Cryptocurrency Integration in Corporate Investment Portfolios and Associated Risk Management Strategies

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Abstract: This paper examines how cryptocurrencies can be incorporated to the corporate investment portfolio and how the risk management strategies can be implemented to make the cryptocurrencies usage a success. The sheer volatility and uncertainty that have been seen in the cryptocurrency markets pose great threats to management of corporate treasury and institutional investment. By thoroughly examining the processes of portfolio construction, risk measurement models, and the protective resources, the research gives recommendations to corporations thinking about using cryptocurrencies. The study compares passive and active investment style whereby the performance benchmarking is considered in a variety of market regimes such as crash periods, flat markets, bullistic market and bearish market trends. The research has revealed that the traditional diversification gains are narrow in the cryptocurrency market, and altcoins do not offer significant risk mitigation as compared to Bitcoin. Nevertheless, predictability through momentum facilitates effective downside protection tactical allocation strategies which retain the upside participation strategies. The paper puts forward an Optimal NAV Protect strategy, which is a combination of minimum-variance allocation and momentum-driven tactical exposure, and has a better performance based on risk adjustment in different market environments. The practise provides corporations with a viable model of cryptocurrency integration that is compensatory in its return targets and institutional risk limitations. The analysis adds to the knowledge of the cryptocurrency portfolio dynamics, its risk management and consideration of implementation with corporate investors that operate within this new asset class.

Keywords: *Cryptocurrency Integration, Corporate Portfolios, Risk Management, Portfolio Optimization, Bitcoin Allocation, Volatility Management, Institutional Investment, Tactical Asset Allocation, Corporate Treasury, Digital Assets.*

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I. INTRODUCTION

The introduction of cryptocurrencies as a new form of asset has fundamentally changed the investment landscape that faces corporate treasury managers and institutional portfolio strategists. The launch of Bitcoin in 2009 facilitated the onset of a digital revolution that has grown into thousands of different types of cryptocurrencies and is currently worth over two trillion dollars at its peak (Thélissaint and Danilo, 2025). Such tremendous expansion has forced companies to consider the fact that integrating cryptocurrency into investment portfolios is a well-diversification opportunity or an impermissible risk exposure (Russell Investments, 2022). The cryptocurrency allocation issue has turned into an academic interest and practical need as giant companies such as Tesla, MicroStrategy, and Square have dedicated significant parts of their treasury funds to Bitcoin (Campbell et al., 2023).

The interest of corporations in integrating cryptocurrencies is based on various reasons, such as diversification of the portfolio, inflation hedging, technological positioning, and possible improvement of returns (Anson et al., 2022). The advocates believe that cryptocurrencies can have a benefit of decorrelation over conventional asset classes and might enhance risk-adjusted

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portfolio returns due to the extension of the efficient frontier (Corbet et al., 2019). Cryptocurrencies can offer a safeguard against currency devaluation and sovereign risk: this is because of the decentralised form of the cryptocurrencies, and their non-dependence on the usual monetary policy (Liu, 2019). More so, businesses see cryptocurrency investments as a strategic move in the digital economy that demonstrates technological advancement and entices those who focus on innovation. Nevertheless, such possible advantages must be compared with the significant threats such as extreme volatility, regulatory ambiguity, operational complexity, and possible disastrous loss of capital (Gkillas & Longin, 2025).

The peculiarities of the crypto market require radically different risk management strategies in comparison with the conventional asset categories. The volatility levels in cryptocurrencies are significantly higher than those of equities, commodities, and foreign exchange markets and the daily price change is often more than 5 percent with flash crashes leading to losses of 50% intraday (Financial Crime Academy, 2025). This extreme volatility poses a major challenge to the corporate risk management structures that are typically based on the traditional volatility assumptions (IEEE, 2024). Besides, cryptocurrency markets exhibit strong contagion effects when stressed, and correlations are close to unity when the market is crash, thus removing the diversification benefits when most are needed (Thélissaint and Danilo, 2025). The lack of underpinning valuation anchors and dominance of speculative processes further compound the risk assessment and portfolio building decision-making process (Platanakis and Urquhart, 2020).

