 10 and 5 are riskier than those in the other groups. Similar to Fig. 2, P8-EW and P8-CW are divided by 100 for presentation in Figure 3; they do not lower RVaR for any weight allocations. However, P8-VW performs better, with results reported at the level, and yields RCVaR values lower than 1.00, indicating notable diversification for weight allocations to the crypto portfolio of up to 10%. In other groups, while RCVaR decreases with wealth allocations up to 30%, it doubles in crypto portfolios with wealth allocations over 60% relative to equity portfolios. Similar results are observed across other equity portfolios at both confidence levels, suggesting the overall stability of our results and the importance of crypto-portfolios in minimizing the downside risk and expected shortfall of equity indices during the sample period.

We present the relative expected shortfall of the CW portfolios at the 1% confidence level in Table 10. The portfolios in Groups 1, 4, 7, and 9 deliver relatively low RCVaR for all markets. For example, the RCVaR values for P1-CW in the Canadian stock market are below 1.04 for all wealth allocation proportions. Similarly, the RCVaR values for P1-CW are not lower than 1.86 in any market except Japan, where it is lower than 2.56.

(Insert Figure 3 about here)

(Please insert Table 10 about here)

5. Robustness checks

5.1. Alternative cryptocurrency portfolios

Given that our baseline results are based on a specific grouping technique, for robustness, we reconstruct EW, CW, and VW portfolios using ten different cryptocurrencies (quintile portfolios). Compared to the RVaR values of the decile groups (see Figure 2), the RVaR values of the quintile crypto-

portfolios (Fig. 4) are much lower. Interestingly, the drastic impact of DOGE, REQ, and NMR in the previous portfolios (decile groups) is minimized in the reconstructed portfolios (quintile groups). This result indicates two possibilities: (i) the inclusion of relatively stable assets in the portfolio; (ii) better diversification due to more cryptocurrencies in the reconstructed portfolio. However, based on the existing literature on portfolio diversification, we assume that adding correlated risky trading patterns to a crypto portfolio does not offer significant diversification benefits. For instance, as decile portfolios in Groups 5-6 deliver relatively high RVaR in earlier results, when their constituents form Group 3 in quintile portfolios, they similarly deliver relatively higher RVaR than portfolios in other groups. This finding aligns with the principle of financial contagion, forming portfolios of homogenous (or highly correlated) assets elevates and transmits risk rather than reducing risk and offering diversification benefits (Ali et al., 2023).

In Table 11, we assess the relative CVaR of the quintile portfolios, finding substantial improvements in diversification benefits relative to decile portfolios reported in Table 10. For example, the RCVaR values in the decile portfolios P5-CW and P6-CW for the French market are lower than 1.00 for crypto weight allocations of up to 10% and 25%, respectively. However, in the quintile portfolio, when the constituents of these two portfolios form Group-3, the RCVaR value of P3-CW for the French market is found to be lower than 1.00 for a crypto weight allocation of up to 30%. Thus, our results are robust and not sensitive to the confidence level or the equity index examined. Consistent with considering the importance of constructing cryptocurrency portfolios to represent the cryptocurrency market, the results indicate that constructing crypto-portfolios, specifically diversified crypto-portfolios with several cryptocurrencies, reduces the relative downside risk and expected shortfall of the G7 markets.

(Please insert Figure 4 about here)

5.2. *A Composite cryptocurrency index*

We construct a novel composite cryptocurrency index as a representative of the overall performance of the cryptocurrency market. We are motivated by several aspects. First, cryptocurrencies are often compared with well-diversified equity indices, such as the G7 equity markets; therefore, it is important to construct a cryptocurrency index for meaningful comparisons. Otherwise, comparing a well-diversified equity index with individual cryptocurrencies or poorly diversified crypto portfolios may not yield a meaningful comparison to test the diversification benefits of this emerging asset class. Additionally, regarding the mechanism for index construction, it is essential to select a reasonable number of cryptocurrencies that represent different types. For instance, the S&P500 index includes the stocks of the leading 500 US firms, the FTSE100 includes the stocks of the leading 100 UK firms, and the CAC40 includes the stocks of the leading 40 French firms. As the cryptocurrency market is an emerging asset class

with a limited number of reliable assets that have been traded on crypto exchanges between 2018 and 2025, it is impractical to construct a 500-cryptocurrency index with complete data.

Further, the S&P500 and FTSE100 indices are constructed by examining a broad universe of over 7,000 and 1,900 well-known firms, respectively, with long data histories. However, some indices include relatively fewer firms, such as the CAC40 (FTMIB) index, which consists of 40 blue-chip firms in France (Italy). Motivated by this, we construct an index using the 40 well-traded liquid cryptocurrencies with price stability and high market capitalization. The constituents are selected from 650 large cryptocurrencies based on market capitalization, providing rationale and reliability for the selection and construction procedures. Precisely, among the 50 already chosen cryptocurrencies, we drop ten cryptocurrencies with relatively smaller market capitalization, lower liquidity, and higher VaR and CVaR, namely DOGE, MKR, BTG, ELF, DCR, WAXP, NTRN, IOST, REQ, and NMR.⁴

We similarly construct EW, CW, and VW indices and examine their diversification benefits for investors holding G7 equity indices. Note that, unlike earlier results, where CW (VW) portfolios represent the capitalization (volume) of five or ten constituents, in the case of the cryptocurrency index, it indicates the capitalization (trading volume) of the forty constituents. Thus, as the cryptocurrency index represents the composite effect of the market, we label it a composite cryptocurrency index (CC40). Following our earlier exposition of results, we compute the VaR of the equity-CC40 mixed portfolios relative to the corresponding equity index. The results of RVaR for a comprehensive range of weight proportions are presented in Figure 5, which are astonishing in light of our conjecture. In the case of the VW index (the right block of Figure 5), CC40 reduces the downside risk of the Japanese market for weight allocations for up to 45%, French and German markets for up to 70%, UK and US markets for up to 75%, and Italian and Canadian markets for any weight allocation to the crypto index without any exception.

The CW and EW versions of the CC40 index follow the same trend in terms of offering diversification benefits to the equity indices. While the diversification benefits of the EW and CW index compositions are relatively weaker than those of the VW index composition, they are noticeably higher than those of the decile and quintile portfolios. The highest RVaR value for the EW, CW, and VW versions of the CC40 index is observed for the Japanese market, which remains under 3.5, 2.6, and 1.9, respectively. For other markets, the RVaR values remain under 2.6, 2.1, and 1.5, which are significantly lower than those of the quintile and decile portfolios. Interestingly, when we examine the relative expected shortfall in Figure 6, the results are not only robust but also strengthened. For example, while RVaR values for the Japanese market are lower than 1.00 for up to 45%, RCVaR values are lower than 1.00 for up to 50% wealth allocation. Likewise, the diversification benefits of VW CC40 for the French and German markets increases

⁴ First, we rank cryptocurrencies on their VaR and CVaR values at 1% and 5% confidence levels. Second, among them, we skip 10 cryptocurrencies with the lowest market capitalization.

from 70% to 75%, while the UK and US markets improved from 75% to 85%. Additionally, the Italian and Canadian markets saw further improvements across all weight allocations. In sum, the diversification benefits of our novel CC40 index are robust to both downside risk and expected shortfall.

(Please insert Figure 5 about here)

As we examine the diversification benefit of the cryptocurrency market for equity indices, a larger proportion of investment is modeled to be in equities. In such investment scenarios, mixed portfolios contain a large proportion of wealth in equities relative to the other asset (CC40 in our case). However, the results show that even with a 60~40 (50~50) wealth allocation, where 60% (50%) of the wealth is invested in one of the G7 equity indices and the remaining 40% (50%) in the VW CC40 portfolio, an investor can diversify across G7 equity markets with CC40. Results evidence the utility of diversified cryptocurrency portfolios for diversifying equity. We also replicate these results for the country-level indices maintained by national stock exchanges—S&P500 (US), TSX (Canada), FTSE100 (UK), DAX (Germany), CAC40 (France), FTSE MIB (Italy), and Nikkei225 (Japan), finding our results to be robust. Since the Sharpe ratio is another important metric for investors, specifically mean-variance investors, we also examine the Sharpe ratios of the equity-crypto mixed portfolios and find that our results stand out without exception: crypto portfolios, specifically CC40, substantially increase the Sharpe ratio of the equity indices.

6. Conclusions

We highlight the comparative utility of diversifying equity with cryptocurrency portfolios versus using one or a few individual cryptocurrencies. We substantially extend a literature, which so far has focused on individual cryptocurrencies, to determine whether they offer diversification benefits to investors holding well-diversified equity portfolios. Motivated by modern portfolio theory and rational investing ideology and practice, which strongly emphasize forming diversified portfolios, we construct several equal-, capitalization-, and volume-weighted cryptocurrency portfolios and examine their diversification benefits relative to the G7 equity markets.

Results reveal significant performance differences in utility between crypto-portfolios and their constituents in both intra- and inter-market settings. Crypto-portfolios outperform their constituents in most cases, as measured by VaR and CVaR. Stablecoins (e.g., USDT) reduce the downside risk of crypto-portfolios, whereas DOGE, ANT, and NTRN, among other cryptocurrencies with notably high standard deviation, kurtosis, VaR, and CVaR values, increase the downside risk and expected shortfall of crypto-portfolios. To avoid concerns about arbitrariness in the portfolio formation process, we construct portfolios with varying numbers of constituents: decile portfolios, quintile portfolios, and a novel composite cryptocurrency index, CC40, comprising the 40 most reliable cryptocurrencies, based on market

capitalization, length of trading histories, liquidity, and relative price stability. We select cryptocurrencies that have been actively traded from February 2018 to December 2025. We subsequently construct 13,720 equity-cryptocurrency mixed portfolios using a variety of wealth allocation proportions.

In contrast to existing studies that examine the diversification benefits of a few individual cryptocurrencies without specifying wealth-allocation proportions, we extend the investigation across a comprehensive range of weight proportions at the individual and portfolio (or index) levels. While diversification benefits vary, crypto-portfolios offer superior diversification for equity than individual cryptocurrencies. Furthermore, the results suggest that investors need to consider the heterogeneity of possible portfolios for optimal diversification in their respective contexts. Overall, we find that CC40 outperforms the other crypto-portfolios, with volume-weighted index composition performing the best, followed by capitalization and equal-weighted index compositions.

Results suggest that cryptocurrencies are not homogeneous in their exposure to downside risk and expected shortfall; therefore, constructing crypto portfolios and designing relevant investment policies and strategies are crucial for effective portfolio construction. Employing portfolio-based strategies is most likely to yield stable, reliable results than seeking diversification with individual cryptos. However, the CC40 index formed for this study performs best at reducing both downside risk and expected shortfall for the G7 equity indices, regardless of the confidence interval used or the weight allocated to the cryptocurrency index relative to the equity index.

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Figure 1. Framework to analyze crypto portfolios' performance relative to their constituents

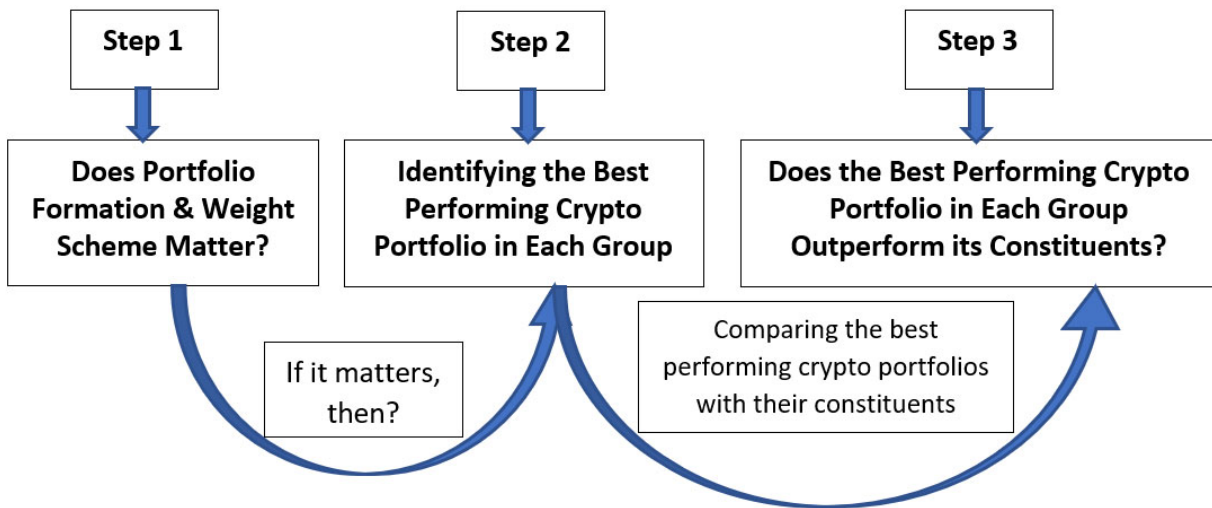


Table 1. Details of the selected cryptocurrencies

Ticker	Cryptocurrency	Capitalization (USD millions)	Ticker	Cryptocurrency	Capitalization (USD millions)
BTC	Bitcoin	1,277,807	ANT	Aragon	351
ETH	Ethereum	419,317	DCR	Decred	227
USDT	Tether USDt	112,632	SC	Siacoin	287
BNB	BNB	90,238	DASH	Dash	325
XRP	XRP	29,966	QTUM	Qtum	270
DOGE	Dogecoin	18,155	BAT	Basic Attention Coin	293
ADA	Cardano	15,810	ENJ	Enjin Coin	308
TRX	Tron	11,966	ZRX	Ox Protocol	309
LINK	Chainlink	8,763	LRC	Loopring	205
BCH	Bitcoin Cash	7,896	TEL	Telcoin	173
LTC	Litecoin	5,421	ICX	ICON	159
ETC	Ethereum Clasic	3,539	NTRN	Neutron	151
XMR	Monero	2,927	STORJ	Storj	158
XLM	Stellar	3,069	RLC	iExec RLC	144
MKR	Maker	2,712	WAXP	WAX	136
THETA	Theta Network	1,549	LSK	Lisk	145
KCS	KuCoin	920	DGB	DigiByte	141
NEO	Neo	803	PRO	Propy	179
XTZ	Tezos	813	ARK	Arkham	382
GNO	Gnosis	728	XEM	NEM	129
MANA	Decentraland	673	IOST	IOST	117
BTG	Bitcoin Gold	481	XNO	Nano	125
GLM	Golem	338	POWR	Powerledger	110
ZEC	Zcash	429	REQ	Request	100
ELF	aelf	292	NMR	Numeraire	109

This table presents the tickers, full names, and market capitalization of the sample in US dollar (USD) as of July 16, 2024, the day empirical work was initiated.

Table 2. Descriptive statistics of cryptocurrencies and crypto portfolios

	Cryptocurrency					Crypto-portfolio		
Group 1=>	BTC	ETH	USDT	BNB	XRP	P1-EW	P1-CW	P1-VW
Mean	0.186	0.187	0.005 ^p	0.378 ^b	0.235	0.198	0.196	0.146
St. Dev.	3.93	5.17	0.96 ^b	5.82	6.60 ^p	3.60	3.87	2.67
Skew	-0.12 ^b	-0.15	-4.80 ^p	2.24	2.62	-0.27	-0.32	-0.15
Kurt	6.32	5.21 ^b	292.65 ^p	40.28	29.42	6.94	5.93	5.65
Sharpe	0.05	0.04	0.01 ^p	0.06	0.04	0.06 ^b	0.05	0.05
Group 2=>	DOGE	ADA	TRX	LINK	BCH	P2-EW	P2-CW	P2-VW
Mean	0.497	0.194	0.245	0.403	0.157 ^p	0.299	0.317	0.789 ^b
St. Dev.	10.54 ^p	6.46	5.85	7.12	6.53	5.47 ^b	5.75	7.98
Skew	17.46 ^p	1.49	2.08	0.67	1.31	1.06	0.51 ^b	9.45
Kurt	529.31 ^p	14.99	33.07	7.47 ^b	12.61	20.73	7.93	237.23
Sharpe	0.05	0.03	0.04	0.06	0.02 ^p	0.05	0.06	0.10 ^b
Group 3=>	LTC	ETC	XMR	XLM	MKR	P3-EW	P3-CW	P3-VW
Mean	0.131 ^p	0.172	0.162	0.170	0.194	0.166	0.221	0.466 ^b
St. Dev.	5.69	6.46	5.28	6.70 ^p	6.32	4.90 ^b	5.27	6.24
Skew	0.32	0.99	-0.10 ^b	3.83 ^p	0.60	-0.32	0.53	2.14
Kurt	6.82 ^b	8.38	8.30	48.51 ^p	10.33	6.95	11.45	28.04
Sharpe	0.02 ^p	0.03	0.03	0.03	0.03	0.03	0.04	0.07 ^b
Group 4=>	THETA	KCS	NEO	XTZ	GNO	P4-EW	P4-CW	P4-VW
Mean	0.299 ^b	0.221	0.045 ^p	0.146	0.142	0.171	0.193	0.390
St. Dev.	7.39 ^p	6.85	6.62	6.99	5.67	5.16 ^b	5.62	6.72
Skew	0.43	6.13 ^p	0.95	1.03	0.31	-0.37	-0.19 ^b	0.95
Kurt	4.66 ^b	129.27 ^p	11.68	9.94	4.64	5.23	5.34	9.80
Sharpe	0.04	0.03	0.01 ^p	0.02	0.03	0.03	0.03	0.06 ^b
Group 5=>	MANA	BTG	GLM	ZEC	ELF	P5-EW	P5-CW	P5-VW
Mean	0.373	0.099 ^p	0.222	0.236	0.122	0.210	0.356	0.905 ^b
St. Dev.	9.42 ^p	9.05	7.30	6.77	7.62	5.77 ^b	6.62	8.64
Skew	7.19 ^p	3.35	1.99	0.90	4.11	0.32 ^b	2.61	6.85
Kurt	129.83 ^p	39.74	21.38	9.07	73.81	7.41 ^b	36.05	130.99
Sharpe	0.04	0.01 ^p	0.03	0.03	0.02	0.04	0.05	0.10 ^b
Group 6=>	ANT	DCR	SC	DASH	QTUM	P6-EW	P6-CW	P6-VW
Mean	0.978 ^b	0.115	0.095	0.104	0.076 ^p	0.274	0.197	0.502
St. Dev.	25.86 ^p	6.03	6.96	6.87	6.81	7.36	5.81 ^b	7.01
Skew	30.05 ^p	0.82	0.63	2.51	0.63	10.83	0.82 ^b	2.02
Kurt	1144.88 ^p	7.87	7.76 ^b	33.21	8.11	301.88	14.67	26.82
Sharpe	0.04	0.02	0.01	0.02	0.01 ^p	0.04	0.03	0.07 ^b
Group 7=>	BAT	ENJ	ZRX	LRC	TEL	P7-EW	P7-CW	P7-VW
Mean	0.178	0.220	0.155 ^p	0.160	0.573	0.257	0.318	0.829 ^b
St. Dev.	6.50	8.23	7.42	7.95	11.27 ^p	6.37 ^b	6.46	7.71
Skew	0.43	2.65	1.19	1.51	2.89 ^p	0.13 ^b	0.14	1.59
Kurt	5.44	29.37 ^p	11.04	10.59	29.04	4.49	4.04 ^b	11.59
Sharpe	0.03	0.03	0.02	0.02 ^p	0.05	0.04	0.05	0.11 ^b
Group 8=>	ICX	NTRN	STORJ	RLC	WAXP	P8-EW	P8-CW	P8-VW

Mean	0.025 ^p	7.799 ^b	0.211	0.293	0.103	1.686	1.596	1.009
St. Dev.	7.16 ^b	324.38 ^p	8.27	8.92	8.12	38.957	38.861	9.71
Skew	0.27 ^b	45.15 ^p	2.51	5.33	2.51	45.13	45.10	4.85
Kurt	5.38 ^b	2039.5 ^p	24.54	108.65	31.09	2038.3	2036.6	64.14
Sharpe	0.00 ^p	0.02	0.03	0.03	0.01	0.02	0.02	0.10 ^b
Group 9=>	LSK	DGB	PRO	ARK	XEM	P9-EW	P9-CW	P9-VW
Mean	0.007	0.166	0.446	0.167	-0.084 ^p	0.140	0.130	0.758 ^b
St. Dev.	7.02	7.38	11.64 ^p	8.25	6.75	5.33 ^b	5.53	7.75
Skew	1.19	1.10	5.32 ^p	2.22	0.46	0.55	0.19 ^b	2.45
Kurt	13.40	7.90	59.22 ^p	27.62	9.05	6.25	4.27 ^b	26.13
Sharpe	0.00	0.02	0.04	0.02	0.00 ^p	0.03	0.02	0.10 ^b
Group 10=>	IOST	XNO	POWR	REQ	NMR	P10-EW	P10-CW	P10-VW
Mean	0.091 ^p	0.164	0.158	0.302	0.368	0.217	0.344	1.302 ^b
St. Dev.	7.18	8.24	7.43	10.09	10.26 ^p	5.98 ^b	7.00	10.89
Skew	0.74	3.12	1.82	12.20 ^p	7.23	0.46 ^b	2.32	8.39
Kurt	8.22 ^b	32.25	19.68	321.19 ^p	111.19	10.94	27.92	174.44
Sharpe	0.01 ^p	0.02	0.02	0.03	0.04	0.04	0.05	0.12 ^b

The best performer of each metric in each row is marked with 'b,' whereas the poorest performer is marked with 'p.' A higher value of mean return and Sharpe ratio (standard deviation, skewness, and kurtosis) indicates a better (poorer) performance and vice versa. The sample period spans between February 1, 2018, and December 1, 2025.