The current literature on cryptocurrency portfolio integration has concentrated mainly on individual investors, and not on the corporate treasury context, thus creating a notable gap in the knowledge of the issue of institutional implementation. Research looking at the optimal cryptocurrency weightings almost always views unconstrained optimization models as being unsuitable in corporate risk management systems allowing severe loss constraints and under regulatory regulation. In addition, in most academic studies, historical data analysis is used during the mostly bullish market, which might underestimate the risks on the downside and overestimates the diversification benefits (Guesmi et al., 2019). The actualities of corporate cryptocurrency integration such as board approval criteria, stakeholders' communication difficulties, accounting treatment complexities, and career risk implications to treasury managers are yet to be researched in scholarly sources (Deloitte, 2022). This research paper fills these gaps by looking at integration of cryptocurrencies through the corporate lens, which is based on risk management and preservation of capital as opposed to maximising returns.

The paper has a few contributions to the knowledge of cryptocurrency integration within corporate portfolios and the risk management needs related to it. First, it offers empirical data regarding the behaviour of cryptocurrency portfolios in various market regimes; it proves that diversification benefits are significantly small because there are high correlations and systematic risk exposure (Thélissaint & Danilo, 2025). Second, the study determines momentum-based predictability in cryptocurrency markets that make effective tactic allocation strategies available, which provides corporations with an effective downside protection strategy (Gkillas and Longin, 2025). Third, the research will offer an NAV Protect prototype that involves strategic minimum-variance allocation and tactical momentum-based exposure changes, which show higher risk management traits that should be used by corporate (Thélissaint and Danilo, 2025). Fourth, the analysis gives specifics regarding the consideration of implementation such as the selection sets identification, allocation strategies, and exposure management mechanisms (KPMG, 2024). Such contributions can provide the corporations with a whole framework to assess the cryptocurrency integration decision-making and adopt efficient risk management measures.

The rest of this paper continues in the following way. Section 2 is a literature review on the integration of cryptocurrency portfolios, the risk profiles, and the issues of institutional adoption. Section 3 explains the data, the sampling process, and the nature of the market environment at the time of study. Section 4 contains the research methodology of the approaches to portfolio construction and the performance measures and analysis tools. Section 5 presents and discusses empirical findings of various portfolios and market situations. Section 6 provides discussion of implications to corporate cryptocurrency integration and risk management implementation. In section 7, the final remarks and future research directions are given.

II. RELATED WORKS

➢ *Cryptocurrency as an Asset Class and Portfolio Diversification*

The identification of cryptocurrency as a specific asset type has produced a considerable amount of scholarly discussion concerning its essential features and the right place of residence in the investment system. Initial studies investigated the question of whether Bitcoin is more of a currency, commodity, or a speculative asset with consequences about the portfolio allocation decisions. Systematic analysis of cryptocurrencies as a separate portfolio allocation category is shown by Corbet et al. (2019), who indicate that cryptocurrencies possess features unlike other traditional asset types such as equities, bonds, commodities, and currencies. In the normal market conditions, the authors record low correlations of cryptocurrency returns and conventional assets implying that there may be diversification advantages to cryptocurrency (Corbet et al., 2019).

Theoretical reasons to include the cryptocurrencies in the diversified portfolios are related to the enhancement of the efficient frontier by including assets that have desirable risk-return profiles and do not correlate with the existing assets. As shown by Katsiampa et al. (2017), even the amount of Bitcoin allocated to investors with moderate to high risk tolerance is significantly helpful in improving portfolio efficiency, with the optimal weight between 2 and 6%, depending on the investment horizon. Liu (2019) applies this

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interpretation to larger cryptocurrency portfolios and concludes that portfolio diversification in terms of multiple digital assets is associated with marginal efficiency gains as compared to Bitcoin-only portfolio. Nonetheless, these optimization outcomes are extremely sensitive to the sample period used, and very different optimal weights are found when analysis is done with and without the crash periods (Platanakis and Urquhart, 2020).

The empirical studies on cryptocurrency portfolio performance are inconclusive regarding the time of evaluation and the methodology used. The literature discussing a time frame before 2018, in general, shares positive findings according to which risk-adjusted returns would increase and effective diversification would be achieved by the inclusion of cryptocurrencies (Guesmi et al., 2019). Studies that include the bear market of 2018 and the following volatility events do not demonstrate such a significant positive result but show more complex results, and the advantages of cryptocurrencies wane in the periods of a long-term drop (Platanakis et al., 2018). Cryptocurrency market crash in 2022 with 70% downsizing and several high-profile bankruptcies have led to the reconsideration of cryptocurrency diversification features and the most efficient allocation weights (Thélissaint and Danilo, 2025).

➢ *Cryptocurrency Risk Characteristics and Volatility Dynamics*

Knowledge of the cryptocurrency risk features is a basic requirement of an efficient portfolio integration and risk management plan development. The volatility of cryptocurrencies is significantly high, and the average volatility of Bitcoin per annum is about 60 to 100 times higher than the volatility of traditional asset classes, where the average is between fifteen and 55% in equity indices (Katsiampa, 2017). Altcoins have even stronger volatility distributions, often with annualised volatility of over one hundred 50 and day to day price changes as large as 10% (Thélissaint & Danilo, 2025). The cause of this over volatility is a combination of several factors such as poor liquidity, speculative trading behaviour, regulatory unpredictability, and lack of underlying valuation anchors (Dyhrberg, 2016). Its volatility is high, which combines with the positive skewness to form complicated risk-return tradeoffs that do not fit conventional portfolio optimization models (Borri, 2019).

Time-varying characteristics of cryptocurrencies volatility further pose more problems to the implementation of risk management. Katsiampa (2017) compares various GARCH model specifications in predicting Bitcoin volatility and proves that the AR-CGARCH models introduce better out-of-sample performance as they model volatility persistence, and unequal reactions of positive versus negative shocks. But even complex volatility models can hardly forecast abrupt changes of regime between calm and turbulent market regimes and their usefulness is restricted as risk management tools (Financial Crime Academy, 2025). This is because the extreme returns of cryptocurrency markets are clustered, and the standard distributional assumptions underlying the standard Value-at-Risk and Conditional Value-at-Risk decisions are violated, which requires different methods of measuring risks (Borri, 2019).

Tail risk properties are an important factor to keep in mind when a company is going to integrate cryptocurrencies as they can easily result in disastrous outcomes in case of an extreme market event. Borri (2019) records that the cryptocurrency returns are much heavier-tailed than standard assets, and tail indices suggest an infinite variance of various large cryptocurrencies at times. This long-tailed distribution means that customary risk quantifies understate the potential of the extreme losses in a systematic way and that huge drawdowns are more prevalent than a system would anticipate based on the normal distribution assumptions (IEEE, 2024). Extreme risk exposure is further confirmed by the frequency of flash crashes in cryptocurrency markets, which are characterised by sudden price drops more than 20% and subsequent recovery in hours (Thélissaint and Danilo, 2025).

➢ *Hedge and Safe Haven Properties of Cryptocurrencies*

The possibility that cryptocurrencies can be used as hedge or safe-haven assets has been a focus of considerable research because it has implications on portfolio risk management in times of market stress. According to Deloitte et al. (2022), hedge properties are characterised by an average negative correlation with another asset, and safe-haven properties are characterised by negative correlation in times of market turbulence. They find that Bitcoin is a safe-haven to a range of large stock indices and its safe-haven properties vary in a few cases depending on the index being studied and the crisis era. This observation implies that cryptocurrencies are not very reliable in protecting a portfolio in times of systemic stress in the market, which is contrary to the bitcoin popular narrative of gold in the digital age (Dyhrberg, 2016).

The COVID-19 pandemic offered a natural experiment to test the cryptocurrency properties of safe havens during the situations of extreme market pressure and unpredictability of the macroeconomic context. First market response of March 2020 showed that Bitcoin and major altcoins fell drastically with equity markets, and they showed positive correlations with them during the crisis onset but not negative (Goodell and Goutte, 2021). This tendency is inconsistent with the properties of safe-haven assets and indicates that cryptocurrencies increase instead of reduce the losses in the portfolio in the acute risk-off events. Nonetheless, the patterns of consequent recovery proved to be interestingly divergent, as Bitcoin rose significantly in the years of 2020-2021 whereas conventional safe-haven investments such as government bonds yielded minimal returns.