Table 3. VaR and CVaR of cryptocurrencies and crypto portfolios

	Cryptocurrency					Crypto-portfolio		
Group 1=>	BTC	ETH	USDT	BNB	XRP	P1-EW	P1-CW	P1-VW
VaR(5%)	5.91 ^P	7.98 ^P	3.19	4.21 ^P	4.94 ^P	5.48	6.05	4.05 ^b
CVaR(5%)	40.37 ^P	50.54 ^P	135.34 ^P	106.41 ^P	70.21 ^P	38.87	40.18	26.61 ^b
VaR(1%)	15.09 ^P	18.65 ^P	62.78 ^P	47.38 ^P	30.75 ^P	14.62	14.94	9.85 ^b
CVaR(1%)	263.55 ^P	315.93 ^P	1467.4 ^P	1091.72 ^P	706.70 ^P	258.27	257.38	169.54 ^b
Group 2=>	DOGE	ADA	TRX	LINK	BCH	P2-EW	P2-CW	P2-VW
VaR(5%)	208.48 ^P	5.47 ^P	1.53	8.83 ^P	6.27 ^P	4.65 ^b	7.37	60.69
CVaR(5%)	260.04 ^P	62.05 ^P	91.40 ^P	63.80 ^P	60.11 ^P	77.68	55.54 ^b	239.85
VaR(1%)	16.48	24.95 ^P	40.09 ^P	23.92 ^P	23.73 ^P	32.37	21.03 ^b	136.74
CVaR(1%)	2671.8 ^P	504.66 ^P	905.85 ^P	431.67 ^P	464.39 ^P	681.35	383.31 ^b	4026.00
Group 3=>	LTC	ETC	XMR	XLM	MKR	P3-EW	P3-CW	P3-VW
VaR(5%)	7.93 ^P	7.42 ^P	7.79 ^P	4.85 ^P	7.75 ^P	7.65	6.40	1.93 ^b
CVaR(5%)	54.83 ^P	53.95 ^P	59.30 ^P	74.41 ^P	66.90 ^P	53.47 ^b	59.74	79.68
VaR(1%)	20.65 ^P	20.39 ^P	22.73 ^P	35.49 ^P	26.09 ^P	20.18 ^b	23.51	34.35
CVaR(1%)	364.29 ^P	370.63 ^P	411.46 ^P	901.84 ^P	493.10 ^P	354.15 ^b	452.11	772.72
Group 4=>	THETA	KCS	NEO	XTZ	GNO	P4-EW	P4-CW	P4-VW
VaR(5%)	10.25 ^P	23.61 ^P	7.37	7.77 ^P	8.15 ^P	8.30	8.73	7.41 ^b
CVaR(5%)	61.13 ^P	185.93 ^P	67.15 ^P	62.94 ^P	48.63	52.18 ^b	55.63	61.71
VaR(1%)	22.14 ^P	94.94 ^P	26.51 ^P	24.29 ^P	17.72	19.28 ^b	20.58	23.67
CVaR(1%)	369.22 ^P	2528.58 ^P	509.32 ^P	455.16 ^P	294.71	324.53 ^b	349.33	447.14
Group 5=>	MANA	BTG	GLM	ZEC	ELF	P5-EW	P5-CW	P5-VW
VaR(5%)	37.97 ^P	3.01	3.96	7.83 ^P	10.26 ^P	7.89	5.03 ^b	33.97
CVaR(5%)	125.99 ^P	96.17 ^P	75.38 ^P	61.03 ^P	161.71 ^P	57.17 ^b	92.54	161.05
VaR(1%)	74.51 ^P	44.40 ^P	31.63 ^P	23.32 ^P	77.59 ^P	21.64 ^b	41.20	87.92
CVaR(1%)	2288.4 ^P	1083.8 ^P	682.53 ^P	431.91 ^P	1939.25 ^P	388.07 ^b	958.59	2533.72
Group-6=>	ANT	DCR	SC	DASH	QTUM	P6-EW	P6-CW	P6-VW
VaR(5%)	121.54 ^P	7.41 ^P	8.96 ^P	0.87	8.75 ^P	71.86	6.22	2.67 ^b
CVaR(5%)	658.46 ^P	52.94	64.33	90.73 ^P	64.34	262.32	70.14 ^b	90.00
VaR(1%)	237.92 ^P	20.02	24.42	40.19 ^P	24.55	152.95	28.30 ^b	38.59
CVaR(1%)	3669.5 ^P	360.21	438.51	921.46 ^P	443.97	4547.82	565.44 ^b	860.13
Group-7=>	BAT	ENJ	ZRX	LRC	TEL	P7-EW	P7-CW	P7-VW
VaR(5%)	8.99 ^P	1.15	7.70 ^P	7.46 ^P	1.35	9.41	9.52	6.22 ^b
CVaR(5%)	56.35 ^P	85.79 ^P	66.38 ^P	58.44 ^P	97.67 ^P	56.65	55.78 ^b	57.32
VaR(1%)	20.74 ^P	37.63 ^P	25.85 ^P	22.33 ^P	42.88 ^P	20.61	20.09 ^b	21.74
CVaR(1%)	353.19 ^P	865.05 ^P	493.36 ^P	419.85 ^P	1009.36 ^P	343.08	330.47 ^b	429.11
Group-8=>	ICX	NTRN	STORJ	RLC	WAXP	P8-EW	P8-CW	P8-VW
VaR(5%)	10.41 ^P	1432.46 ^P	2.43	23.46 ^P	1.41	286.50	204.46	5.29 ^b
CVaR(5%)	64.76	12795.3 ^P	74.02	234.53 ^P	98.95 ^P	2557.92	1824.09	89.84 ^b
VaR(1%)	24.00	5074.82 ^P	31.70	116.67 ^P	43.59	1014.40	723.31	46.49 ^b
CVaR(1%)	405.84	95127.3 ^P	711.29	3027.19	994.71	19012.40	13554.23	1323.87 ^b
Group-9=>	LSK	DGB	PRO	ARK	XEM	P9-EW	P9-CW	P9-VW
VaR(5%)	7.09 ^P	8.32 ^P	18.98 ^P	2.83 ^P	9.05 ^P	7.09	8.19	1.64 ^b
CVaR(5%)	71.13 ^P	57.03 ^P	22.90	100.48 ^P	70.26 ^P	46.53 ^b	47.93	77.70
VaR(1%)	28.46 ^P	21.31 ^P	18.47 ^P	43.53 ^P	27.26 ^P	17.29 ^b	17.41	33.21

CVaR(1%)	559.44 ^p	380.91 ^p	747.80 ^p	972.17 ^p	499.03 ^p	300.53	286.29 ^b	759.01
Group 10=>	IOST	XNO	POWR	REQ	NMR	P10-EW	P10-CW	P10-VW
VaR(5%)	8.93 ^p	0.79	4.82 ^p	112.31 ^p	37.69 ^p	7.48	1.89 ^b	62.12
CVaR(5%)	65.56	71.18 ^p	77.38 ^p	156.95 ^p	36.06	67.42 ^b	81.85	185.47
VaR(1%)	24.98	32.01 ^p	32.19 ^p	124.92 ^p	33.66 ^p	26.45 ^b	35.43	112.13
CVaR(1%)	452.51	767.18 ^p	681.68 ^p	4508.63 ^p	1361.52 ^p	504.16 ^b	800.02	3506.25

Notes: This table reports the VaR and CVaR at 1% and 5% confidence levels. VaR (CVaR) is the four-moment modified value-at-risk (conditional value-at-risk), estimated using Cornish-Fisher expansion. The values marked "**b**" indicate the best-performing crypto portfolios in each group. In contrast, the values marked with "**p**" indicate that the constituents of the corresponding portfolios deliver higher VaR and CVaR than the best-performing crypto-portfolio. The sample period spans between February 1, 2018, and December 1, 2025.

Table 4. Descriptive statistics, VaR, and CVaR of the equity indices

	US	Canada	UK	Germany	France	Italy	Japan
Mean	0.053 ^b	0.034	0.015	0.018	0.024	0.035	0.021
St. Dev.	1.26	1.19	1.19 ^b	1.33	1.30	1.43	1.20
Kurt.	13.418	26.26	15.54	11.49	11.16	18.38	8.32 ^b
Skew.	-0.38	-0.95	-0.73	-0.39	-0.59	-1.44	-0.13 ^b
Sharpe	0.04 ^b	0.03	0.01	0.01	0.02	0.02	0.02
VaR(5%)	1.81	1.60 ^b	1.81	2.01	2.03	2.32	1.79
CVaR(5%)	17.88	25.07	18.60	17.71	17.29	24.43	13.53 ^b
VaR(1%)	7.10	10.48	7.48	6.98	6.78	9.86	5.20 ^b
CVaR(1%)	138.54	216.66	145.29	131.31	126.26	191.31	93.91 ^b

This table reports the mean return (Mean), standard deviation (St. Dev.), Skewness (Skew), Kurtosis (Kurt), Sharpe ratio (Sharpe), and VaR and CVaR of the G7 equity markets. US, Canada, UK, Germany, France, Italy, and Japan indicate Morgan Stanley Capital International (MSCI) equity indices of these countries. VaR (CVaR) is the four-moment modified value-at-risk (conditional value-at-risk), estimated using Cornish-Fisher expansion. The values marked "**b**" indicate the best-performing index according to the measures listed in the first column. The sample period spans between February 1, 2018, and December 1, 2025.

Table 5. Downside risk in equity-cryptocurrency mixed portfolios

	Cryptocurrency										Crypto-portfolio					
Confidence level =>	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%
Group1=>	BTC		ETH		USDT		BNB		XRP		P1-EW		P1-CW		P1-VW	
US	1.79 ^P	5.83	1.90 ^P	5.54	1.59	6.33 ^P	1.74	6.00	1.83 ^P	5.52	1.84	6.07 ^b	1.86	6.11	1.79 ^b	6.29
Canada	1.64	8.63	1.79 ^P	8.20	1.44	9.39 ^P	1.67 ^P	8.58	1.76 ^P	7.84	1.73	9.10	1.74	9.06 ^b	1.66 ^b	9.36
UK	1.76	6.49	1.90 ^P	6.44	1.63	6.73	1.81 ^P	6.73	1.86 ^P	6.05	1.84	6.89	1.84	6.86 ^b	1.77 ^b	7.01
Germany	1.94	6.02	2.07 ^P	6.06	1.82	6.28	1.98 ^P	6.18	2.04 ^P	5.75	2.02	6.52	2.02	6.49 ^b	1.96 ^b	6.62
France	1.95 ^P	5.82	2.06 ^P	5.91	1.83	6.09	1.98 ^P	6.04	2.03 ^P	5.65	2.01	6.40	2.02	6.34 ^b	1.95 ^b	6.49
Italy	2.21 ^P	8.48	2.32 ^P	8.43	2.09	8.85	2.27 ^P	8.62	2.31 ^P	8.18	2.23	10.07	2.24	9.96 ^b	2.17 ^b	10.21
Japan	1.87 ^P	5.42 ^P	2.01 ^P	5.72 ^P	1.62	4.67	1.91 ^P	5.70 ^P	1.88 ^P	5.35	1.89	5.58	1.92	5.66	1.81 ^b	5.36 ^b
Group 2=>	DOGE		ADA		TRX		LINK		BCH		P2-EW		P2-CW		P2-VW	
US	3.53 ^P	21.96 ^P	1.96 ^P	5.31	1.74 ^P	5.59	2.01 ^P	5.57	1.94 ^P	5.29	1.95	5.72	1.97	5.61 ^b	0.98 ^b	9.76
Canada	3.84 ^P	24.86 ^P	1.89 ^P	7.63	1.69 ^P	8.31	1.94 ^P	7.77	1.86 ^P	7.73	1.87	8.59	1.91	8.43 ^b	0.92 ^b	12.95
UK	3.59 ^P	22.37 ^P	1.95 ^P	6.19	1.81 ^P	6.55	2.03 ^P	6.21	1.94 ^P	6.10	1.97	6.69	2.00	6.58 ^b	1.03 ^b	10.54
Germany	2.73 ^P	20.79 ^P	2.10 ^P	5.99	1.95 ^P	6.16	2.20 ^P	5.96	2.12 ^P	5.77	2.13	6.43	2.16	6.35 ^b	1.28 ^b	9.67
France	2.80 ^P	20.87 ^P	2.11 ^P	5.78	1.97 ^P	5.96	2.19 ^P	5.82	2.10 ^P	5.66	2.11	6.30	2.14	6.23 ^b	1.29 ^b	9.57
Italy	1.74 ^P	23.62 ^P	2.37 ^P	8.25	2.24 ^P	8.63	2.42 ^P	8.26	2.36 ^P	8.18	2.34	9.82	2.37	9.68 ^b	1.70 ^b	13.14
Japan	3.09 ^P	20.71 ^P	1.99 ^P	5.53	1.93 ^P	5.18	2.13 ^P	5.62	2.05 ^P	5.72	2.04	5.75	2.06	5.67 ^b	1.17 ^b	9.31
Group 3=>	LTC		ETC		XMR		XLM		MKR		P3-EW		P3-CW		P3-VW	
US	1.90 ^P	5.34	1.96 ^P	5.15	1.83	5.49	1.74	5.69 ^P	1.96 ^P	5.49	1.93	5.69	1.93	5.62 ^b	1.88 ^b	5.67
Canada	1.81	8.11 ^P	1.89 ^P	7.71 ^P	1.68	8.61 ^P	1.70	8.00 ^P	1.89 ^P	7.44 ^P	1.85	8.65	1.85	6.82 ^b	1.84 ^b	8.53
UK	1.95 ^P	6.30	1.98 ^P	6.14	1.84	6.26	1.79	6.49	1.98 ^P	6.03	1.96	6.75	1.96	6.73 ^b	1.93 ^b	6.75
Germany	2.10 ^P	5.93	2.13 ^P	5.83	1.94	6.44	1.97	6.12	2.13 ^P	5.81	2.11	6.49	2.11	6.46 ^b	2.08 ^b	6.50
France	2.10 ^P	5.79	2.13 ^P	5.68	1.97	6.16	1.96	6.00	2.12 ^P	5.65	2.10	6.35	2.11	6.32 ^b	2.07 ^b	6.38
Italy	2.35 ^P	8.35	2.38 ^P	8.22	2.36 ^P	8.73	2.37 ^P	8.52	2.38 ^P	7.99	2.33	9.88	2.34	9.84 ^b	2.33 ^b	9.85
Japan	2.04 ^P	5.41	2.07 ^P	5.45	1.95	5.29	1.78	5.91 ^P	2.06 ^P	6.21 ^P	2.02	5.88	2.02	5.76 ^b	1.97 ^b	5.92
Group 4=>	THETA		KCS		NEO		XTZ		GNO		P4-EW		P4-CW		P4-VW	
US	2.05 ^P	5.27	1.54	7.34 ^P	1.95	5.72	1.95	5.27	1.97 ^P	5.58	1.96 ^b	5.99	1.97	5.82	2.00	5.82 ^b
Canada	2.00 ^P	7.52	1.36	9.51 ^P	1.90 ^P	7.92	1.87	7.70	1.88	8.02	1.89 ^b	8.66	1.90	8.62	1.97	8.27 ^b
UK	2.11 ^P	6.14	1.49	8.02 ^P	1.97	6.19	1.97	6.09	1.97	6.40	1.99 ^b	6.78	2.01	6.71	2.04	6.46 ^b
Germany	2.26 ^P	5.98	1.78	6.98 ^P	2.16 ^P	5.88	2.16 ^P	5.81	2.13	6.10	2.16 ^b	6.53	2.18	6.45	2.22	6.27 ^b
France	2.24 ^P	5.87	1.73	7.16 ^P	2.15 ^P	5.71	2.16 ^P	5.66	2.14 ^P	5.92	2.14 ^b	6.40	2.17	6.31	2.20	6.14 ^b
Italy	2.48 ^P	8.33	2.10	9.42	2.41 ^P	8.23	2.43 ^P	8.01	2.37 ^P	8.47	2.36 ^b	9.93	2.39	9.72	2.44	9.49 ^b
Japan	2.19 ^P	5.48 ^P	1.50	7.32 ^P	2.08 ^P	5.22	2.11 ^P	5.33	2.04	5.38	2.07 ^b	5.65	2.11	5.74	2.12	5.44 ^b
Group 5=>	MANA		BTG		GLM		ZEC		ELF		P5-EW		P5-CW		P5-VW	