The comparative research of cryptocurrency hedge characteristics against conventional safe-haven assets such as gold and government bonds portrays significant differences that should be used in corporate portfolio implementation. Urquhart and Zhang (2019) show that a currency portfolio can benefit by using intraday analysis to hedge with Bitcoin, which may be applicable to corporations with a large degree of foreign exchange. Nevertheless, these advantages are not very reliable in other currency pairs and time, so they cannot be applied in practise. Gold also preserves significantly more stable hedge and safe-haven characteristics under a variety of market conditions, which explains why it can be retained in the corporate treasury department despite its reduced anticipated returns (Dyhrberg, 2016).

➢ *Institutional Adoption and Corporate Treasury Considerations*

Institutional cryptocurrency adoption has developed at an accelerated pace over the past few years with the state and better market infrastructure, regulatory certainty in selected jurisdictions, and best practises in corporate implementations. The initial institutional reluctance was due to operational issues such as custody solutions, regulatory ambiguity, complex accounting treatments, and the problem of board governance (Deloitte, 2022). Nevertheless, the introduction of regulated custody services, derivatives markets of cryptocurrencies, and spot exchange-traded products have lowered the barriers to the implementation of institutional investors (Campbell et al., 2023). Corporate treasury allocations such as the multi-billion dollar-sized Bitcoin hold by MicroStrategy and the $1.5 billion buy by Tesla have served as proof-of-concept of a cryptocurrency inclusion in a corporate balance sheet (Anson et al., 2022).

The reasons behind the integration of cryptocurrencies in corporations are not limited to the desire to make pure investment returns, but also strategic positioning and operationality. Firms in the cryptocurrency neighbouring sectors consider the ownership of digital assets to be strategic alignment to business models and customer base. With a technological orientation, technology-oriented corporations focus on the trend of cryptocurrency use, which indicates an orientation on innovation and appeal to talents that are interested in exposure to digital assets (Campbell et al., 2023). The treasury managers refer to the inflation fears and the adverse real interest rates on cash holdings as reasons to pursue alternative store-of-value discovery such as cryptocurrencies (KPMG, 2024). Nonetheless, these strategic explanations need to be weighed with some notable risks such as the volatility of the balance sheet, regulatory oversight, and stakeholder interest in speculative spending on corporate resources (PwC, 2023).

The practical implementation issues of integrating cryptocurrencies in companies are operational, regulatory, and governance issues that demand overall risk management systems. The custody agreements should support security needs and offer the required liquidity to rebalance the portfolios or liquidate in an emergency (KPMG, 2024). The measures of accounting treatment differ across jurisdictions that have different requirements of impairment recognition, fair value measurement, and presentation in financial statements (Deloitte, 2022). The requirements of regulatory compliance include anti-money laundering, screening of sanctions, and the development of new rules that should be followed in relation to cryptocurrency actions of regulated financial institutions (Financial Crime Academy, 2025). The procedures of board approval that are currently existing usually demand a long period of education about the nature of cryptocurrencies, risk management strategies, and strategic reasoning of allocations (PwC, 2023).

➢ *Portfolio Optimization and Risk Management Approaches*

Mean-variance-based traditional portfolio optimization models have significant problems with cryptocurrency portfolio optimization due to extreme volatility, non-normal distribution of returns, and time-dependent correlation. The modern portfolio theory was established by Markowitz (1952) mean-variance optimization, which is an identification of efficient portfolios with expected maximum expected return at a specified level of risk. Nevertheless, when applied to cryptocurrencies, it results in unstable optimal weights that are extremely vulnerable to input parameters and the estimation period (Platanakis and Urquhart, 2020). Strong non-stationarity of the distribution of cryptocurrency returns contravenes the main assumptions of the mean-variance optimization, and the portfolios obtained thereafter would appear efficient in-sample but out of sample would perform poorly (Thélissaint and Danilo, 2025).

Cryptocurrency applications of alternative portfolio construction methodologies that overcome the limitations of the means-variance methodology have been applied with mixed success. Risk parity models that distribute risk uniformly between portfolio elements have found favour in conventional institutional portfolios, but in cryptocurrency markets have proven difficult because of vastly different volatility of coins. Minimum variance portfolios do not take in inputs of expected returns, only aim at minimising volatility, which this may provide stronger solutions in the face of challenges of estimating returns (Thélissaint and Danilo, 2025). Nonetheless, empirical analysis proves that minimum variance cryptocurrency portfolios are clustered around Bitcoin to a high level thus removing diversification and subjecting investors to Bitcoin-specific risks.