US	0.66	8.77 ^P	1.77 ^P	5.93 ^P	1.89 ^P	5.30	1.99 ^P	5.60 ^P	1.64 ^P	6.54 ^P	1.99	5.54 ^b	1.90	6.03	1.07 ^b	9.17
Canada	0.45	12.31 ^P	1.73 ^P	8.08	1.82 ^P	8.03	1.91 ^P	7.88	1.57 ^P	9.33 ^P	1.90	8.78 ^b	1.79	9.19	0.84 ^b	12.88
UK	0.79	10.02 ^P	1.76 ^P	6.63	1.94 ^P	6.55	2.00 ^P	6.05	1.72 ^P	7.50 ^P	2.00	6.76 ^b	1.92	7.00	1.08 ^b	10.08
Germany	1.09	9.43 ^P	2.02 ^P	6.19	2.11 ^P	6.26	2.10 ^P	6.08	1.94 ^P	6.77 ^P	2.16	6.57 ^b	2.08	6.75	1.31 ^b	9.39
France	1.03	9.56 ^P	1.95 ^P	6.17	2.10 ^P	6.16	2.10 ^P	5.91	1.90 ^P	6.85 ^P	2.14	6.45 ^b	2.06	6.69	1.24 ^b	9.61
Italy	1.40	12.41 ^P	2.25 ^P	8.64	2.36 ^P	8.81	2.36 ^P	8.34	2.23 ^P	9.32 ^P	2.36	10.04 ^b	2.30	10.27	1.63 ^b	13.28
Japan	0.67	10.23 ^P	1.89 ^P	5.63 ^P	2.01 ^P	5.45 ^P	2.08 ^P	4.99	1.74 ^P	6.37 ^P	2.05	5.27 ^b	1.91	6.05	0.89 ^b	9.74
Group-6=>	ANT		DCR		SC		DASH		QTUM		P6-EW		P6-CW		P6-VW	
US	85.80 ^P	73.01 ^P	1.89 ^P	5.35	2.03 ^P	5.03	1.86 ^P	5.81	2.01 ^P	5.24	0.99 ^b	9.90	1.97	5.82 ^b	1.94	5.91
Canada	86.93 ^P	76.25 ^P	1.84 ^P	7.57	1.97 ^P	7.39	1.76 ^P	8.30	1.93 ^P	7.35	0.90 ^b	13.14	1.88	8.61	1.88	8.40 ^b
UK	92.24 ^P	86.54 ^P	1.95 ^P	5.97	2.06 ^P	6.04	1.88 ^P	6.51	2.03 ^P	5.86	0.40 ^b	13.71	1.99	6.66	1.98	6.61 ^b
Germany	89.20 ^P	68.96 ^P	2.12 ^P	5.79	2.25 ^P	5.86	2.04 ^P	6.21	2.18 ^P	5.64	0.54 ^b	13.35	2.15	6.45	2.13	6.43 ^b
France	89.05 ^P	71.67 ^P	2.10 ^P	5.69	2.22 ^P	5.76	2.06 ^P	6.00	2.17 ^P	5.48	0.70 ^b	12.61	2.14	6.30	2.14	6.25 ^b
Italy	83.00 ^P	44.04 ^P	2.36 ^P	8.17	2.47 ^P	8.23	2.34 ^P	8.52	2.42 ^P	7.86	1.27 ^b	15.94	2.37	9.76	2.38	9.58 ^b
Japan	92.58 ^P	83.47 ^P	2.04 ^P	5.12	2.12 ^P	5.48	1.98 ^P	5.62	2.12 ^P	5.44	0.41 ^b	13.05	2.06	5.62 ^b	2.04	5.75
Group-7=>	BAT		ENJ		ZRX		LRC		TEL		P7-EW		P7-CW		P7-VW	
US	2.01	5.31	1.86	5.73 ^P	2.05 ^P	5.56 ^P	2.01	4.86	1.84	5.66 ^P	2.06	5.54	2.07	5.56	2.03 ^b	5.54 ^b
Canada	1.91	7.64	1.83	7.84 ^P	2.00 ^P	7.67	1.97	6.89	1.80	7.09	2.00	8.05	2.02	8.06	1.99 ^b	7.82 ^b
UK	2.07 ^P	5.97	1.88	6.55 ^P	2.07 ^P	6.20	2.06 ^P	5.79	1.88	6.29 ^P	2.09	6.39	2.11	6.37	2.05 ^b	6.24 ^b
Germany	2.19	5.75	2.10	6.18 ^P	2.25 ^P	5.91	2.23 ^P	5.59	2.13	5.97	2.25	6.24	2.26	6.22	2.23 ^b	6.05 ^b
France	2.18	5.59	2.06	6.15 ^P	2.22 ^P	5.78	2.18	5.57	2.10	5.94	2.23	6.16	2.24	6.13	2.20 ^b	5.97 ^b
Italy	2.45	7.99	2.36	8.63	2.46 ^P	8.19	2.45 ^P	7.84	2.38	7.86	2.45	9.46	2.46	9.41	2.44 ^b	9.20 ^b
Japan	2.07	5.59 ^P	2.02	5.95 ^P	2.11 ^P	5.33	2.12 ^P	5.46	1.91	5.62 ^P	2.12	5.74	2.13	5.77	2.09 ^b	5.58 ^b
Group 8=>	ICX		NTRN		STORJ		RLC		WAXP		P8EW		P8CW		P8VW	
US	2.09 ^P	5.47	143.23 ^P	507.37 ^P	1.90 ^P	5.28	1.38	7.78 ^P	1.81 ^P	5.26	28.58	100.95	20.35	71.65	1.55 ^b	6.67 ^b
Canada	2.01 ^P	7.83	143.22 ^P	507.33 ^P	1.85 ^P	7.66	1.18	10.60 ^P	1.75 ^P	7.78	28.57	100.91	20.34	71.61	1.43 ^b	9.57 ^b
UK	2.12 ^P	6.21	143.21 ^P	507.31 ^P	1.94 ^P	6.26	1.12	10.02 ^P	1.93 ^P	6.93	28.56	100.86	20.33	71.55	1.40 ^b	8.37 ^b
Germany	2.27 ^P	5.98	143.21 ^P	507.29 ^P	2.12 ^P	6.01	1.63	8.27 ^P	2.10 ^P	6.45	28.55	100.76	20.31	71.40	1.79 ^b	7.45 ^b
France	2.26 ^P	5.86	143.21 ^P	507.30 ^P	2.05 ^P	6.04	1.54	8.43 ^P	2.08 ^P	6.35	28.55	100.78	20.31	71.44	1.71 ^b	7.54 ^b
Italy	2.49 ^P	8.29	143.21 ^P	507.29 ^P	2.36 ^P	8.41	1.82	11.25 ^P	2.35 ^P	8.77	28.54	100.68	20.29	71.29	2.01 ^b	11.12 ^b
Japan	2.16 ^P	5.61	14323.6 ^P	50740.6 ^P	1.95 ^P	6.08	1.36	8.99 ^P	2.00 ^P	6.38	28.58	100.93	20.35	71.61	1.44 ^b	7.49 ^b
Group 9=>	LSK		DGB		PRO		ARK		XEM		P9-EW		P9-CW		P9-VW	
US	1.94 ^P	5.05	1.96 ^P	5.17	0.89	7.09 ^P	2.06 ^P	7.61 ^P	2.02 ^P	5.40	1.99	5.96	2.00	5.80	1.90 ^b	5.77 ^b
Canada	1.87 ^P	7.54	1.91 ^P	7.44	0.85	8.50 ^P	1.94 ^P	10.53 ^P	1.92 ^P	7.71	1.91	8.91	1.92	8.74	1.85 ^b	8.19 ^b
UK	1.98 ^P	6.42	2.02 ^P	5.98	1.00	7.26 ^P	2.02 ^P	9.03 ^P	2.01 ^P	6.09	1.99	7.13	2.00	6.93	1.90 ^b	6.60 ^b
Germany	2.17 ^P	5.99	2.16 ^P	5.70	1.22	7.05 ^P	2.23 ^P	8.54 ^P	2.18 ^P	5.76	2.15	6.83	2.17	6.63	2.09 ^b	6.26 ^b

France	2.14 ^p	5.85	2.15 ^p	5.61	1.15	7.16 ^p	2.23 ^p	8.49 ^p	2.16 ^p	5.69	2.13	6.75	2.15	6.56	2.07 ^b	6.22 ^b
Italy	2.42 ^p	8.25	2.42 ^p	7.88	1.61	9.58 ^p	2.44 ^p	11.96 ^p	2.43 ^p	8.05	2.36	10.51	2.38	10.19	2.35 ^b	9.53 ^b
Japan	2.07 ^p	5.69 ^p	2.12 ^p	5.21	1.02	6.90 ^p	1.96 ^p	6.04 ^p	2.10 ^p	4.93	2.03	5.48	2.06	5.41 ^b	1.95 ^b	5.75
Group 10=>	IOST		XNO		POWR		REQ		NMR		P10-EW		P10-CW		P10-VW	
US	2.02 ^p	5.09	1.80 ^p	5.79	1.91 ^p	5.29	0.76 ^p	14.67 ^p	0.83 ^p	8.02 ^p	1.99	5.59 ^b	1.94	5.75	0.22 ^b	11.09
Canada	1.96 ^p	7.27	1.70 ^p	8.01	1.89 ^p	8.06	0.52 ^p	16.22 ^p	0.61 ^p	10.58 ^p	1.90	8.61 ^b	1.87	8.57	0.43 ^b	12.91
UK	2.07 ^p	5.94	1.80 ^p	6.60	2.01 ^p	6.47	0.34	14.23 ^p	0.69 ^p	9.10 ^p	2.01	6.77 ^b	1.98	6.77	0.60 ^b	10.99
Germany	2.24 ^p	5.69	2.05 ^p	5.98	2.14 ^p	6.15	0.08	13.06 ^p	0.73	9.15 ^p	2.16	6.50 ^b	2.10	6.55	0.90 ^b	10.30
France	2.21 ^p	5.54	2.01 ^p	5.93	2.13 ^p	6.01	0.15	12.76 ^p	0.47	9.72 ^p	2.13	6.44 ^b	2.04	6.59	0.94 ^b	9.92
Italy	2.47 ^p	7.92	2.33 ^p	8.21	2.38 ^p	8.72	0.77	15.08 ^p	1.42	11.41 ^p	2.38	9.79 ^b	2.38	9.79	1.44 ^b	13.26
Japan	2.17 ^p	5.62	1.87 ^p	5.91	2.08 ^p	5.77	1.08 ^p	16.66 ^p	0.69 ^p	8.70 ^p	2.09	5.95 ^b	2.00	6.13	0.01 ^b	12.68

This table reports the downside risk of the equity-crypto mixed portfolios at 1% and 5% confidence levels (Conf. Lev.). VaR is the four-moment modified value-at-risk, estimated using Cornish-Fisher expansion. In each case (pair), 90% of wealth is invested in an equity index, whereas the remaining 10% is invested in a cryptocurrency (left block) or a crypto portfolio (right block). The values marked with "**b**" indicate the best-performing crypto-portfolio in each group (row), whereas the values marked with "**p**" indicate the constituents of the corresponding portfolios that deliver higher VaR (poorer performance) than the best-performing crypto-portfolio. The sample period spans between February 1, 2018, and December 1, 2025.

Table 6. Further evidence on the downside risk in equity-cryptocurrency mixed portfolios

	Cryptocurrency					Crypto-portfolio		
Panel A: 85% equity and 15% cryptocurrency (85~15)								
Confidence level =>	5%	5%	5%	5%	5%	5%	5%	5%
Group 1=>	BTC	ETH	USDT	BNB	XRP	P1-EW	P1-CW	P1-VW
US	1.86 ^P	2.06 ^P	1.52	1.59	1.69	1.88	1.92	1.79 ^b
Canada	1.74 ^P	1.99 ^P	1.38	1.58	1.71 ^P	1.81	1.84	1.68 ^b
UK	1.84 ^P	2.09 ^P	1.55	1.74	1.81 ^P	1.90	1.92	1.78 ^b
Germany	2.00 ^P	2.23 ^P	1.73	1.91	1.98 ^P	2.06	2.08	1.94 ^b
France	2.00 ^P	2.21 ^P	1.74	1.90	1.95 ^P	2.04	2.07	1.93 ^b
Italy	2.23 ^P	2.44 ^P	1.99	2.19 ^P	2.24 ^P	2.25	2.28	2.14 ^b
Japan	1.99 ^P	2.23 ^P	1.54	1.91 ^P	1.85 ^P	1.98	2.03	1.84 ^b
Group 2=>	DOGE	ADA	TRX	LINK	BCH	P2-EW	P2-CW	P2-VW
US	14.14 ^P	2.06 ^P	1.65 ^P	2.21 ^P	2.06 ^P	2.04	2.12	1.52 ^b
Canada	14.41 ^P	2.05 ^P	1.68 ^P	2.20 ^P	2.02 ^P	2.01	2.11	1.47 ^b
UK	13.81 ^P	2.06 ^P	1.80 ^P	2.29 ^P	2.09 ^P	2.09	2.18	1.22 ^b
Germany	12.32 ^P	2.18 ^P	1.91 ^P	2.44 ^P	2.25 ^P	2.22	2.31	0.79 ^b
France	12.52 ^P	2.18 ^P	1.92 ^P	2.42 ^P	2.21 ^P	2.21	2.29	0.80 ^b
Italy	10.84 ^P	2.42 ^P	2.19 ^P	2.61 ^P	2.45 ^P	2.42	2.50	0.19 ^b
Japan	12.64 ^P	2.11 ^P	1.99 ^P	2.40 ^P	2.24 ^P	2.20	2.27	0.86 ^b
Group 3=>	LTC	ETC	XMR	XLM	MKR	P3-EW	P3-CW	P3-VW
US	2.06 ^P	2.11 ^P	1.95 ^P	1.40	2.13 ^P	2.05	2.02	1.80 ^b
Canada	2.03 ^P	2.08 ^P	1.86 ^P	1.46	2.09 ^P	2.00	2.02	1.85 ^b
UK	2.15 ^P	2.16 ^P	2.01 ^P	1.54	2.19 ^P	2.13	2.10	1.92 ^b
Germany	2.27 ^P	2.30 ^P	2.07 ^P	1.74	2.31 ^P	2.25	2.22	2.05 ^b
France	2.26 ^P	2.29 ^P	2.09 ^P	1.71	2.29 ^P	2.24	2.21	2.04 ^b
Italy	2.47 ^P	2.50 ^P	2.34 ^P	2.06	2.50 ^P	2.44	2.43	2.31 ^b
Japan	2.26 ^P	2.29 ^P	2.15 ^P	1.54	2.29 ^P	2.21	2.17	1.97 ^b
Group 4=>	THETA	KCS	NEO	XTZ	GNO	P4-EW	P4-CW	P4-VW
US	2.31 ^P	0.65	2.11	2.09	2.15 ^P	2.12 ^b	2.14	2.14
Canada	2.33 ^P	0.41	2.13 ^P	2.08	2.12 ^P	2.10 ^b	2.13	2.17
UK	2.44 ^P	0.55	2.15	2.17	2.19 ^P	2.19 ^b	2.22	2.21
Germany	2.56 ^P	1.03	2.33 ^P	2.35 ^P	2.32	2.33 ^b	2.37	2.39
France	2.53 ^P	0.89	2.30	2.34 ^P	2.32 ^P	2.31 ^b	2.35	2.36
Italy	2.72 ^P	1.39	2.54 ^P	2.58 ^P	2.52 ^P	2.51 ^b	2.56	2.59
Japan	2.52 ^P	0.60	2.30 ^P	2.32 ^P	2.28	2.29 ^b	2.35	2.32
Group 5=>	MANA	BTG	GLM	ZEC	ELF	P5-EW	P5-CW	P5-VW
US	1.61 ^P	1.36 ^P	1.87 ^P	2.16 ^P	1.01 ^P	2.13	1.77	0.74 ^b
Canada	1.80 ^P	1.41 ^P	1.88 ^P	2.15 ^P	1.04 ^P	2.10	1.67	1.02 ^b
UK	1.21 ^P	1.47 ^P	2.01 ^P	2.22 ^P	1.22 ^P	2.19	1.83	0.61 ^b
Germany	0.80 ^P	1.76 ^P	2.17 ^P	2.28 ^P	1.52 ^P	2.33	2.00	0.28 ^b
France	0.92 ^P	1.67 ^P	2.14 ^P	2.27 ^P	1.43 ^P	2.29	1.95	0.41 ^b
Italy	0.53 ^P	1.95 ^P	2.39 ^P	2.51 ^P	1.82 ^P	2.50	2.21	0.07 ^b
Japan	1.32 ^P	1.74 ^P	2.09 ^P	2.32 ^P	1.25 ^P	2.25	1.81	0.87 ^b
Group 6=>	ANT	DCR	SC	DASH	QTUM	P6-EW	P6-CW	P6-VW
US	156.76 ^P	2.04 ^P	2.25 ^P	1.75 ^P	2.20 ^P	1.63 ^b	2.06	1.87
Canada	157.21 ^P	2.05 ^P	2.24 ^P	1.73 ^P	2.18 ^P	1.66 ^b	2.03	1.90
UK	162.50 ^P	2.13 ^P	2.31 ^P	1.85	2.27 ^P	2.64	2.14	2.00 ^b

Germany	160.60 ^P	2.29 ^P	2.49 ^P	2.00	2.40	2.41	2.27	2.13 ^b
France	160.38 ^P	2.24 ^P	2.44 ^P	2.03	2.38 ^P	2.14 ^b	2.27	2.15
Italy	155.33 ^P	2.47 ^P	2.67 ^P	2.29 ^P	2.59 ^P	1.24 ^b	2.48	2.40
Japan	162.86 ^P	2.25 ^P	2.39 ^P	1.99	2.40	2.50	2.24	2.10 ^b
Group 7=>	BAT	ENJ	ZRX	LRC	TEL	P7-EW	P7-CW	P7-VW
US	2.22 ^P	1.69	2.23 ^P	2.13 ^P	1.52	2.27	2.29	2.09 ^b
Canada	2.17 ^P	1.72	2.22 ^P	2.14 ^P	1.54	2.26	2.29	2.11 ^b
UK	2.29 ^P	1.74	2.27 ^P	2.24 ^P	1.65	2.35	2.37	2.15 ^b
Germany	2.43 ^P	2.01	2.41 ^P	2.41 ^P	1.94	2.48	2.50	2.33 ^b
France	2.41 ^P	1.95	2.40 ^P	2.33 ^P	1.89	2.45	2.47	2.30 ^b
Italy	2.61 ^P	2.23	2.60 ^P	2.57 ^P	2.13	2.65	2.66	2.52 ^b
Japan	2.34 ^P	2.00	2.35 ^P	2.33 ^P	1.75	2.39	2.41	2.25 ^b
Group 8=>	ICX	NTRN	STORJ	RLC	WAXP	P8-EW	P8-CW	P8-VW
US	2.37 ^P	2148.6 ^P	1.80 ^P	0.13	1.65 ^P	42.93	30.61	0.59 ^b
Canada	2.34 ^P	2148.5 ^P	1.81 ^P	0.09	1.63 ^P	42.92	30.60	0.46 ^b
UK	2.45 ^P	2148.4 ^P	1.90 ^P	0.18	1.85 ^P	42.91	30.59	0.44 ^b
Germany	2.57 ^P	2148.4 ^P	2.10 ^P	0.57	2.03 ^P	42.90	30.58	0.96 ^b
France	2.54 ^P	2148.4 ^P	1.99 ^P	0.40	2.01 ^P	42.91	30.58	0.84 ^b
Italy	2.73 ^P	2148.5 ^P	2.28 ^P	0.64	2.25 ^P	42.90	30.57	1.13 ^b
Japan	2.49 ^P	2148.6 ^P	1.97 ^P	0.23	1.95 ^P	42.93	30.60	0.56 ^b
Group 9=>	LSK	DGB	PRO	ARK	XEM	P9-EW	P9-CW	P9-VW
US	2.06 ^P	2.12 ^P	0.64	2.12 ^P	2.25 ^P	2.13	2.17	1.75 ^b
Canada	2.04 ^P	2.14 ^P	0.64	2.04 ^P	2.19 ^P	2.10	2.14	1.76 ^b
UK	2.15 ^P	2.24 ^P	0.37	2.06 ^P	2.24 ^P	2.15	2.20	1.82 ^b
Germany	2.34 ^P	2.35 ^P	0.13	2.30 ^P	2.40 ^P	2.29	2.35	2.01 ^b
France	2.29 ^P	2.33 ^P	0.25	2.28 ^P	2.36 ^P	2.27	2.32	1.97 ^b
Italy	2.54 ^P	2.57 ^P	0.22	2.51 ^P	2.61 ^P	2.48	2.53	2.28 ^b
Japan	2.28 ^P	2.37 ^P	0.28	1.95 ^P	2.36 ^P	2.22	2.29	1.91 ^b
Group 10=>	IOST	XNO	POWR	REQ	NMR	P10-EW	P10-CW	P10-VW
US	2.22 ^P	1.56	1.93 ^P	6.34 ^P	1.29	2.16	1.89 ^b	3.17
Canada	2.22 ^P	1.51	2.02 ^P	5.74 ^P	1.61	2.13	1.88 ^b	2.70
UK	2.34 ^P	1.59	2.14 ^P	5.34 ^P	1.44	2.23	2.00 ^b	2.35
Germany	2.48 ^P	1.90 ^P	2.25 ^P	4.58 ^P	1.44	2.33	2.07	1.89 ^b
France	2.45 ^P	1.81 ^P	2.22 ^P	4.47 ^P	1.83 ^P	2.28	1.98	1.80 ^b
Italy	2.65 ^P	2.14 ^P	2.43 ^P	3.57 ^P	0.59	2.54	2.39	1.15 ^b
Japan	2.46 ^P	1.71	2.24 ^P	6.41 ^P	1.34	2.31	2.00 ^b	3.22
Panel B: 50% equity and 50% cryptocurrency (85~15)								
Group 1=>	BTC	ETH	USDT	BNB	XRP	P1-EW	P1-CW	P1-VW
US	3.09 ^P	4.10 ^P	0.81	0.17	0.61	2.89	3.18	2.28 ^b
Canada	3.12 ^P	4.14 ^P	0.73	0.36	0.77	2.95	3.22	2.30 ^b
UK	3.20 ^P	4.24 ^P	0.76	0.59	0.94	3.04	3.29	2.37 ^b
Germany	3.24 ^P	4.28 ^P	0.94	0.66	1.00	3.08	3.33	2.42 ^b
France	3.23 ^P	4.26 ^P	0.93	0.65	0.97	3.06	3.32	2.39 ^b
Italy	3.25 ^P	4.27 ^P	1.12	0.68	1.00	3.10	3.35	2.46 ^b
Japan	3.34 ^P	4.35 ^P	0.79	0.90	1.08	3.15	3.41	2.47 ^b
Group 2=>	DOGE	ADA	TRX	LINK	BCH	P2-EW	P2-CW	P2-VW
US	100.42 ^P	2.97 ^P	0.89	4.50 ^P	3.31 ^P	2.69 ^b	3.88	28.37
Canada	99.83 ^P	3.08 ^P	1.09	4.58 ^P	3.38 ^P	2.77 ^b	3.96	27.82
UK	98.79 ^P	3.06 ^P	1.21	4.70 ^P	3.46 ^P	2.89 ^b	4.02	27.06