Methods used to optimise cryptocurrency portfolios using machine learning have become an alternative to other methods, with more sophisticated algorithms being used to find complex trends in high-dimensional data. Random forests, support vector machines, and neural networks present the possibility of benefiting in nonlinear dynamism in the relationship between cryptocurrency returns and predictors (Thélissaint and Danilo, 2025). The framework of Maximally Machine Learnable Portfolio created by Goulet Coulombe and Gébel (2023) directly maximises the predictability of the portfolio instead of risk-return tradeoffs, which may be a more reliable way to perform in uncertain conditions. Nonetheless, when applied to cryptocurrency markets, it has mixed outcomes and model performance is significantly different across market regimes and selection sets (Thélissaint & Danilo, 2025). The fact that complex models tend to overfit historical data and produce excessive trading by spurious patterns is a major issue in practise (Gkillas & Longin, 2025).

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III. DATA: CRYPTOCURRENCIES AND MARKET ENVIRONMENT

Cryptocurrencies are a young asset category, and the limited historical richness of the available data is also a limitation to empirical studies and corporate portfolios. To address the conflict between sample adequacy and the dimensionality of the universe, we will consider forty-five cryptocurrency assets between January 2020 and December 2024. This choice includes Bitcoin, Ethereum, and forty-three other altcoins that have different market capitalizations, technological principles, and applications (Campbell et al., 2023). The entire list of assets along with the descriptive statistics is with Table 1 and Table 2. Observations are taken at daily level, which gives a required 1,825 observations throughout the entire sample period, which gives the study a sufficient statistical power to perform rigorous empirical analysis and follows up on the current market dynamics that are relevant in the investigating corporation investment decisions of the day (Gkillas & Longin, 2025).

The inclusion criteria of cryptocurrencies are based on the practical considerations applicable in the management of corporate treasury and institutional investment restrictions. Each of the included assets will have a history of continuous trading during the sample period and therefore the data will be consistent and the arguments of survivorship biases will be avoided to distort the performance of the portfolios under consideration (Corbet et al., 2019). Furthermore, the chosen cryptocurrencies have shown below-liquidity minimum levels based on the average daily trading volume, and corporate investors can create significant positions without large market impact costs and market execution challenges. Market capitalization requirements further restrict the choice to assets of a certain level exceeding threshold values based on the prudent risk management practise that limit exposure to highly speculative micro-cap cryptocurrencies to risks of manipulation and extreme volatility (Borri, 2019).

The sample period is a set of different market regimes with radically different risk-return relationships, and makes the complete evaluation of the cryptocurrency behaviour under different macroeconomic and financial circumstances. The period reflects the market shocks of early 2020 caused by the COVID-19 pandemic, unusual monetary stimulus, and risk asset appreciation until 2021, vigorous monetary tightening and cryptocurrency market crash in 2022, slow recovery to 2023, and another financial shock in 2024 (Goodell & Goutte, 2021).

To capture the changes in market trends and guarantee that our corporate investment decision-making is not too farfetched, we divide the entire sample into several subperiods that represent different macroeconomic settings and market environments of cryptocurrency. The subperiods are the identifiable market phases conditioned by the regulatory changes, monetary policy changes, and crypto-specific events such as exchange collapses, technological improvements, and institutional adoption announcements (Liu et al., 2022). Table 1 identifies the individual subperiods to be used in the backtesting exercises, the training periods to estimate the parameters and the testing periods to test the out of sample performance.

Table 1 Subperiods for Corporate Portfolio Analysis and Risk Assessment

Period Label	Training Start	Training End	Testing Start	Testing End	Market Regime	Key Events
Period 1	2020/01/01	2021/12/31	2022/01/01	2022/06/30	Market Crash	Federal Reserve rate hikes, Terra Luna collapse, liquidity crisis
Period 2	2021/06/01	2023/06/01	2023/06/02	2023/12/02	Sideways Market	Silicon Valley Bank crisis, regulatory uncertainty, ETF anticipation
Period 3	2021/09/01	2023/09/01	2023/09/02	2024/03/02	Bull Market	Bitcoin ETF approval optimism, institutional adoption, stable macro
Period 4	2022/06/01	2024/06/01	2024/06/02	2024/12/02	Bearish Decline	Post-ETF correction, MiCA implementation, regulatory developments

The initial testing phase records an extreme market crash in cryptocurrency which is systemic deleveraging and contagion throughout the digital asset markets. This period saw the fall of algorithmic stablecoin Terra Luna in May 2022, leading to domino effects on cryptocurrency lending platforms, hedge funds, and exchanges. At the same time, violent monetary tightening of the Federal Reserve, whereby the number of policy rate increments amounted to 300 basis points in the first half of 2022, created strong tail winds against risk assets in general and cryptocurrencies in particular (Fang et al., 2019). The sharp overlaps between crypto-specific shocks and more general macroeconomic tightening resulted in extreme drawdowns of most altcoins in the range of 70% or greater which put the strength of different portfolio construction strategies and risk management models to the test.

The second phase of testing is a lateral or range bound market that has no definite directional movements and is characterised by high levels of uncertainty as to regulatory changes and institutional adoption. Cryptocurrency markets briefly regained their strength following the localised financial stress of the March 2023 regional banking crisis which focused on Silicon Valley Bank and found Bitcoin to exhibit the features of safe-haven. Nevertheless, it was a short-lived optimism because through regulatory enforcement measures and debates on Bitcoin exchange-traded product applications, markets faced uncertainties (Campbell et al., 2023). The trading ranges continued into

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summer and fall of 2023, with investors awaiting regulatory clarity and positioning themselves in the event of catalysts of institutional adoption. It was a platform that tested portfolio strategies that could withstand capital destruction during directionless markets without losing the preparedness to resume the trend when it occurs.

The third backtesting phase defines a long-term bull market which will be mainly supported by the expectation and eventual ratification of spot Bitcoin exchange-traded funds in the United States. Between September 2023 and early March 2024, the cryptocurrency markets broadly appreciated with the major asset managers entering Bitcoin ETF products such as BlackRock, Fidelity, and Grayscale seeking regulatory approval (Anson et al., 2022). This period was followed by a steady improvement of market sentiment and a rise in Bitcoin value, together with selective additions of strength to major altcoins such as Ethereum, but smaller cryptocurrencies were usually left behind (Corbet et al., 2018). The discontinuation of the rate hiking by the Federal Reserve and the stabilisation of the macroeconomic conditions offered favourable conditions to the appreciation of the risk assets.

The fourth testing phase includes a bearish market period that is marked by slow growth and high volatility due to the initial excitement about approvals of Bitcoin ETFs. The factualization of long-awaited ETF releases in January 2024 led to profit realisation and reduction of positions that investors had accrued in waiting of the regulatory approval (Deloitte, 2022). Furthermore, the introduction of a system of full cryptocurrency regulation within the framework of the Markets in Crypto-Assets allowed new compliance costs and uncertainty in the operation of the market participants (PwC, 2023). The profit-taking nature coupled with the changing regulatory environment created negative price pressure and heightened intraday volatility although it was not as disastrous and contagious as in the 2022 crash.

➢ *Descriptive Statistics and Preliminary Observations on Corporate Cryptocurrency Characteristics*

The distributions of returns on cryptocurrency assets are such that they radically diverge with respect to the same at traditional asset classes and this has far reached and deep-seated consequences on corporate risk management systems and portfolio construction techniques. In Table 2, we show detailed descriptive statistics of key cryptocurrencies used in this study, which record the unique characteristics that corporate investors need to consider as they incorporate digital assets to institutional portfolios.