Germany	98.47 ^P	3.07 ^P	1.19	4.76 ^P	3.52 ^P	2.91 ^b	4.04	26.89
France	98.45 ^P	3.09 ^P	1.21	4.74 ^P	3.48 ^P	2.91 ^b	4.03	26.84
Italy	98.19 ^P	3.07 ^P	1.18	4.71 ^P	3.47 ^P	2.91 ^b	4.04	26.97
Japan	97.06 ^P	3.16 ^P	1.52	4.79 ^P	3.65 ^P	3.07 ^b	4.13	26.21
Group 3=>	LTC	ETC	XMR	XLM	MKR	P3-EW	P3-CW	P3-VW
US	4.05 ^P	3.87 ^P	3.93 ^P	2.10 ^P	4.01 ^P	3.94	3.34	1.17 ^b
Canada	4.14 ^P	3.91 ^P	4.00 ^P	1.84 ^P	4.05 ^P	3.46	3.34	1.38 ^b
UK	4.24 ^P	3.98 ^P	4.10 ^P	1.67 ^P	4.18 ^P	4.11	3.55	1.50 ^b
Germany	4.25 ^P	4.03 ^P	4.08 ^P	1.59 ^P	4.19 ^P	4.13	3.56	1.51 ^b
France	4.24 ^P	4.02 ^P	4.08 ^P	1.63 ^P	4.17 ^P	4.11	3.56	1.51 ^b
Italy	4.23 ^P	4.00 ^P	4.08 ^P	1.52	4.15 ^P	4.13	3.59	1.55 ^b
Japan	4.33 ^P	4.12 ^P	4.20 ^P	1.62 ^P	4.30 ^P	4.18	3.63	1.59 ^b
Group 4=>	THETA	KCS	NEO	XTZ	GNO	P4-EW	P4-CW	P4-VW
US	5.18 ^P	10.76 ^P	3.83 ^P	3.95 ^P	4.20 ^P	4.25	4.44	3.82 ^b
Canada	5.27 ^P	10.84 ^P	3.94 ^P	4.04 ^P	4.28 ^P	4.32	4.52	3.94 ^b
UK	5.38 ^P	10.52 ^P	3.94	4.14 ^P	4.37 ^P	4.40	4.60	3.98 ^b
Germany	5.43 ^P	10.06 ^P	4.04	4.23 ^P	4.40 ^P	4.45	4.65	4.07 ^b
France	5.41 ^P	10.27 ^P	4.00	4.22 ^P	4.39 ^P	4.44	4.64	4.06 ^b
Italy	5.39 ^P	10.05 ^P	4.01	4.23 ^P	4.40 ^P	4.45	4.64	4.07 ^b
Japan	5.45 ^P	10.24 ^P	4.11	4.25 ^P	4.45 ^P	4.50	4.73	4.13 ^b
Group 5=>	MANA	BTG	GLM	ZEC	ELF	P5-EW	P5-CW	P5-VW
US	18.60 ^P	1.28 ^P	2.13 ^P	4.04 ^P	4.75 ^P	4.07	0.28 ^b	16.25
Canada	18.49 ^P	1.10 ^P	2.25 ^P	4.14 ^P	4.51 ^P	4.13	0.28 ^b	16.32
UK	17.72 ^P	0.89 ^P	2.39 ^P	4.22 ^P	4.22 ^P	4.22	0.56 ^b	15.66
Germany	17.67 ^P	0.80 ^P	2.46 ^P	4.21 ^P	4.03 ^P	4.27	0.61 ^b	15.59
France	17.71 ^P	0.84 ^P	2.43 ^P	4.20 ^P	4.13 ^P	4.24	0.56 ^b	15.71
Italy	17.95 ^P	0.86 ^P	2.42 ^P	4.21 ^P	4.08 ^P	4.24	0.52 ^b	15.83
Japan	17.68 ^P	0.49	2.50 ^P	4.31 ^P	4.14 ^P	4.28	0.57 ^b	15.82
Group 6=>	ANT	DCR	SC	DASH	QTUM	P6-EW	P6-CW	P6-VW
US	603.11 ^P	3.84 ^P	4.61 ^P	0.66	4.44 ^P	33.31	3.26	1.54 ^b
Canada	602.48 ^P	3.89 ^P	4.66 ^P	0.82	4.51 ^P	32.80	3.36	1.70 ^b
UK	605.65 ^P	3.95 ^P	4.72 ^P	1.00	4.62 ^P	33.68	3.48	1.85 ^b
Germany	606.65 ^P	4.01 ^P	4.80 ^P	1.03	4.64 ^P	33.93	3.50	1.85 ^b
France	606.09 ^P	3.98 ^P	4.76 ^P	1.07	4.64 ^P	33.53	3.52	1.89 ^b
Italy	605.24 ^P	3.97 ^P	4.78 ^P	1.06	4.60 ^P	33.40	3.52	1.89 ^b
Japan	605.98 ^P	4.09 ^P	4.84 ^P	1.19	4.76 ^P	33.10	3.62	2.02 ^b
Group 7=>	BAT	ENJ	ZRX	LRC	TEL	P7-EW	P7-CW	P7-VW
US	4.61 ^P	0.75	4.02 ^P	3.82 ^P	0.37	4.79	4.86	3.26 ^b
Canada	4.65 ^P	0.88	4.08 ^P	3.89 ^P	0.48	4.85	4.92	3.34 ^b
UK	4.77 ^P	0.94	4.16 ^P	4.02 ^P	0.61	4.94	5.01	3.41 ^b
Germany	4.81 ^P	1.09	4.20 ^P	4.09 ^P	0.76	4.99	5.05	3.49 ^b
France	4.79 ^P	1.06	4.19 ^P	4.04 ^P	0.73	4.97	5.03	3.48 ^b
Italy	4.78 ^P	1.02	4.16 ^P	4.03 ^P	0.70	4.95	5.01	3.44 ^b
Japan	4.83 ^P	1.28	4.27 ^P	4.13 ^P	0.78	5.03	5.09	3.58 ^b
Group 8=>	ICX	NTRN	STORJ	RLC	WAXP	P8-EW	P8-CW	P8-VW
US	5.30	7162.3 ^P	1.44 ^P	10.87 ^P	0.95	143.25	102.22	6.95 ^b
Canada	5.35	7162.2 ^P	1.53 ^P	10.85 ^P	0.95	143.24	102.21	6.97 ^b
UK	5.45	7162.2 ^P	1.67 ^P	10.83 ^P	1.17	143.23	102.21	6.89 ^b
Germany	5.47	7162.2 ^P	1.75 ^P	10.25 ^P	1.20	143.23	102.21	6.57 ^b

France	5.46	7162.2 ^p	1.67 ^p	10.41 ^p	1.23	143.23	102.21	6.64 ^b
Italy	5.44	7162.2 ^p	1.65 ^p	10.74 ^p	1.17	143.23	102.21	6.80 ^b
Japan	5.50	7162.3 ^p	1.84 ^p	10.31 ^p	1.29	143.24	102.22	6.64 ^b
Group-9=>	LSK	DGB	PRO	ARK	XEM	P9-EW	P9-CW	P9-VW
US	3.63 ^p	4.23 ^p	9.45 ^p	2.11 ^p	4.64 ^p	3.74	4.24	1.01 ^b
Canada	3.70 ^p	4.32 ^p	9.35 ^p	2.11 ^p	4.67 ^p	3.83	4.31	1.12 ^b
UK	3.84 ^p	4.44 ^p	9.03 ^p	2.04 ^p	4.70 ^p	3.89	4.36	1.23 ^b
Germany	3.91 ^p	4.42 ^p	9.04 ^p	2.20 ^p	4.76 ^p	3.92	4.41	1.30 ^b
France	3.86 ^p	4.41 ^p	9.11 ^p	2.18 ^p	4.73 ^p	3.90	4.40	1.29 ^b
Italy	3.86 ^p	4.43 ^p	9.07 ^p	2.29 ^p	4.75 ^p	3.94	4.42	1.31 ^b
Japan	3.97 ^p	4.54 ^p	8.88 ^p	1.88 ^p	4.81 ^p	3.96	4.46	1.37 ^b
Group-10=>	IOST	XNO	POWR	REQ	NMR	P10-EW	P10-CW	P10-VW
US	4.53 ^p	0.15	2.61 ^p	53.53 ^p	17.89 ^p	4.00	1.32 ^b	29.52
Canada	4.63 ^p	0.04	2.80 ^p	52.41 ^p	18.12 ^p	4.07	1.40 ^b	28.84
UK	4.76 ^p	0.06	2.90 ^p	51.68 ^p	17.79 ^p	4.16	1.60 ^b	28.26
Germany	4.79 ^p	0.27	2.90 ^p	51.41 ^p	18.10 ^p	4.13	1.51 ^b	28.12
France	4.76 ^p	0.16	2.90 ^p	51.15 ^p	18.33 ^p	4.10	1.45 ^b	27.90
Italy	4.74 ^p	0.20	2.84 ^p	51.17 ^p	17.84 ^p	4.17	1.60 ^b	27.97
Japan	4.88 ^p	0.23	3.04 ^p	52.43 ^p	17.51 ^p	4.20	1.60 ^b	28.94

This table reports the downside risk (VaR) of the equity-cryptocurrency mixed portfolios at the 5% confidence level. VaR is the four-moment modified value-at-risk, estimated using Cornish-Fisher expansion. In Panel A (Panel B), 85% (50%) of wealth is invested in an equity index, whereas the remaining 15% (50%) is invested in a cryptocurrency or crypto portfolio. The values marked with "b" indicate the best-performing crypto-portfolio in each group (row), whereas the values marked with "p" indicate the constituents of the corresponding portfolios that deliver higher VaR (poorer performance) than the best-performing crypto-portfolio. The sample period spans between February 1, 2018, and December 1, 2025.

Table 7. Expected shortfall of equity-cryptocurrency mixed portfolios

	Cryptocurrency										Crypto-portfolio					
Confidence Level =>	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%
Group 1=>	BTC		ETH		USDT		BNB		XRP		P1-EW		P1-CW		P1-VW	
US	15.03	108.16	14.51	99.96	15.88 ^P	122.29 ^P	15.40	113.37 ^P	14.40	101.21	15.59 ^b	112.55 ^b	15.69	113.04	16.01	118.18
Canada	21.00	173.26	20.21	161.43	22.41 ^P	193.14 ^P	20.99	172.45	19.41	154.17	22.12	182.17	22.03 ^b	180.97 ^b	22.59	188.88
UK	16.38	123.31	16.41	120.10	16.70	130.12	17.00	128.40	15.55	112.47	17.32	130.75	17.26 ^b	130.16 ^b	17.49	134.25
Germany	15.55	110.39	15.77	109.51	15.94	117.69	15.99	113.91	15.09	103.41	16.72	120.31	16.65 ^b	119.54 ^b	16.86	123.35
France	15.11	105.48	15.43	106.01	15.54	113.03	15.69	110.60	14.85	101.10	16.44	117.51	16.32 ^b	116.14 ^b	16.56	120.20
Italy	21.27	161.33	21.28	158.66	21.93	171.10	21.70	164.15	20.76	153.84	24.79	196.60	24.56 ^b	194.01 ^b	25.02	200.39
Japan	14.15 ^P	97.58 ^P	14.96 ^P	102.22 ^P	12.17	84.17	14.85 ^P	103.71 ^P	14.03 ^P	96.47	14.51	100.69	14.70	101.98	13.91 ^b	96.83 ^P
Group 2=>	DOGE		ADA		TRX		LINK		BCH		P2-EW		P2-CW		P2-VW	
US	45.17 ^P	556.19 ^P	14.06	94.18	14.46	103.81 ^P	14.74 ^P	99.52	14.00	93.98	14.96	103.33	14.74 ^b	100.41 ^b	22.99	210.98
Canada	51.21 ^P	626.35 ^P	19.08	147.50	20.36	165.73 ^P	19.47	149.89	19.24	149.98	21.16	168.75	20.86 ^b	164.67 ^b	29.96	283.72
UK	45.93 ^P	566.16 ^P	15.92	114.03	16.58	124.04 ^P	16.11	113.60	15.72	112.21	17.05	124.78	16.83 ^b	121.69 ^b	24.71	227.61
Germany	43.39 ^P	518.05 ^P	15.68	107.93	15.88	113.63	15.74	105.68	15.18	102.48	16.65	116.82	16.51 ^b	114.57 ^b	23.08	204.62
France	43.48 ^P	520.75 ^P	15.21	102.86	15.48	108.84	15.44	102.59	14.94	100.24	16.37	114.04	16.24 ^b	112.01 ^b	22.88	202.17
Italy	50.73 ^P	567.43 ^P	20.97	154.39	21.67	164.63	21.09	153.92	20.78	152.83	24.37	189.55	24.11 ^b	186.12 ^b	31.19	276.10
Japan	42.82 ^P	521.42 ^P	14.53	98.74	13.70	91.60	14.93 ^P	98.79	15.01 ^P	102.07 ^P	15.05	102.51	14.90 ^b	100.41 ^b	22.15	197.82
Group 3=>	LTC		ETC		XMR		XLM		MKR		P3-EW		P3-CW		P3-VW	
US	14.05	95.54	13.70	90.42	14.32	100.14	14.67	106.48 ^P	14.46	98.11	14.84	102.60	14.71 ^b	101.39 ^b	14.81	103.52
Canada	20.02 ^P	159.05 ^P	19.25 ^P	149.25 ^P	21.01 ^P	172.50 ^P	19.71 ^P	159.04 ^P	18.65 ^P	142.97 ^P	21.27	170.48	18.21 ^b	141.49 ^b	21.05	168.38
UK	16.16	116.38	15.84	112.41	16.61	123.93	16.42	123.57	15.60	109.89	17.14	126.01	17.11 ^b	125.68 ^b	17.19	127.10
Germany	15.52	106.20	15.34	103.57	16.47	119.97 ^P	15.82	112.98	15.29	103.12	16.75	118.41	16.70 ^b	117.88 ^b	16.80	119.59
France	15.21	102.85	15.01	99.98	15.89	113.18	15.55	110.28	14.94	99.50	16.43	115.12	16.39 ^b	114.65 ^b	16.54	116.79
Italy	21.14	156.67	20.90	153.38	21.88	166.59	21.45	162.08	20.39	148.22	24.48	191.04	24.45 ^b	190.63 ^b	24.48	190.92
Japan	14.30	95.05	14.43	95.65	13.93	93.54	15.15 ^P	110.76 ^P	16.10 ^P	112.87 ^P	15.30	105.64	15.04 ^b	103.07 ^b	15.40	107.91
Group 4=>	THETA		KCS		NEO		XTZ		GNO		P4-EW		P4-CW		P4-VW	
US	14.09	92.01	18.12 ^P	146.86 ^P	14.93	103.58	13.96	93.59	14.65	99.89	15.52	108.91	15.17 ^b	105.16	15.26	104.93 ^b
Canada	18.98	143.39	22.70 ^P	198.57 ^P	19.70	153.78	19.20	149.32	19.91	156.06	21.30	169.95	21.24	168.98	20.60 ^b	160.60 ^b
UK	16.00	110.41	19.50 ^P	162.93 ^P	15.92	113.83	15.72	111.44	16.39	118.21	17.23	126.18	17.10	124.47	16.65 ^b	118.97 ^b
Germany	15.82	105.12	17.52 ^P	135.18 ^P	15.44	104.15	15.32	102.73	15.91	109.43	16.88	118.58	16.72	116.40	16.42 ^b	112.13 ^b
France	15.59	102.87	17.88 ^P	140.09 ^P	15.07	100.53	14.98	99.14	15.53	105.19	16.59	115.73	16.43	113.50	16.12 ^b	109.29 ^b
Italy	21.28	154.47	23.26	185.20 ^P	20.93	153.24	20.48	147.93	21.43	158.87	24.60	191.48	24.19	186.47	23.77 ^b	180.96 ^b
Japan	14.65 ^P	94.69	17.98 ^P	147.21 ^P	13.90	90.12	14.19	92.44	14.23	94.12	14.84	99.66	15.09	101.27	14.49 ^b	94.76 ^b

Group 5=>	MANA		BTG		GLM		ZEC		ELF		P5-EW		P5-CW		P5-VW	
US	20.43 ^P	194.02 ^P	15.24 ^P	112.08 ^P	13.99	95.34	14.74 ^P	100.36 ^P	16.43 ^P	127.41 ^P	14.58 ^b	98.48 ^b	15.62	111.41	21.82	196.62
Canada	27.98 ^P	277.12 ^P	19.90	160.85	19.90	157.65	19.65	152.67	22.49 ^P	191.15 ^P	21.59 ^b	172.63 ^b	22.43	184.20	29.76	283.94
UK	23.24 ^P	219.95 ^P	16.70	127.75 ^P	16.73	122.60	15.67	110.12	18.57 ^P	147.61 ^P	17.21 ^b	125.81 ^b	17.70	132.95	23.79	217.01
Germany	22.29 ^P	202.44 ^P	16.02	114.20	16.29	113.80	15.86	109.74	17.21 ^P	128.24 ^P	16.97 ^b	119.40 ^b	17.33	125.10	22.52	198.25
France	22.52 ^P	206.38 ^P	15.91	114.54	16.05	111.60	15.50	105.70	17.35 ^P	130.49 ^P	16.70 ^b	116.99 ^b	17.20	124.22	22.93	204.00
Italy	29.23 ^P	265.01 ^P	21.71	165.93	22.20	167.24	21.16	156.43	23.18 ^P	181.03	24.87 ^b	194.35 ^b	25.36	200.80	31.47	280.86
Japan	23.62 ^P	226.89 ^P	14.65 ^P	103.09 ^P	14.38 ^P	96.66 ^P	13.44	85.21	16.13 ^P	122.19 ^P	14.00 ^b	91.64 ^b	15.61	111.78	22.86	212.55
Group 6=>	ANT		DCR		SC		DASH		QTUM		P6-EW		P6-CW		P6-VW	
US	254.16 ^P	420.10 ^P	14.07	96.08	13.50	86.69	15.06	107.20 ^P	13.94	91.87	23.21	213.46	15.18 ^b	105.37 ^b	15.43	108.45
Canada	262.61 ^P	478.11 ^P	18.87	146.48	18.59	140.54	20.40	164.68	18.48	140.43	30.23	287.89	21.20	169.30	20.81 ^b	164.88 ^b
UK	291.20 ^P	636.70 ^P	15.42	108.90	15.69	108.86	16.54	122.35	15.26	105.33	30.93	308.93	16.97	123.63	16.94 ^b	123.16 ^b
Germany	248.95 ^P	279.05 ^P	15.22	102.64	15.52	102.47	16.07	113.62	14.95	98.45	30.31	299.04	16.71 ^b	117.01 ^b	16.72	117.31
France	254.79 ^P	343.36 ^P	14.99	100.75	15.26	100.38	15.63	108.31	14.59	94.77	28.86	279.67	16.36	113.42	16.34 ^b	113.12 ^b
Italy	186.98 ^P	199.89 ^P	20.75	152.39	21.00	152.22	21.49	160.88	20.12	144.52	36.82	345.94	24.27	187.85	23.96 ^b	184.14 ^b
Japan	284.78 ^P	562.07 ^P	13.64	88.27	14.52	95.53	14.69	100.81 ^P	14.45	94.62	29.51	293.90	14.77 ^b	99.16 ^b	15.13	103.04
Group 7=>	BAT		ENJ		ZRX		LRC		TEL		P7-EW		P7-CW		P7-VW	
US	14.10	93.33	14.91 ^P	105.69 ^P	14.71 ^P	98.50 ^P	13.13	83.67	14.84 ^P	105.67 ^P	14.67 ^b	97.62 ^b	14.74	97.84	14.77	98.91
Canada	19.10	147.25	19.49	153.66 ^P	19.27	146.82	17.52	129.82	17.93	138.65	20.10	154.70	20.17	154.83	19.74 ^b	150.65 ^b
UK	15.53	107.74	16.66 ^P	123.90 ^P	16.07	112.67	15.16	103.79	16.20	119.08 ^P	16.51	116.08	16.49	115.47	16.28 ^b	114.39 ^b
Germany	15.23	100.91	16.10 ^P	112.39 ^P	15.61	104.19	14.91	96.91	15.78	108.44 ^P	16.37	110.89	16.34	110.22	16.06 ^b	107.66 ^b
France	14.87	97.28	16.00 ^P	112.33 ^P	15.33	101.09	14.83	97.17	15.67	108.00 ^P	16.16	109.17	16.12	108.36	15.87 ^b	106.12 ^b
Italy	20.44	147.43	21.81	163.70	20.92	151.76	20.14	144.14	20.24	147.22	23.71	180.02	23.61	178.69	23.26 ^b	175.20 ^b
Japan	14.65	97.78	15.51 ^P	108.38 ^P	14.21	92.41	14.52	95.59	14.77	103.84 ^P	15.13	101.34	15.21	101.93	14.88 ^b	98.96 ^b
Group 8=>	ICX		NTRN		STORJ		RLC		WAXP		P8-EW		P8-CW		P8-VW	
US	14.51	95.68	1279.3 ^P	9510.4 ^P	13.96	95.13	18.97 ^P	160.14 ^P	13.80	95.86	254.62	1891.01	180.79	1341.19	16.84 ^b	132.97 ^b
Canada	19.60	149.83	1279.2 ^P	9509.7 ^P	19.13	149.31	24.94 ^P	226.76 ^P	19.27	153.47	254.53	1890.32	180.69	1340.53	23.09 ^b	200.21 ^b
UK	16.10	111.66	1279.1 ^P	9509.3 ^P	16.09	116.45	23.57 ^P	214.74 ^P	17.54	131.57	254.41	1889.31	180.55	1339.28	20.38 ^b	173.54 ^b
Germany	15.77	104.62	1279.1 ^P	9508.9 ^P	15.75	108.41	20.26 ^P	167.62 ^P	16.65	118.25	254.16	1887.12	180.19	1336.12	18.75 ^b	147.08 ^b
France	15.51	102.14	1279.1 ^P	9509.1 ^P	15.74	109.96	20.52 ^P	172.54 ^P	16.44	116.31	254.23	1887.70	180.29	1337.00	18.89 ^b	150.36 ^b
Italy	21.14	153.30	1279.1 ^P	9508.9 ^P	21.33	158.70	27.08	231.95 ^P	22.08	166.64	253.99	1885.60	179.95	1333.96	27.13 ^b	226.53 ^b
Japan	14.84	97.77	1279.4 ^P	9511.2 ^P	15.73	112.34	21.57 ^P	187.71 ^P	16.40	118.24	254.59	1890.63	180.70	1340.39	18.48 ^b	153.17 ^b
Group 9=>	LSK		DGB		PRO		ARK		XEM		P9-EW		P9-CW		P9-VW	
US	13.43	88.56	13.76	91.41	16.98 ^P	152.87 ^P	19.28 ^P	145.48 ^P	14.26	95.06	15.50	108.08	15.15	104.27 ^b	15.14 ^b	106.29
Canada	18.82	145.69	18.67	143.04	20.01	185.31 ^P	25.55 ^P	212.85 ^P	19.21	148.54	21.87	175.26	21.52	171.52	20.38 ^b	161.31 ^b
UK	16.43	118.81	15.53	108.46	17.42 ^P	155.03 ^P	22.27 ^P	177.51 ^P	15.69	110.74	18.00	134.26	17.58	129.61	16.90 ^b	124.66 ^b

Germany	15.69	106.48	15.08	100.48	17.20 ^p	147.26 ^p	21.43 ^p	163.48 ^p	15.18	101.22	17.54	125.49	17.10	120.54	16.36 ^b	114.46 ^b
France	15.37	103.71	14.88	98.40	17.37 ^p	150.66 ^p	21.34 ^p	162.49 ^p	15.00	99.70	17.34	123.76	16.95	119.28	16.26 ^b	113.99 ^b
Italy	20.98	153.54	20.19	145.32	23.22	198.43 ^p	29.23 ^p	237.31 ^p	20.53	148.64	25.89	204.84	25.20	197.34	23.87 ^b	183.90 ^b
Japan	14.91	100.87	13.95	89.70	16.64 ^p	146.70 ^p	15.63 ^p	111.13 ^p	13.27	83.39	14.44	96.60	14.31 ^b	94.55 ^b	15.10	104.94
Group 10=>	IOST		XNO		POWR		REQ		NMR		P10-EW		P10-CW		P10-VW	
US	13.62	88.24	14.97 ^p	108.16 ^p	13.97	94.78	31.95 ^p	349.36 ^p	18.94 ^p	174.41 ^p	14.71 ^b	99.73 ^b	15.03	104.49	25.28	254.03
Canada	18.32	138.13	19.75	159.75	20.01	157.15	35.59 ^p	380.54 ^p	24.33 ^p	235.44 ^p	21.23	168.71 ^b	21.15 ^b	169.05	29.50	291.60
UK	15.47	106.45	16.68	126.42 ^p	16.60	119.47	31.34 ^p	332.62 ^p	21.11 ^p	200.84 ^p	17.26	125.80 ^b	17.25 ^b	126.68	25.39	245.70
Germany	15.11	98.75	15.60	109.06	16.04	110.66	29.23 ^p	300.20 ^p	21.29 ^p	201.89 ^p	16.83 ^b	117.87 ^b	16.92	120.47	24.19	225.81
France	14.78	95.68	15.45	108.29	15.74	107.63	28.64 ^p	292.08 ^p	22.27 ^p	218.66 ^p	16.68 ^b	117.10 ^b	16.96	122.22	23.41	216.52
Italy	20.30	145.25	20.86	154.84	22.00	164.82	34.45 ^p	335.27 ^p	27.04 ^p	242.24 ^p	24.34	188.18	24.20 ^b	186.91 ^b	31.33	284.14
Japan	14.88	97.85	15.25	109.82	15.15	102.71	35.94 ^p	399.15 ^p	20.25 ^p	192.01 ^p	15.55 ^b	106.45 ^b	15.90	112.40	28.51	293.58

Notes: This table reports the conditional value at risk (CVaR) of the equity-crypto mixed portfolios at the 1% and 5% confidence levels (Conf. Lev.). CVaR is the four-moment modified conditional value-at-risk, estimated using Cornish-Fisher expansion. In each case (pair), 90% of wealth is invested in an equity index, whereas the remaining 10% is invested in a cryptocurrency (left block) or a crypto portfolio (right block). The values marked with "b" indicate the best-performing crypto-portfolio in each group (row), whereas the values marked with "p" indicate the constituents of the corresponding portfolios that deliver higher VaR (poorer performance) than the best-performing crypto-portfolio. The sample period spans between February 1, 2018, and December 1, 2025.

Table 8. Further evidence on the expected shortfall of equity-cryptocurrency mixed portfolios

	Cryptocurrency					Crypto-portfolio		
Panel A: 85% equity and 15% cryptocurrency (85~15)								
Group 1=>	BTC	ETH	USDT	BNB	XRP	P1-EW	P1-CW	P1-VW
US	13.79	13.56	14.85 ^p	16.54 ^p	14.90 ^p	14.22 ^b	14.34	14.62
Canada	18.746	17.938	20.998 ^p	21.079 ^p	18.543	19.89	19.69 ^b	20.48
UK	15.14	15.47	15.76	18.37 ^p	15.59	15.97	15.89 ^b	16.16
Germany	14.57	15.12	15.08	17.13 ^p	15.26	15.56	15.49 ^b	15.64
France	14.12	14.79	14.68	16.88 ^p	15.07	15.27	15.14 ^b	15.35
Italy	19.45	19.52	20.67	21.80	19.95	22.65	22.27 ^b	23.06
Japan	14.68 ^p	15.93 ^p	11.50	17.55 ^p	15.61 ^p	14.82	15.17	13.79 ^b
Group 2=>	DOGE	ADA	TRX	LINK	BCH	P2-EW	P2-CW	P2-VW
US	57.90 ^p	13.59	15.10 ^p	14.40 ^p	13.63	14.22	13.69 ^b	38.89
Canada	60.46 ^p	17.24	19.56 ^p	17.58	17.37	19.23	18.45 ^b	44.53
UK	57.58 ^p	15.68	16.95 ^p	15.57	15.16	16.28	15.73 ^b	39.19
Germany	61.04 ^p	15.81 ^p	16.41 ^p	15.48	14.79	16.06	15.68 ^b	36.91
France	59.70 ^p	15.22	16.05 ^p	15.22	14.63	15.75	15.36 ^b	36.74
Italy	71.16 ^p	19.82	21.25	19.48	19.21	22.34	21.70 ^b	44.29
Japan	60.16 ^p	16.00 ^p	15.53	16.37 ^p	16.34 ^p	16.16	15.72 ^b	38.43
Group-3=>	LTC	ETC	XMR	XLM	MKR	P3-EW	P3-CW	P3-VW
US	13.30	13.35	13.48	16.02 ^p	13.61	13.70 ^b	13.88	15.27
Canada	17.91	17.49	18.90	19.57 ^p	16.35	19.17 ^b	19.88	20.01
UK	15.34	15.25	15.83	17.51 ^p	14.96	16.01 ^b	16.19	17.37
Germany	14.91	14.89	16.11 ^p	16.99 ^p	15.02	15.85 ^b	15.96	17.03
France	14.67	14.62	15.52 ^p	16.79 ^p	14.60	15.51 ^b	15.65	16.78
Italy	19.47	19.33	20.43	21.62	18.52	22.14 ^b	22.29	23.19
Japan	15.12	15.43	14.70	18.05 ^p	18.12 ^p	16.22	16.03 ^b	17.52
Group 4=>	THETA	KCS	NEO	XTZ	GNO	P4-EW	P4-CW	P4-VW
US	13.69	25.00 ^p	14.48 ^p	13.57	13.78	14.31	14.07 ^b	14.52
Canada	17.07	28.99 ^p	17.82	17.24	17.64	18.82	18.80	18.43 ^b
UK	15.57	26.93 ^p	15.50	15.18	15.44	16.07	16.05	15.91 ^b
Germany	15.70	23.58 ^p	15.16	15.03	15.29	15.98	15.92	15.86 ^b
France	15.51	24.6 ^p 9	14.87	14.72	14.95	15.69	15.62	15.57 ^b
Italy	19.75	28.64 ^p	19.50	18.86	19.73	22.24	21.79	21.53 ^b
Japan	15.88 ^p	26.90 ^p	15.11	15.59 ^p	14.82	15.50 ^b	15.95	15.57
Group 5=>	MANA	BTG	GLM	ZEC	ELF	P5-EW	P5-CW	P5-VW
US	28.32 ^p	17.97 ^p	14.71 ^p	14.17 ^p	22.02 ^p	13.82 ^b	16.75	30.85
Canada	34.56 ^p	20.75 ^p	19.01	17.62	26.74 ^p	19.62 ^b	22.69	37.77
UK	31.12 ^p	18.69 ^p	17.03 ^p	14.93	23.71 ^p	16.30 ^b	18.68	32.55
Germany	31.14 ^p	18.08 ^p	16.76 ^p	15.45	21.74 ^p	16.26 ^b	18.32	31.14
France	31.21 ^p	17.99 ^p	16.67 ^p	15.12	22.22 ^p	16.02 ^b	18.30	31.70
Italy	37.32 ^p	22.34	21.59	19.52	26.89 ^p	22.71 ^b	25.16	39.42
Japan	33.90 ^p	18.83 ^p	16.42 ^p	14.32	22.82 ^p	14.98 ^b	18.69	33.97
Group 6=>	ANT	DCR	SC	DASH	QTUM	P6-EW	P6-CW	P6-VW
US	687.27 ^p	13.09	13.30	16.16 ^p	13.51	40.48	14.63 ^b	16.25
Canada	690.62 ^p	16.48	16.92	19.90 ^p	16.52	46.48	19.23 ^b	20.01
UK	721.49 ^p	14.45	15.42	17.35 ^p	14.68	49.70	16.28 ^b	17.46
Germany	685.52 ^p	14.55	15.37	16.99 ^p	14.63	49.25	16.23 ^b	17.32
France	692.24 ^p	14.36	15.21	16.50 ^p	14.24	47.45	15.80 ^b	16.85
Italy	629.62 ^p	18.96	19.59	21.27	18.37	54.71	22.22 ^b	22.84
Japan	713.54 ^p	14.46	15.83	17.23 ^p	15.65	51.40	15.95 ^b	17.45
Group-7=>	BAT	ENJ	ZRX	LRC	TEL	P7-EW	P7-CW	P7-VW
US	13.41	16.64 ^p	14.83 ^p	12.92	17.25 ^p	13.85 ^b	13.95	14.50
Canada	16.97	19.71 ^p	18.09 ^p	15.88	19.17 ^p	17.84 ^b	17.93	17.98
UK	14.80	18.22 ^p	16.18 ^p	14.92	18.75 ^p	15.64 ^b	15.64	15.90
Germany	14.76	17.65 ^p	15.77 ^p	14.82	18.37 ^p	15.70	15.69 ^b	15.74
France	14.42	17.53 ^p	15.59 ^p	14.78	18.30 ^p	15.52	15.48 ^b	15.57
Italy	18.67	22.12 ^p	19.94	18.61	21.08	21.30	21.20 ^b	21.22
Japan	15.67	18.52 ^p	15.51	15.79	17.89 ^p	15.98	16.06	15.97 ^b
Group-8=>	ICX	NTRN	STORJ	RLC	WAXP	P8-EW	P8-CW	P8-VW

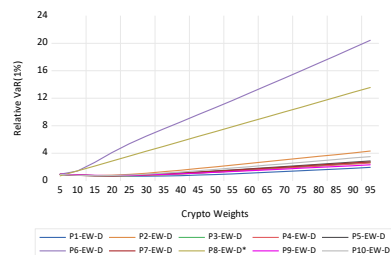
US	14.41	1919.2 ^p	14.90	28.57 ^p	16.18	382.99	272.64	20.35 ^b
Canada	18.08	1919.1 ^p	18.63	33.40 ^p	20.36	382.87	272.51	25.15 ^b
UK	15.97	1919.1 ^p	16.79	34.04 ^p	20.00	382.75	272.37	23.90 ^b
Germany	15.82	1919.1 ^p	16.59	29.77 ^p	19.04	382.61	272.16	22.40 ^b
France	15.60	1919.1 ^p	16.61	30.21 ^p	18.80	382.65	272.22	22.39 ^b
Italy	19.87	1919.1 ^p	20.96	36.05 ^p	22.89	382.53	272.05	29.30 ^b
Japan	16.21	1919.3 ^p	18.01	33.74 ^p	20.44	382.92	272.52	23.43 ^b
Group 9=>	LSK	DGB	PRO	ARK	XEM	P9-EW	P9-CW	P9-VW
US	13.53	13.30	16.59 ^p	22.05 ^p	13.93	14.54	14.05 ^b	15.98
Canada	17.66	16.74	17.98	27.24 ^p	17.45	19.79	19.18 ^b	19.75
UK	16.68	15.11	17.18 ^p	25.37 ^p	15.39	17.03	16.47 ^b	17.50
Germany	16.02	14.93	17.74 ^p	24.45 ^p	14.91	16.77	16.17 ^b	16.90
France	15.80	14.78	17.74 ^p	24.55 ^p	14.82	16.63	16.10 ^b	16.89
Italy	20.02	18.59	22.52	31.72 ^p	19.06	24.04	23.00	22.83 ^b
Japan	16.66 ^p	14.98 ^p	18.05 ^p	19.39 ^p	14.33	14.79	14.58 ^b	17.28
Group 10=>	IOST	XNO	POWR	REQ	NMR	P10-EW	P10-CW	P10-VW
US	13.29	15.61 ^p	14.92 ^p	50.12 ^p	22.82 ^p	13.96 ^b	15.49	37.06
Canada	16.36	18.78	19.17 ^p	52.38 ^p	26.31 ^p	18.97 ^b	20.15	39.72
UK	15.06	17.59 ^p	16.95 ^p	50.18 ^p	24.31 ^p	16.42 ^b	17.54	37.29
Germany	14.88	16.50 ^p	16.54 ^p	49.27 ^p	25.31 ^p	16.32 ^b	17.45	36.53
France	14.57	16.53 ^p	16.32 ^p	48.46 ^p	25.48 ^p	16.22 ^b	17.59	35.21
Italy	18.67	20.61	21.39	54.10 ^p	31.02 ^p	22.03 ^b	22.95	42.19
Japan	16.25	17.97 ^p	17.30 ^p	57.72 ^p	25.55 ^p	16.92 ^b	18.49	42.77
Panel B: 50% equity and 50% cryptocurrency (50~50)								
Group 1=>	BTC	ETH	USDT	BNB	XRP	P1-EW	P1-CW	P1-VW
US	17.92 ^p	23.41 ^p	22.34 ^p	49.83 ^p	34.31 ^p	17.64	18.08	13.16 ^b
Canada	18.41 ^p	23.77 ^p	26.01 ^p	50.65 ^p	35.07 ^p	18.46	18.69	14.07 ^b
UK	20.44 ^p	25.70 ^p	26.33 ^p	53.06 ^p	35.05 ^p	19.64	20.46	14.48 ^b
Germany	20.51 ^p	25.76 ^p	24.07 ^p	52.27 ^p	35.05 ^p	19.72	20.55	14.41 ^b
France	20.15 ^p	25.48 ^p	23.46 ^p	51.75 ^p	34.86 ^p	19.37	20.20	14.18 ^b
Italy	19.20 ^p	24.59 ^p	24.13 ^p	51.15 ^p	34.93 ^p	19.15	19.56	14.91 ^b
Japan	23.66 ^p	28.52 ^p	22.98 ^p	54.36 ^p	36.78 ^p	22.52	23.65	16.36 ^b
Group 2=>	DOGE	ADA	TRX	LINK	BCH	P2-EW	P2-CW	P2-VW
US	103.28 ^p	29.39 ^p	43.60 ^p	30.71 ^p	29.09 ^p	35.19	25.96 ^b	122.02
Canada	99.38 ^p	29.85 ^p	43.37 ^p	30.91 ^p	29.19 ^p	35.65	26.45 ^b	123.68
UK	92.31 ^p	31.85 ^p	44.98 ^p	32.05 ^p	30.52 ^p	36.78	27.93 ^b	125.35
Germany	87.49 ^p	32.38 ^p	45.26 ^p	32.15 ^p	30.53 ^p	36.73	28.11 ^b	125.86
France	89.62 ^p	31.70 ^p	44.78 ^p	31.99 ^p	30.35 ^p	36.30	27.71 ^b	125.13
Italy	87.19 ^p	31.25 ^p	44.24 ^p	31.31 ^p	29.74 ^p	35.84	27.18 ^b	124.79
Japan	77.64 ^p	33.92 ^p	46.62 ^p	34.52 ^p	33.28 ^p	39.13	30.25 ^b	130.60
Group 3=>	LTC	ETC	XMR	XLM	MKR	P3-EW	P3-CW	P3-VW
US	26.47 ^p	26.43 ^p	27.44 ^p	36.91 ^p	29.57 ^p	24.42	26.18 ^b	38.66
Canada	26.95	26.90	28.10	37.29 ^p	29.49 ^p	28.52	28.16 ^b	38.60
UK	27.84 ^p	27.99 ^p	29.50 ^p	38.94 ^p	32.96 ^p	26.68 ^b	29.80	39.86
Germany	27.77 ^p	27.93 ^p	29.78 ^p	39.27 ^p	33.39 ^p	26.80 ^b	29.82	39.94
France	27.63 ^p	27.74 ^p	29.54 ^p	38.86 ^p	32.69 ^p	26.45 ^b	29.50	39.58
Italy	27.38 ^p	27.35 ^p	29.03 ^p	38.55 ^p	30.66 ^p	25.68 ^b	29.02	39.13
Japan	29.55	29.90 ^p	31.21 ^p	41.66 ^p	37.64 ^p	29.79 ^b	32.41	42.53
Group-4=>	THETA	KCS	NEO	XTZ	GNO	P4-EW	P4-CW	P4-VW
US	29.61 ^p	91.21 ^p	32.05 ^p	30.08 ^p	23.96	24.58 ^b	26.07	29.59
Canada	30.08 ^p	93.17 ^p	32.43 ^p	30.33 ^p	24.39	25.24 ^b	26.62	30.16
UK	31.35 ^p	93.81 ^p	33.53 ^p	31.73 ^p	25.34	26.39 ^b	28.08	31.22
Germany	31.55 ^p	92.47 ^p	33.35 ^p	31.85 ^p	25.44	26.40 ^b	28.16	31.32
France	31.40 ^p	93.36 ^p	33.25 ^p	31.58 ^p	25.31	26.25 ^b	27.91	31.09
Italy	30.90 ^p	93.13 ^p	33.03 ^p	30.99 ^p	25.11	25.92 ^b	27.42	30.86
Japan	32.94 ^p	96.19 ^p	35.01 ^p	33.94 ^p	26.70	28.39 ^b	30.27	33.00
Group 5=>	MANA	BTG	GLM	ZEC	ELF	P5-EW	P5-CW	P5-VW
US	63.35 ^p	47.63 ^p	36.57 ^p	29.55 ^p	79.08 ^p	27.21 ^b	44.91	81.24
Canada	65.89 ^p	47.51 ^p	36.94 ^p	30.05 ^p	79.97 ^p	28.17 ^b	46.48	83.57
UK	68.39 ^p	48.27 ^p	38.18 ^p	30.49 ^p	80.67 ^p	29.17 ^b	46.66	84.60

Germany	70.03 ^p	48.24 ^p	38.37 ^p	30.74 ^p	80.09 ^p	29.21 ^b	46.78	84.60
France	69.49 ^p	47.87 ^p	38.34 ^p	30.61 ^p	80.12 ^p	29.01 ^b	46.65	84.36
Italy	68.75 ^p	47.35 ^p	37.50 ^p	30.38 ^p	80.07 ^p	28.65 ^b	46.96	84.94
Japan	72.89 ^p	50.84 ^p	39.99 ^p	31.90 ^p	81.98 ^p	31.24 ^b	49.41	88.18
Group-6=>	ANT	DCR	SC	DASH	QTUM	P6-EW	P6-CW	P6-VW
US	3246.5 ^p	24.86	30.82	43.63 ^p	30.67	132.03	33.08 ^b	43.38
Canada	3237.2 ^p	25.37	31.32	43.94 ^p	30.90	134.38	33.39 ^b	43.62
UK	3255.9 ^p	26.84	32.78	45.08 ^p	32.09	140.14	34.60 ^b	44.69
Germany	3259.6 ^p	27.09	32.63	45.25 ^p	32.20	141.53	34.75 ^b	44.81
France	3259.1 ^p	26.77	32.55	44.69 ^p	31.87	140.59	34.21 ^b	44.28
Italy	3248.6 ^p	26.34	32.00	44.52 ^p	31.29	139.96	33.96 ^b	44.10
Japan	3252.3 ^p	29.02	34.38	47.41 ^p	34.12	148.67	36.87 ^b	46.74
Group 7=>	BAT	ENJ	ZRX	LRC	TEL	P7-EW	P7-CW	P7-VW
US	27.03	42.24 ^p	33.10 ^p	28.27 ^p	47.69 ^p	27.43	27.13 ^b	28.49
Canada	27.42	42.64 ^p	33.71 ^p	28.76 ^p	48.64 ^p	28.02	27.68 ^b	28.95
UK	28.70 ^p	44.01 ^p	34.36 ^p	30.14 ^p	49.56 ^p	29.00	28.70 ^b	29.94
Germany	28.80 ^p	43.90 ^p	34.13 ^p	30.24 ^p	49.42 ^p	29.02	28.75 ^b	29.96
France	28.50	43.51 ^p	34.04 ^p	30.09 ^p	49.30 ^p	28.89	28.57 ^b	29.74
Italy	28.02	43.10 ^p	34.17 ^p	29.49 ^p	48.54 ^p	28.57	28.27 ^b	29.57
Japan	30.80 ^p	45.95 ^p	34.83 ^p	31.90 ^p	49.17 ^p	30.65	30.35 ^b	31.39
Group 8=>	ICX	NTRN	STORJ	RLC	WAXP	P8-EW	P8-CW	P8-VW
US	31.62	6397.88 ^p	36.06	112.27 ^p	47.67 ^p	1278.88	911.93	45.49 ^b
Canada	32.24	6397.82 ^p	36.79	113.72 ^p	48.96 ^p	1278.79	911.83	46.62 ^b
UK	33.31	6397.79 ^p	37.82	117.64 ^p	51.49 ^p	1278.72	911.74	48.78 ^b
Germany	33.26	6397.79 ^p	38.05	115.85 ^p	51.43 ^p	1278.71	911.73	48.65 ^b
France	33.13	6397.79 ^p	37.75	115.55 ^p	50.91 ^p	1278.72	911.73	48.17 ^b
Italy	32.86	6397.81 ^p	37.35	116.02 ^p	49.83 ^p	1278.73	911.75	48.17 ^b
Japan	34.63	6397.92 ^p	40.03	119.69 ^p	53.31 ^p	1278.82	911.83	50.28 ^b
Group 9=>	LSK	DGB	PRO	ARK	XEM	P9-EW	P9-CW	P9-VW
US	34.16 ^p	27.87 ^p	12.08	53.24 ^p	34.13 ^p	23.67 ^b	23.94	38.55
Canada	35.08 ^p	28.27 ^p	12.25	54.71 ^p	34.71 ^p	24.67 ^b	24.88	39.21
UK	36.66 ^p	29.61 ^p	14.51	54.93 ^p	35.12 ^p	24.90 ^b	25.15	39.83
Germany	36.63 ^p	29.71 ^p	14.92	54.58 ^p	34.66 ^p	24.83 ^b	24.92	39.51
France	36.44 ^p	29.53 ^p	14.74	54.69 ^p	34.54 ^p	24.77 ^b	24.97	39.45
Italy	35.84 ^p	29.09 ^p	14.40	56.47 ^p	34.79 ^p	25.42	25.37 ^b	39.60
Japan	38.24 ^p	30.63 ^p	16.65	53.09 ^p	35.51 ^p	25.60 ^b	25.75	41.08
Group 10=>	IOST	XNO	POWR	REQ	NMR	P10-EW	P10-CW	P10-VW
US	31.12 ^p	34.18 ^p	37.40 ^p	83.50 ^p	21.90	30.69 ^b	39.00	92.56
Canada	31.36 ^p	34.56 ^p	37.52 ^p	87.13 ^p	22.23	31.10 ^b	39.67	94.03
UK	32.97	37.16 ^p	39.10 ^p	93.44 ^p	24.11	33.07 ^b	41.17	97.01
Germany	32.86	36.86 ^p	39.30 ^p	95.50 ^p	24.54	33.34 ^b	41.28	97.67
France	32.64	36.81 ^p	38.99 ^p	95.14 ^p	23.37	33.11 ^b	41.10	96.58
Italy	32.06 ^p	36.13 ^p	38.37 ^p	93.15 ^p	24.67	31.84 ^b	40.20	96.32
Japan	35.11	39.41 ^p	41.55 ^p	100.77 ^p	27.91	36.30 ^b	44.38	101.47

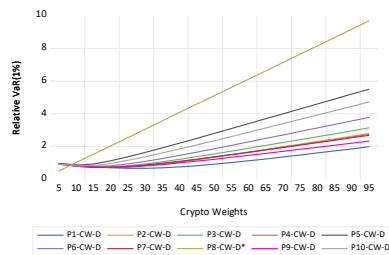
This table reports the expected shortfall (CVaR) of the equity-crypto mixed portfolios at the 5% confidence level. CVaR is the four-moment modified conditional value-at-risk, estimated using Cornish-Fisher expansion. In Panel A (Panel B), 85% (50%) of wealth is invested in an equity index, whereas the remaining 15% (50%) is invested in a cryptocurrency or crypto portfolio. The values marked with 'b' indicate the best-performing crypto-portfolio in each group (row), whereas the values marked with 'p' indicate the constituents of the corresponding portfolios that deliver higher VaR (poorer performance) than the best-performing crypto-portfolio. The sample period spans between February 1, 2018, and December 1, 2025.

Figure 2. Relative VaR of the equity-cryptocurrency mixed portfolios

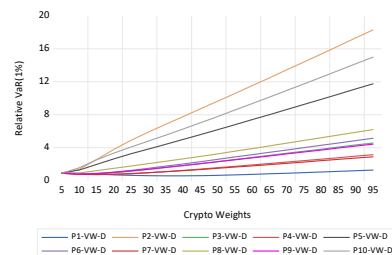
US-EW Crypto Portfolios



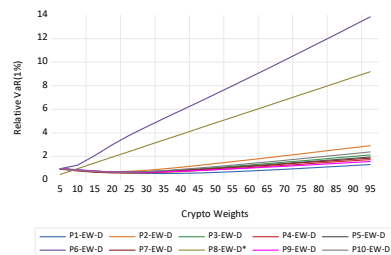
US-CW Crypto Portfolios



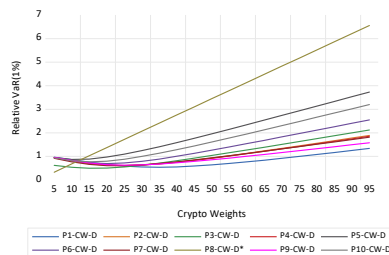
US-VW Crypto Portfolios



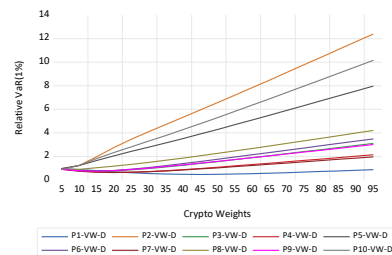
Canada-EW Crypto Portfolios



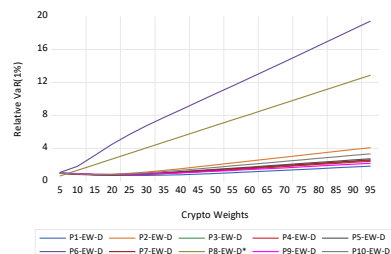
Canada-CW Crypto Portfolios



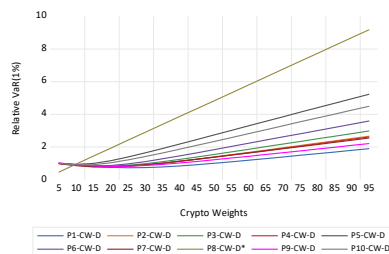
Canada-VW Crypto Portfolios



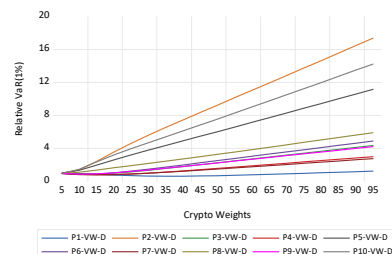
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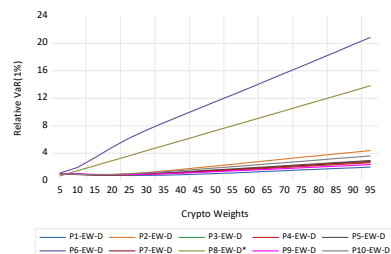
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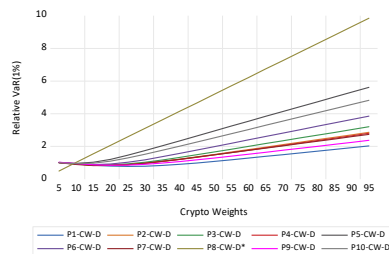
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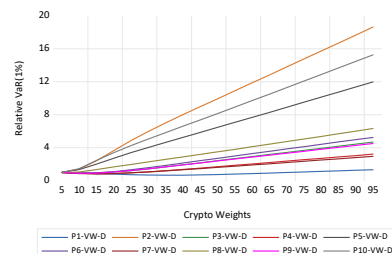
Germany-EW Crypto Portfolios



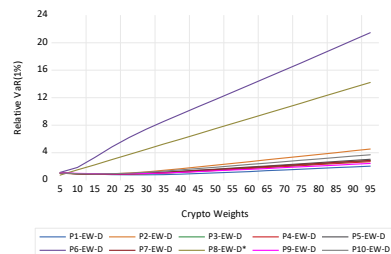
Germany-CW Crypto Portfolios



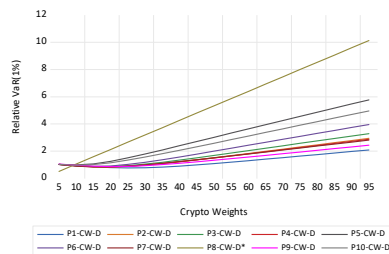
Germany-VW Crypto Portfolios



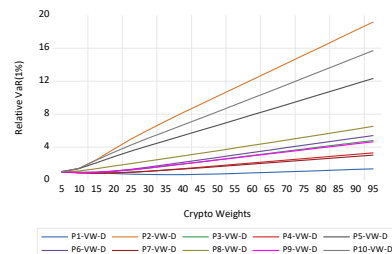
France-EW Crypto Portfolios



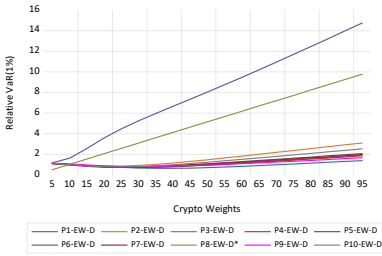
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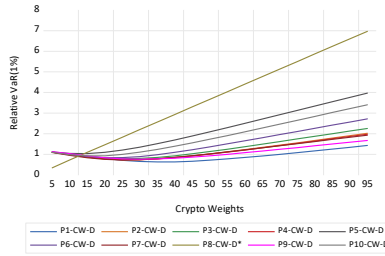
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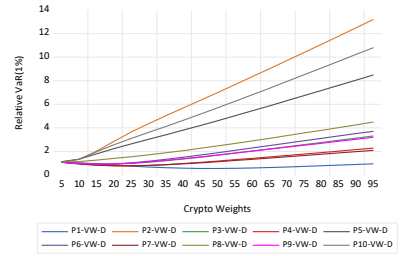
Italy-EW Crypto Portfolios



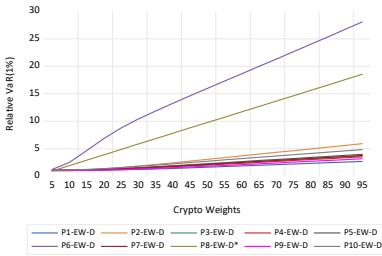
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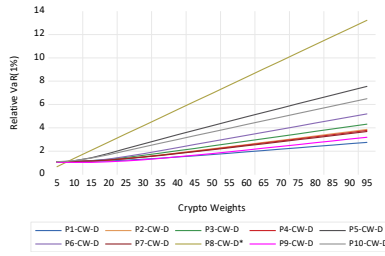
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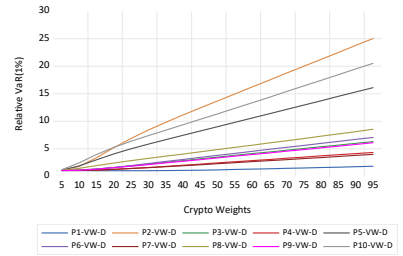
Japan-EW Crypto Portfolios



Japan-CW Crypto Portfolios



Japan-VW Crypto Portfolios



This figure presents the relative downside risk (RVaR) of the equity-crypto mixed portfolios at the 1% confidence level. RVaR values lower than 1.00 indicate reduction in the downside risk of the equity index under study by adding a specific proportion of wealth invested in the corresponding crypto-portfolio. VaR is calculated using the four-moment modified value-at-risk via Cornish-Fisher expansion. The sample period spans between February 1, 2018, and December 1, 2025.

Table 9. Relative downside risk of the equity-cryptocurrency mixed portfolios

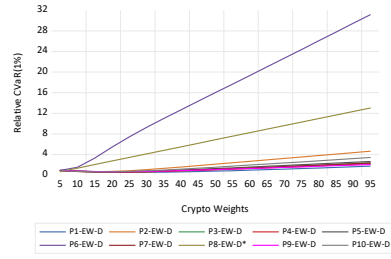
Crypto Weights ↓	US	CN	UK	GR	FR	IT	JP	US	CN	UK	GR	FR	IT	JP
P1-CW								P2-CW						
5	L	L	L	L	L	L	H	L	L	L	L	L	L	H
10	L	L	L	L	L	L	H	L	L	L	L	L	L	H
15	L	L	L	L	L	L	H	L	L	L	L	L	L	H
20	L	L	L	L	L	L	H	L	L	L	L	L	L	H
25	L	L	L	L	L	L	H	L	L	L	L	L	L	H
30	L	L	L	L	L	L	H	L	L	L	L	L	L	H
35	L	L	L	L	L	L	H	L	L	L	L	L	L	H
40	L	L	L	L	L	L	H	L	L	H	H	H	L	H
45	L	L	L	L	L	L	H	H	L	H	H	H	L	H
50	L	L	L	L	L	L	H	H	L	H	H	H	L	H
55	L	L	H	H	H	L	H	H	L	H	H	H	H	H
60	H	L	H	H	H	L	H	H	H	H	H	H	H	H
65	H	L	H	H	H	L	H	H	H	H	H	H	H	H
70	H	L	H	H	H	L	H	H	H	H	H	H	H	H
75	H	L	H	H	H	L	H	H	H	H	H	H	H	H
80	H	L	H	H	H	H	H	H	H	H	H	H	H	H
85	H	H	H	H	H	H	H	H	H	H	H	H	H	H
90	H	H	H	H	H	H	H	H	H	H	H	H	H	H
95	H	H	H	H	H	H	H	H	H	H	H	H	H	H
P3-CW								P4-CW						
5	L	L	L	L	L	L	H	L	L	L	L	L	L	H
10	L	L	L	L	L	L	H	L	L	L	L	L	L	H
15	L	L	L	L	L	L	H	L	L	L	L	L	L	H
20	L	L	L	L	L	L	H	L	L	L	L	L	L	H
25	L	L	L	L	L	L	H	L	L	L	L	L	L	H
30	L	L	L	L	L	L	H	L	L	L	L	L	L	H
35	L	L	H	H	H	L	H	L	L	L	L	L	L	H
40	H	L	H	H	H	L	H	L	L	H	H	H	L	H
45	H	L	H	H	H	L	H	H	L	H	H	H	L	H
50	H	L	H	H	H	H	H	H	L	H	H	H	L	H
55	H	H	H	H	H	H	H	H	L	H	H	H	H	H
60	H	H	H	H	H	H	H	H	H	H	H	H	H	H
65	H	H	H	H	H	H	H	H	H	H	H	H	H	H
70	H	H	H	H	H	H	H	H	H	H	H	H	H	H
75	H	H	H	H	H	H	H	H	H	H	H	H	H	H
80	H	H	H	H	H	H	H	H	H	H	H	H	H	H
85	H	H	H	H	H	H	H	H	H	H	H	H	H	H
90	H	H	H	H	H	H	H	H	H	H	H	H	H	H
95	H	H	H	H	H	H	H	H	H	H	H	H	H	H
P5-CW								P6-CW						
5	L	L	L	L	L	L	L	L	L	L	L	L	L	H
10	L	L	L	L	L	L	L	L	L	L	L	L	L	H
15	L	L	L	L	L	L	H	L	L	L	L	L	L	H
20	H	L	H	H	H	L	H	L	L	L	L	L	L	H
25	H	L	H	H	H	H	H	L	L	L	L	L	L	H
30	H	H	H	H	H	H	H	L	L	H	H	H	L	H
35	H	H	H	H	H	H	H	H	L	H	H	H	L	H
40	H	H	H	H	H	H	H	H	L	H	H	H	L	H
45	H	H	H	H	H	H	H	H	H	H	H	H	H	H
50	H	H	H	H	H	H	H	H	H	H	H	H	H	H
55	H	H	H	H	H	H	H	H	H	H	H	H	H	H
60	H	H	H	H	H	H	H	H	H	H	H	H	H	H
65	H	H	H	H	H	H	H	H	H	H	H	H	H	H
70	H	H	H	H	H	H	H	H	H	H	H	H	H	H

75	H	H	H	H	H	H	H	H	H	H	H	H	H	H
80	H	H	H	H	H	H	H	H	H	H	H	H	H	H
85	H	H	H	H	H	H	H	H	H	H	H	H	H	H
90	H	H	H	H	H	H	H	H	H	H	H	H	H	H
95	H	H	H	H	H	H	H	H	H	H	H	H	H	H
P7-CW								P8-CW						
5	L	L	L	L	L	L	H	H	H	H	H	H	H	H
10	L	L	L	L	L	L	H	H	H	H	H	H	H	H
15	L	L	L	L	L	L	H	H	H	H	H	H	H	H
20	L	L	L	L	L	L	H	H	H	H	H	H	H	H
25	L	L	L	L	L	L	H	H	H	H	H	H	H	H
30	L	L	L	L	L	L	H	H	H	H	H	H	H	H
35	L	L	L	L	H	L	H	H	H	H	H	H	H	H
40	H	L	H	H	H	L	H	H	H	H	H	H	H	H
45	H	L	H	H	H	L	H	H	H	H	H	H	H	H
50	H	L	H	H	H	L	H	H	H	H	H	H	H	H
55	H	L	H	H	H	H	H	H	H	H	H	H	H	H
60	H	H	H	H	H	H	H	H	H	H	H	H	H	H
65	H	H	H	H	H	H	H	H	H	H	H	H	H	H
70	H	H	H	H	H	H	H	H	H	H	H	H	H	H
75	H	H	H	H	H	H	H	H	H	H	H	H	H	H
80	H	H	H	H	H	H	H	H	H	H	H	H	H	H
85	H	H	H	H	H	H	H	H	H	H	H	H	H	H
90	H	H	H	H	H	H	H	H	H	H	H	H	H	H
95	H	H	H	H	H	H	H	H	H	H	H	H	H	H
P9-CW								P10-CW						
5	L	L	L	L	L	L	H	L	L	L	L	L	L	H
10	L	L	L	L	L	L	L	L	L	L	L	L	L	H
15	L	L	L	L	L	L	H	L	L	L	L	L	L	H
20	L	L	L	L	L	L	H	L	L	L	H	H	L	H
25	L	L	L	L	L	L	H	H	L	H	H	H	L	H
30	L	L	L	L	L	L	H	H	L	H	H	H	H	H
35	L	L	L	L	L	L	H	H	L	H	H	H	H	H
40	L	L	L	L	H	L	H	H	L	H	H	H	H	H
45	L	L	H	H	H	L	H	H	H	H	H	H	H	H
50	H	L	H	H	H	L	H	H	H	H	H	H	H	H
55	H	L	H	H	H	L	H	H	H	H	H	H	H	H
60	H	L	H	H	H	L	H	H	H	H	H	H	H	H
65	H	L	H	H	H	H	H	H	H	H	H	H	H	H
70	H	H	H	H	H	H	H	H	H	H	H	H	H	H
75	H	H	H	H	H	H	H	H	H	H	H	H	H	H
80	H	H	H	H	H	H	H	H	H	H	H	H	H	H
85	H	H	H	H	H	H	H	H	H	H	H	H	H	H
90	H	H	H	H	H	H	H	H	H	H	H	H	H	H
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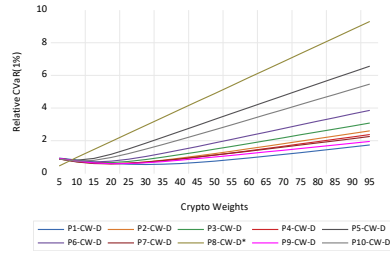
This table reports the relative downside risk of the equity-crypto mixed portfolios at the 1% confidence level, computed as the four-moment modified value-at-risk (VaR) of the equity-crypto portfolios relative to the VaR of the equity-only portfolios. Relative VaR (RVaR) is estimated using Cornish-Fisher expansion. The first column (crypto weights) shows the proportion of wealth allocated to the crypto portfolio relative to the equity index listed in the corresponding column. RVaR values lower than 1.00 are labelled as "L", whereas values higher than 1.00 are labelled as "H". Lower values of RVaR indicate diversification benefits. US, CN, UK, GR, FR, IT, and JP indicate MSCI equity markets representing the US, Canada, United Kingdom, Germany, France, Italy, and Japan, respectively. Other variables are defined in Tables 1, 4, and 5. The sample period spans between February 1, 2018, and December 1, 2025.

Figure 3. Relative CVaR of the equity-cryptocurrency mixed portfolios

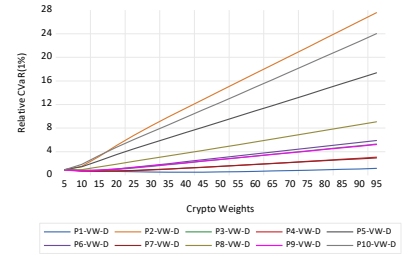
US-EW Crypto Portfolios



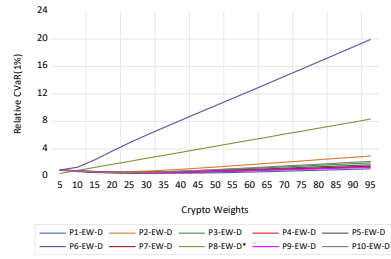
US-CW Crypto Portfolios



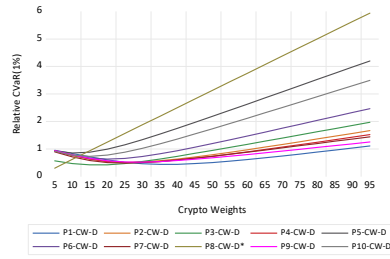
US-VW Crypto Portfolios



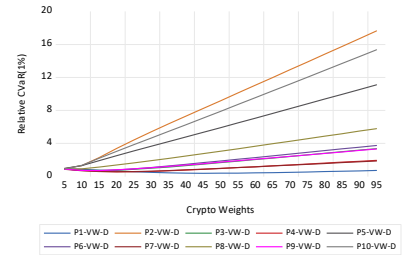
Canada-EW Crypto Portfolios



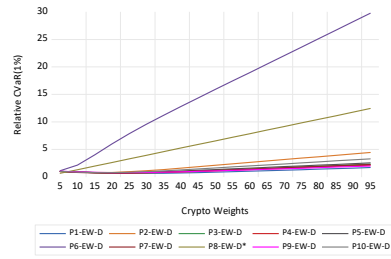
Canada-CW Crypto Portfolios



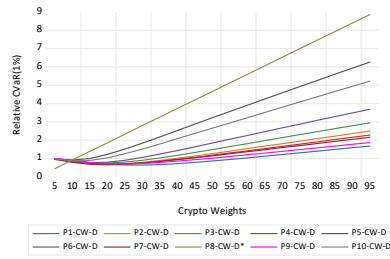
Canada-VW Crypto Portfolios



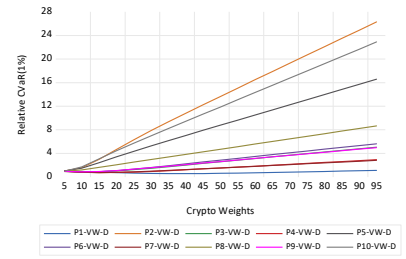
UK-EW Crypto Portfolios



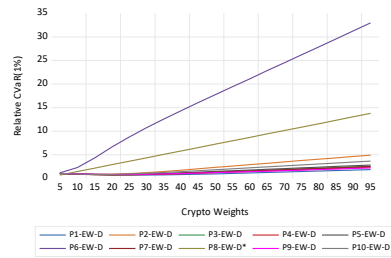
UK-CW Crypto Portfolios



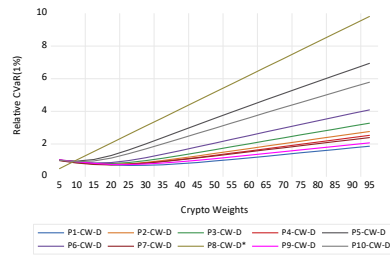
UK-VW Crypto Portfolios



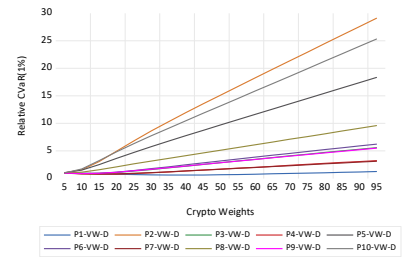
Germany-EW Crypto Portfolios



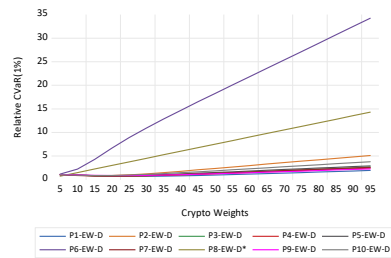
Germany-CW Crypto Portfolios



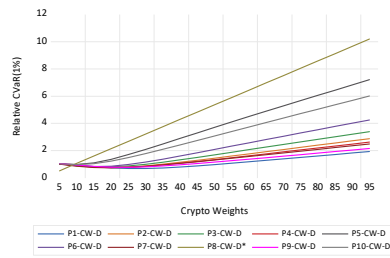
Germany-VW Crypto Portfolios



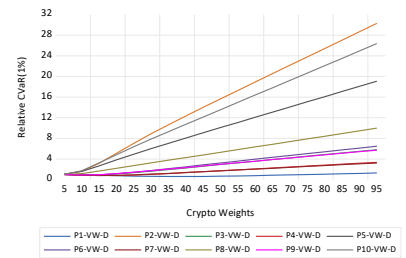
France-EW Crypto Portfolios

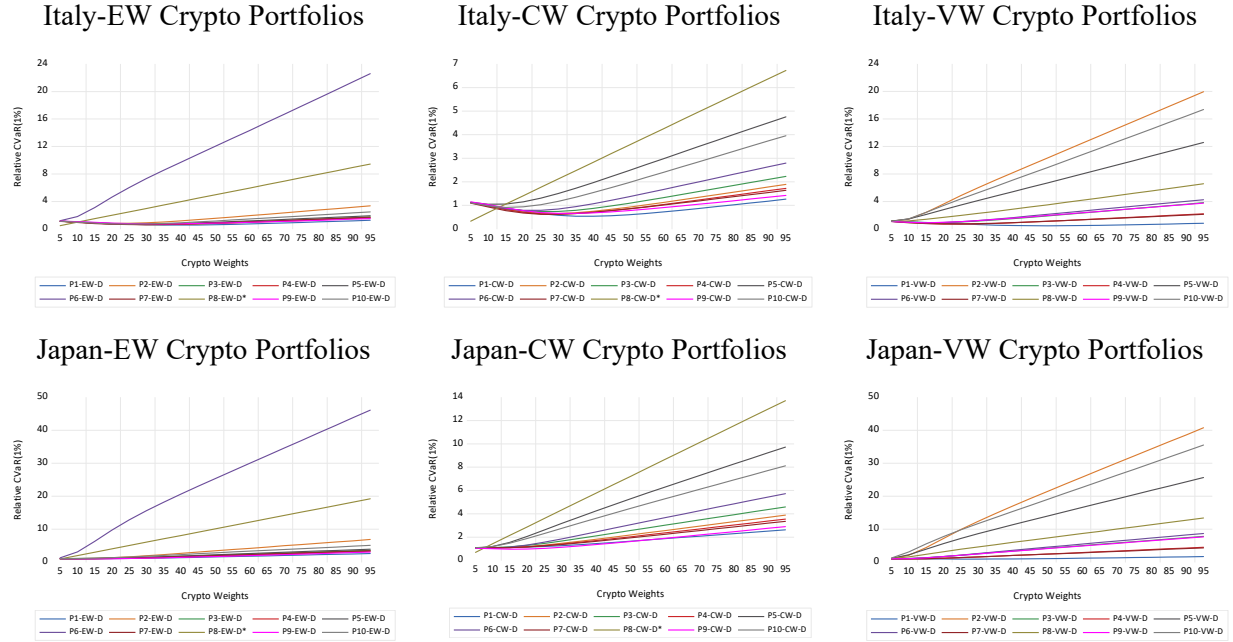


France-CW Crypto Portfolios



France-VW Crypto Portfolios





This figure presents the relative expected shortfall (RCVaR) of the equity-crypto mixed portfolios at the 1% confidence level. RCVaR values lower than 1.00 indicate reduction in the expected shortfall of the equity index under study by adding a specific proportion of wealth invested in the corresponding crypto-portfolio. CVaR is calculated using the four-moment modified conditional value-at-risk via Cornish-Fisher expansion. The sample period spans between February 1, 2018, and December 1, 2025.

Table 10. Relative expected shortfall of the equity-cryptocurrency mixed portfolios

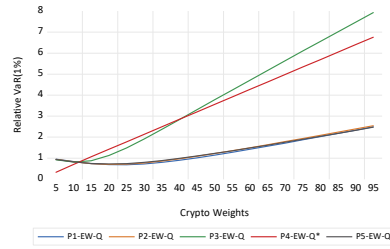
Crypto Weights↓	US	CN	UK	GR	FR	IT	JP	US	CN	UK	GR	FR	IT	JP
	P1-CW							P2-CW						
5	0.87	0.88	0.93	0.94	0.96	1.05	1.00	0.82	0.85	0.91	0.93	0.95	1.05	1.00
10	0.75	0.77	0.83	0.84	0.85	0.94	1.02	0.65	0.69	0.77	0.80	0.82	0.90	1.00
15	0.63	0.64	0.71	0.74	0.74	0.82	1.03	0.55	0.55	0.66	0.71	0.72	0.76	1.03
20	0.55	0.53	0.63	0.66	0.66	0.69	1.07	0.52	0.47	0.62	0.68	0.69	0.65	1.11
25	0.49	0.44	0.58	0.62	0.62	0.58	1.12	0.56	0.44	0.65	0.72	0.72	0.59	1.24
30	0.47	0.39	0.57	0.62	0.62	0.51	1.20	0.63	0.46	0.72	0.81	0.81	0.59	1.40
35	0.49	0.37	0.60	0.66	0.66	0.47	1.28	0.74	0.50	0.82	0.92	0.93	0.62	1.57
40	0.53	0.37	0.65	0.72	0.72	0.47	1.38	0.86	0.56	0.94	1.06	1.07	0.68	1.75
45	0.60	0.40	0.72	0.80	0.81	0.49	1.48	1.00	0.64	1.07	1.20	1.22	0.76	1.93
50	0.68	0.43	0.80	0.89	0.90	0.53	1.58	1.14	0.72	1.20	1.35	1.37	0.85	2.12
55	0.77	0.48	0.88	0.98	1.00	0.59	1.69	1.29	0.81	1.34	1.50	1.53	0.95	2.30
60	0.87	0.54	0.97	1.08	1.10	0.65	1.80	1.44	0.90	1.47	1.65	1.69	1.05	2.49
65	0.98	0.61	1.06	1.18	1.21	0.72	1.90	1.59	1.00	1.61	1.80	1.85	1.16	2.68
70	1.09	0.67	1.15	1.28	1.32	0.80	2.01	1.75	1.09	1.75	1.95	2.01	1.27	2.87
75	1.20	0.74	1.24	1.38	1.43	0.87	2.12	1.90	1.19	1.88	2.10	2.17	1.38	3.06
80	1.31	0.81	1.33	1.49	1.54	0.95	2.23	2.06	1.29	2.02	2.25	2.33	1.49	3.25
85	1.43	0.89	1.43	1.59	1.65	1.03	2.34	2.22	1.39	2.16	2.40	2.49	1.60	3.44
90	1.55	0.96	1.52	1.69	1.75	1.11	2.45	2.38	1.49	2.29	2.55	2.65	1.71	3.63
95	1.67	1.04	1.61	1.79	1.86	1.19	2.56	2.54	1.60	2.43	2.70	2.81	1.82	3.82
	P3-CW							P4-CW						
5	0.81	0.49	0.92	0.94	0.95	1.05	1.00	0.84	0.86	0.92	0.94	0.95	1.05	1.00
10	0.66	0.40	0.79	0.83	0.84	0.93	1.03	0.69	0.71	0.79	0.82	0.83	0.90	1.01
15	0.59	0.35	0.71	0.75	0.76	0.80	1.09	0.58	0.57	0.68	0.72	0.73	0.76	1.04
20	0.59	0.35	0.69	0.74	0.75	0.70	1.22	0.53	0.48	0.63	0.68	0.69	0.64	1.10
25	0.66	0.40	0.74	0.80	0.81	0.66	1.39	0.54	0.43	0.64	0.70	0.71	0.57	1.21
30	0.78	0.47	0.83	0.91	0.93	0.67	1.60	0.60	0.44	0.70	0.77	0.78	0.56	1.34
35	0.92	0.56	0.96	1.06	1.08	0.72	1.81	0.69	0.47	0.78	0.86	0.88	0.58	1.48
40	1.07	0.66	1.11	1.22	1.25	0.80	2.04	0.80	0.52	0.88	0.98	1.00	0.63	1.63
45	1.24	0.77	1.26	1.40	1.43	0.90	2.27	0.92	0.59	0.99	1.10	1.13	0.70	1.79
50	1.41	0.88	1.42	1.58	1.62	1.01	2.50	1.05	0.66	1.11	1.23	1.27	0.78	1.96
55	1.58	0.99	1.58	1.76	1.81	1.13	2.72	1.18	0.74	1.23	1.37	1.41	0.87	2.12
60	1.76	1.10	1.74	1.94	2.00	1.26	2.95	1.32	0.82	1.35	1.50	1.55	0.96	2.29
65	1.94	1.21	1.91	2.13	2.19	1.39	3.18	1.45	0.91	1.47	1.64	1.69	1.06	2.46
70	2.11	1.33	2.07	2.31	2.38	1.51	3.40	1.59	1.00	1.60	1.77	1.84	1.16	2.63
75	2.29	1.44	2.23	2.49	2.57	1.64	3.63	1.73	1.09	1.72	1.91	1.98	1.26	2.80
80	2.47	1.56	2.40	2.67	2.76	1.77	3.85	1.88	1.18	1.84	2.05	2.12	1.35	2.97
85	2.65	1.67	2.56	2.84	2.95	1.90	4.08	2.02	1.27	1.97	2.18	2.27	1.45	3.14
90	2.83	1.79	2.72	3.02	3.14	2.03	4.30	2.16	1.36	2.09	2.32	2.41	1.55	3.31
95	3.01	1.90	2.88	3.20	3.33	2.16	4.52	2.31	1.45	2.21	2.45	2.55	1.66	3.48
	P5-CW							P6-CW						
5	0.82	0.86	0.91	0.94	0.96	1.06	0.98	0.83	0.86	0.91	0.94	0.95	1.05	0.99
10	0.73	0.78	0.85	0.88	0.91	0.98	1.12	0.69	0.71	0.78	0.82	0.83	0.91	0.99
15	0.85	0.81	0.93	0.98	1.03	0.98	1.49	0.63	0.60	0.71	0.76	0.76	0.79	1.07
20	1.10	0.92	1.15	1.22	1.29	1.08	1.99	0.68	0.56	0.73	0.80	0.79	0.72	1.25
25	1.43	1.08	1.44	1.56	1.63	1.24	2.54	0.80	0.58	0.83	0.91	0.91	0.72	1.49
30	1.78	1.27	1.77	1.93	2.02	1.44	3.10	0.96	0.65	0.99	1.09	1.09	0.78	1.78
35	2.14	1.47	2.11	2.32	2.42	1.66	3.65	1.15	0.75	1.17	1.30	1.30	0.88	2.08
40	2.50	1.68	2.46	2.72	2.83	1.90	4.18	1.36	0.87	1.37	1.52	1.53	1.00	2.38
45	2.87	1.90	2.81	3.11	3.24	2.15	4.70	1.57	0.99	1.57	1.75	1.77	1.14	2.69
50	3.23	2.12	3.15	3.50	3.64	2.40	5.21	1.79	1.12	1.78	1.98	2.01	1.29	2.99
55	3.60	2.34	3.50	3.88	4.04	2.65	5.72	2.01	1.26	1.98	2.21	2.26	1.45	3.30
60	3.96	2.56	3.84	4.26	4.43	2.91	6.22	2.24	1.40	2.19	2.44	2.50	1.61	3.60
65	4.32	2.79	4.18	4.64	4.83	3.16	6.72	2.46	1.54	2.40	2.67	2.75	1.77	3.90
70	4.69	3.01	4.52	5.02	5.22	3.42	7.21	2.68	1.68	2.60	2.90	2.99	1.93	4.19

75	5.05	3.23	4.86	5.39	5.61	3.68	7.71	2.90	1.82	2.81	3.13	3.23	2.09	4.49
80	5.41	3.46	5.19	5.76	5.99	3.93	8.20	3.12	1.97	3.01	3.35	3.47	2.25	4.78
85	5.77	3.68	5.53	6.13	6.38	4.18	8.68	3.35	2.11	3.22	3.57	3.70	2.41	5.08
90	6.13	3.91	5.86	6.50	6.76	4.44	9.17	3.57	2.25	3.42	3.80	3.94	2.57	5.37
95	6.49	4.13	6.20	6.87	7.14	4.69	9.65	3.79	2.40	3.62	4.02	4.17	2.73	5.66
P7-CW								P8-CW						
5	0.81	0.82	0.88	0.91	0.93	1.03	1.02	467	299	444	486	507	331	689
10	0.64	0.64	0.72	0.77	0.79	0.86	1.02	968	619	922	1017	1059	697	1427
15	0.54	0.51	0.62	0.67	0.69	0.71	1.03	1461	934	1392	1539	1601	1056	2155
20	0.52	0.44	0.59	0.65	0.67	0.60	1.09	1953	1248	1860	2057	2140	1412	2879
25	0.55	0.42	0.62	0.68	0.70	0.55	1.18	2443	1562	2328	2575	2678	1767	3603
30	0.62	0.44	0.69	0.76	0.78	0.55	1.30	2933	1875	2795	3092	3216	2122	4325
35	0.71	0.48	0.77	0.85	0.88	0.59	1.43	3423	2188	3262	3609	3754	2477	5048
40	0.82	0.53	0.87	0.96	0.99	0.64	1.57	3912	2501	3729	4126	4291	2832	5770
45	0.93	0.59	0.97	1.08	1.11	0.71	1.72	4402	2814	4196	4642	4828	3187	6492
50	1.05	0.66	1.08	1.20	1.24	0.78	1.87	4891	3127	4663	5159	5365	3541	7214
55	1.17	0.74	1.19	1.32	1.37	0.86	2.02	5380	3440	5129	5675	5903	3896	7936
60	1.29	0.81	1.30	1.45	1.50	0.94	2.18	5870	3753	5596	6192	6440	4250	8658
65	1.41	0.89	1.41	1.57	1.63	1.03	2.33	6359	4066	6063	6708	6977	4604	9380
70	1.54	0.97	1.53	1.70	1.76	1.12	2.49	6848	4379	6529	7224	7514	4959	10102
75	1.67	1.05	1.64	1.82	1.89	1.21	2.65	7338	4692	6996	7741	8051	5313	10824
80	1.80	1.13	1.75	1.95	2.02	1.30	2.81	7827	5005	7462	8257	8588	5667	11546
85	1.93	1.21	1.87	2.07	2.15	1.39	2.97	8316	5317	7929	8773	9124	6022	12267
90	2.05	1.29	1.98	2.20	2.28	1.48	3.13	8805	5630	8396	9290	9661	6376	12989
95	2.18	1.37	2.09	2.32	2.42	1.57	3.29	9294	5943	8862	9806	10198	6730	13711
P9-CW								P10-CW						
5	0.84	0.87	0.94	0.96	0.98	1.08	0.98	0.80	0.85	0.91	0.93	0.95	1.01	1.00
10	0.68	0.72	0.82	0.85	0.87	0.96	0.94	0.68	0.71	0.80	0.85	0.90	0.91	1.13
15	0.57	0.59	0.71	0.74	0.77	0.82	0.91	0.73	0.66	0.82	0.90	0.97	0.84	1.41
20	0.52	0.50	0.65	0.68	0.71	0.71	0.92	0.90	0.71	0.97	1.07	1.15	0.87	1.81
25	0.53	0.45	0.63	0.67	0.71	0.63	0.97	1.14	0.81	1.19	1.33	1.41	0.96	2.24
30	0.58	0.45	0.66	0.70	0.74	0.59	1.06	1.41	0.95	1.45	1.62	1.71	1.10	2.68
35	0.65	0.47	0.71	0.76	0.81	0.59	1.16	1.70	1.11	1.72	1.93	2.02	1.28	3.12
40	0.74	0.51	0.78	0.84	0.89	0.61	1.28	1.99	1.29	2.01	2.25	2.35	1.47	3.55
45	0.83	0.55	0.86	0.93	0.98	0.66	1.41	2.30	1.47	2.30	2.57	2.68	1.68	3.97
50	0.93	0.61	0.95	1.03	1.08	0.71	1.55	2.60	1.66	2.58	2.89	3.01	1.89	4.39
55	1.03	0.66	1.04	1.14	1.19	0.77	1.69	2.91	1.85	2.87	3.21	3.34	2.11	4.80
60	1.14	0.73	1.13	1.24	1.30	0.84	1.83	3.22	2.05	3.16	3.53	3.67	2.33	5.21
65	1.24	0.79	1.23	1.35	1.41	0.90	1.97	3.53	2.24	3.45	3.84	4.00	2.55	5.62
70	1.35	0.85	1.32	1.46	1.52	0.98	2.11	3.84	2.44	3.73	4.16	4.32	2.78	6.03
75	1.46	0.92	1.42	1.56	1.63	1.05	2.25	4.15	2.63	4.02	4.47	4.65	3.00	6.43
80	1.56	0.98	1.51	1.67	1.75	1.12	2.40	4.46	2.83	4.30	4.78	4.97	3.22	6.84
85	1.67	1.05	1.61	1.78	1.86	1.20	2.54	4.77	3.03	4.59	5.10	5.30	3.44	7.24
90	1.78	1.12	1.71	1.89	1.97	1.27	2.69	5.08	3.23	4.87	5.40	5.62	3.67	7.64
95	1.89	1.18	1.80	2.00	2.08	1.35	2.83	5.39	3.42	5.15	5.71	5.94	3.89	8.05

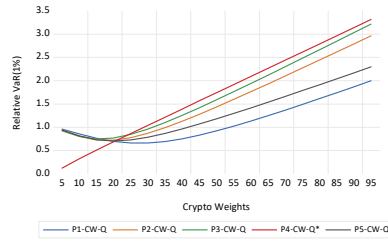
This table reports the relative expected shortfall of the equity-crypto mixed decile portfolios at the 1% confidence level, which is computed as the four-moment modified conditional value-at-risk (CVaR) of the equity-crypto portfolios relative to the CVaR of the equity-only portfolios. Relative CVaR is estimated using Cornish-Fisher expansion. The first column (crypto weights) shows the proportion of wealth allocated to the crypto portfolio relative to the equity index listed in the corresponding column. US, CN, UK, GR, FR, IT, and JP indicate MSCI equity markets representing the US, Canada, United Kingdom, Germany, France, Italy, and Japan, respectively. Other variables are defined in Tables 1, 4, and 5. The sample period spans between February 1, 2018, and December 1, 2025.

Figure 4. Further evidence on the relative VaR of the equity-cryptocurrency mixed portfolios

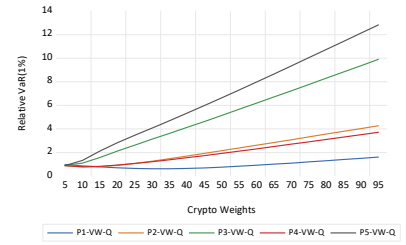
US-EW Crypto Portfolios



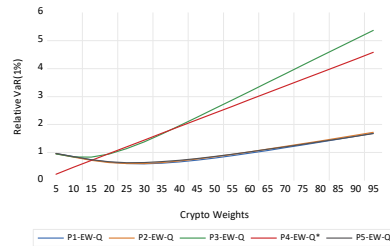
US-CW Crypto Portfolios



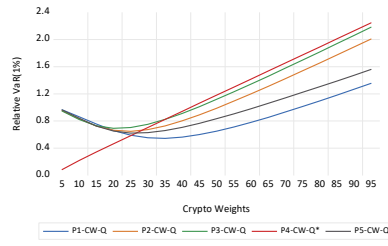
US-VW Crypto Portfolios



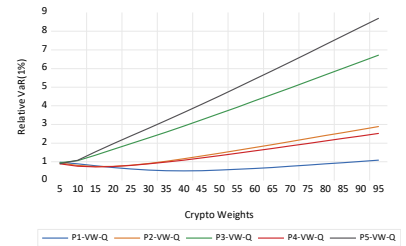
Canada-EW Crypto Portfolios



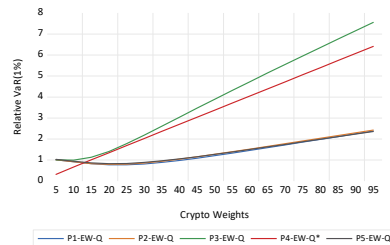
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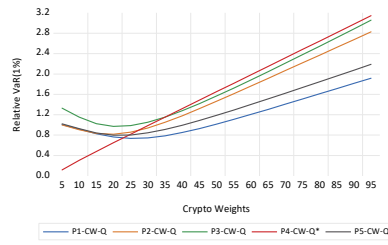
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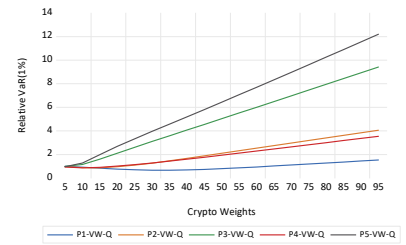
UK-EW Crypto Portfolios



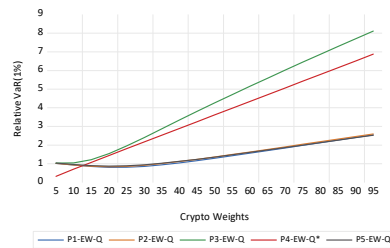
UK-CW Crypto Portfolios



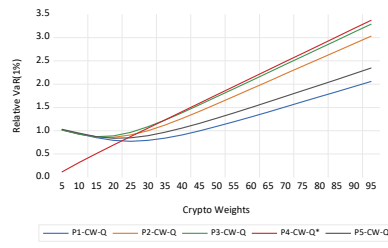
UK-VW Crypto Portfolios



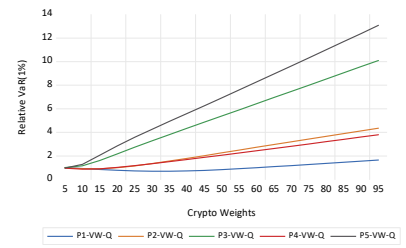
Germany-EW Crypto Portfolios



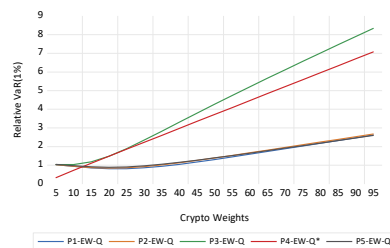
Germany-CW Crypto Portfolios



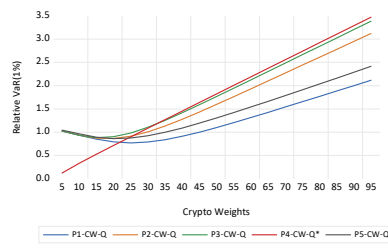
Germany-VW Crypto Portfolios



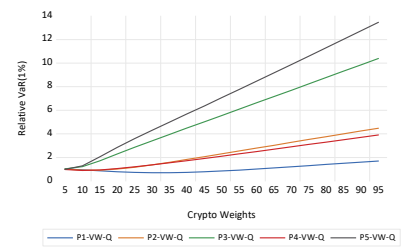
France-EW Crypto Portfolios

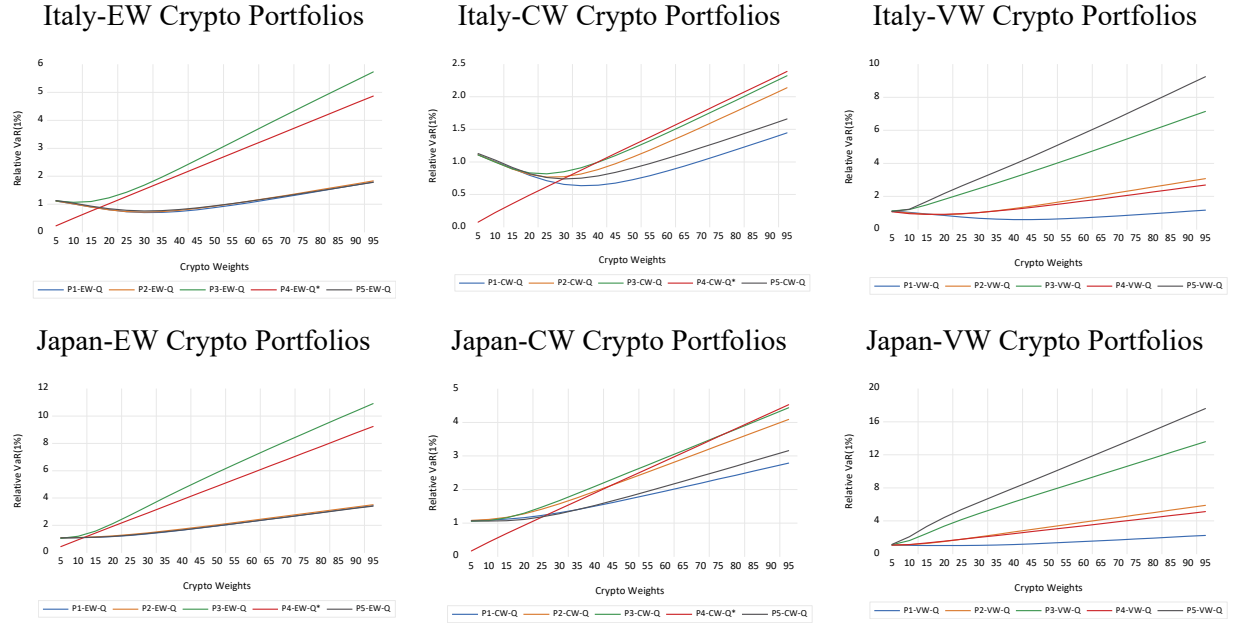


France-CW Crypto Portfolios



France-VW Crypto Portfolios





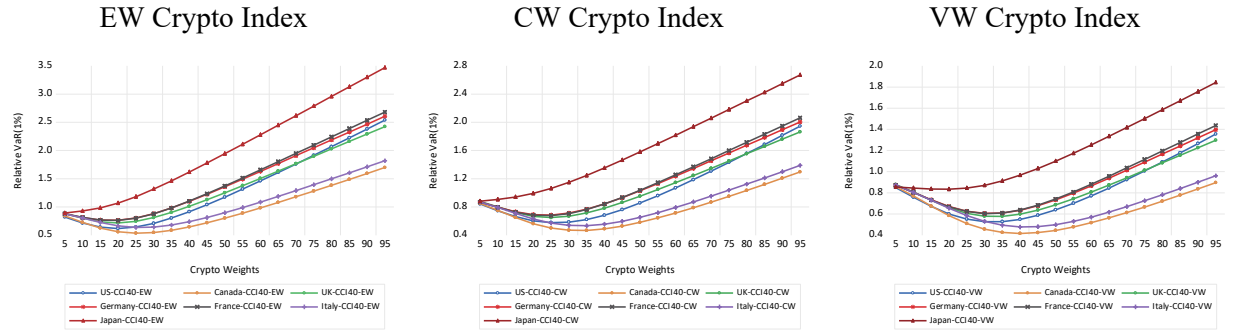
This figure presents the relative downside risk (RVaR) of the equity-crypto mixed portfolios at the 1% confidence level. RVaR values lower than 1.00 indicate a reduction in the downside risk of the equity index under study by adding a specific proportion of wealth invested in the corresponding crypto-portfolio. VaR is calculated using the four-moment modified value-at-risk via Cornish-Fisher expansion. The sample period spans between February 1, 2018, and December 1, 2025.

Table 11. Relative expected shortfall of the equity-cryptocurrency mixed quintile portfolios

Crypto Weight	P1-CW							P2-CW							P3-CW							P5-CW						
	US	CN	UK	GR	FR	IT	JP	US	CN	UK	GR	FR	IT	JP	U S	CN	UK	GR	FR	IT	JP	U S	CN	UK	GR	FR	IT	JP
5	L	L	L	L	L	L	L	L	L	L	L	L	H	L	L	L	H	L	L	H	L	L	L	H	L	L	H	H
10	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	H	L	L	L	H	L	L	L	L	L	H	H
15	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	L	L	L	L	L
20	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	L	L	L	L	L
25	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	L	L	L	L	H
30	L	L	L	L	L	L	H	L	L	L	L	L	L	H	L	L	L	H	H	L	H	L	L	L	L	L	L	H
35	L	L	L	L	L	L	H	L	L	L	H	H	L	H	L	L	H	H	H	L	H	L	L	L	L	L	L	H
40	L	L	L	L	L	L	H	L	L	H	H	H	L	H	H	L	H	H	H	L	H	L	L	L	L	L	L	H
45	L	L	L	L	L	L	H	H	L	H	H	H	L	H	H	L	H	H	H	L	H	L	L	L	L	H	L	H
50	L	L	L	L	L	L	H	H	L	H	H	H	L	H	H	H	H	H	H	H	H	L	L	L	H	H	L	H
55	L	L	L	H	H	L	H	H	L	H	H	H	H	H	H	H	H	H	H	H	H	L	L	H	H	H	L	H
60	L	L	H	H	H	L	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	L	H	H	H	L	H
65	H	L	H	H	H	L	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	L	H	H	H	L	H
70	H	L	H	H	H	L	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	L	H	H	H	L	H
75	H	L	H	H	H	L	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	L	H	H	H	H	H
80	H	L	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
85	H	L	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
90	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
95	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H

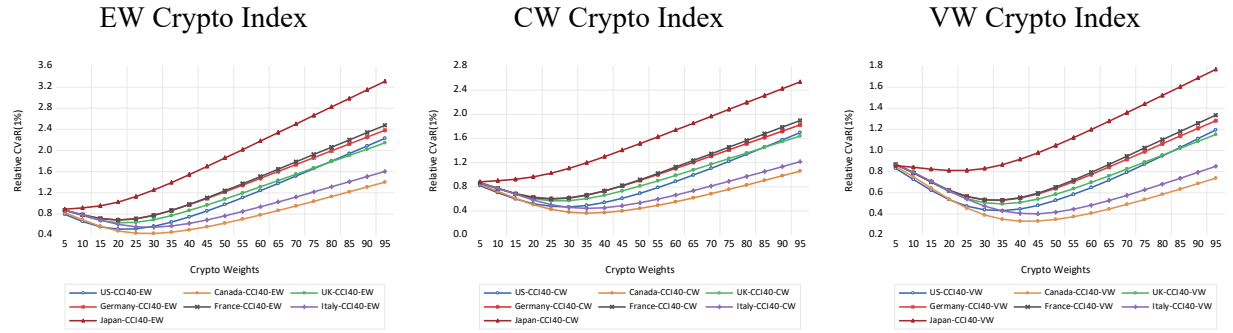
This table reports the relative expected shortfall of the equity-crypto mixed quintile portfolios at the 1% confidence level, which is computed as the four-moment modified conditional value at risk (CVaR) of the equity-crypto portfolios relative to the CVaR of the equity-only portfolios. Relative CVaR (RCVaR) is estimated using Cornish-Fisher expansion. The first column (crypto weights) shows the proportion of wealth allocated to the crypto portfolio relative to the equity index listed in the corresponding column. RCVaR values lower than 1.00 are labelled as "L", whereas values higher than 1.00 are labelled as "H". Lower values of RCVaR indicate diversification benefits. US, CN, UK, GR, FR, IT, and JP indicate MSCI equity indices representing the US, Canada, United Kingdom, Germany, France, Italy, and Japan, respectively. We skip the results of Group-4, as RCVaR values are higher 1.00 for all markets in this group due to the constituent NTRN. Other variables are defined in Tables 1, 4, and 5. The sample period spans between February 1, 2018, and December 1, 2025.

Figure 5. Cryptocurrency index and the relative VaR of the equity-crypto mixed portfolios



This figure presents the relative downside risk (RVaR) of the equity-crypto mixed portfolios at the 1% confidence level. RVaR values lower than 1.00 indicate reduction in the downside risk of the equity index under study by adding a specific proportion of wealth invested in the corresponding crypto index (CC40). VaR is calculated using the four-moment modified value-at-risk via Cornish-Fisher expansion. The sample period spans between February 1, 2018, and December 1, 2025.

Figure 6. Cryptocurrency index and the relative CVaR of the equity-crypto mixed portfolios



Notes: This figure presents the relative expected shortfall (RCVaR) of the equity-crypto mixed portfolios at the 1% confidence level. RCVaR values lower than 1.00 indicate a reduction in the expected shortfall of the equity index under study when a specific proportion of wealth is invested in the corresponding crypto index (CC40). CVaR is calculated using the four-moment modified conditional value-at-risk via Cornish-Fisher expansion. The sample period spans between February 1, 2018, and December 1, 2025.