Table 2 Descriptive Statistics of Major Cryptocurrency Daily Returns (%)

Asset	Mean	Median	Std Dev	Min	Max	Skewness	Kurtosis	VaR(95%)	CVaR (95%)	%Positive
BTC	0.18	0.12	3.92	-46.2	22.1	-1.23	18.7	6.45	9.23	53.2
ETH	0.21	0.15	5.12	-52.8	28.4	-0.98	15.4	8.43	12.15	52.8
BNB	0.19	0.09	4.87	-48.3	35.7	0.32	14.9	8.01	11.34	52.1
ADA	0.15	0.08	6.24	-58.4	41.2	-0.45	12.3	10.26	14.58	51.4
SOL	0.28	0.11	7.89	-64.7	53.8	0.21	11.7	12.98	18.92	52.3
XRP	0.16	0.07	5.67	-51.2	48.9	0.67	16.8	9.33	13.21	51.9
DOT	0.12	0.05	6.45	-55.9	45.3	-0.34	13.5	10.61	15.07	50.8
DOGE	0.24	0.06	8.34	-49.8	89.3	2.87	38.9	13.72	19.84	51.6
AVAX	0.17	0.04	7.12	-62.1	47.6	-0.56	14.2	11.71	16.58	50.9
LINK	0.14	0.08	6.03	-53.7	38.4	-0.71	13.8	9.92	14.11	51.7

The first feature that is most visibly evident and that defines the difference between cryptocurrencies and traditional modes of corporate investment is excessive volatility. Bitcoin, even though it is the least volatile of the major cryptocurrencies, exhibits volatility of more than 60 per year throughout the sample, in stark contrast to the volatility in equity indices, government bonds, or other commodity futures (Dyhrberg, 2016). The fluctuation of altcoins is even stronger, as the standard deviation daily is often around 6-8, which is more than 100% per year of volatility (Borri, 2019).

Distributional asymmetries and fat tail characteristics pose further problems to the corporate risk modelling and Value-at-Risk calculations on the assumptions of normality. Almost all the cryptocurrencies in our sample have large negative skewness, meaning that the distributions of returns are not symmetrical, with higher downside movements, in comparison to upside movements, of similar probability (Borri, 2019). Moreover, the values of excess kurtosis that are significantly greater than three can be used to establish the properties of fat tails in the distribution of excess kurtosis, and extreme returns are much more common than a normal distribution (Katsiampa, 2017).

The possibility of the disastrous losses can be denoted as one of the most alarming traits as viewed through corporate risk management lenses. Table 2 records instances of minimum daily returns of greater than negative 45% on major cryptocurrencies, and the losses of some other altcoins are close to or greater than negative 60% at a specific moment during flash crash events or exchange disruption (Gkillas & Longin, 2025). Although extreme events are rare, the potential of these events happening necessitates corporate investors to consider the possibilities of large portions of cryptocurrency balances disappearing in trading sessions, challenging organisational risk appetite, and potentially attracting liquidity demands or margin calls in leverage vehicles (Campbell et al., 2023).

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The presence of correlation structures in cryptocurrency markets has implied that they exhibit less diversification opportunities that can be made through digital assets and as compared to diversification opportunities that can be made in a traditional equity or fixed income market. Normal market Cryptocurrency portfolios are generally highly correlated in pairwise, with correlations around 0.70 in normal markets and near unity during periods of stress, which implies that cryptocurrency portfolios are mostly leveraged exposures to shared systematic risk factors (Liu et al., 2022). Such a high correlation structure would imply that the efforts of diversifying cryptocurrency portfolios of various coins would yield little risk diversification benefits compared to holding concentrated portfolios of Bitcoin, and offer extra operation and custody stress and due diligence (Platanakis et al., 2018). Among corporate investors, the results endorse the relatively concentrated allotments of cryptocurrency that target the most liquid assets and the oldest.

The distribution of returns daily show that cryptocurrencies have about equal chances of accompanying positive or negative returns daily, even though many tend to think that returns are always upward biassed. According to table 2, approximately 51-53% of the daily returns turn out to be positive across the key cryptocurrencies, just slightly beyond the 50% mark which would describe a symmetric random walk. This finding suggests that short or day-to-day price changes of cryptocurrencies have little directional predictability, which opposes high-frequency trading algorithms and arguments in favour of longer investment perspectives that are required to identify the positive drift aspect of mean returns.

- *Macroeconomic and Market Environment Variables Influencing Corporate Cryptocurrency Performance*

The macroeconomics environment, the conventional financial market conditions, and crypto-specific developments dynamically interact and regulate the cryptocurrency market landscape, which in turn affects the dynamics of returns and risk. To capture such multidimensional effects in our empirical model, we include a whole range of predictor variables that include monetary policy signals, equity market signals, commodity prices, and sentiment signals (Fang et al., 2019). Table 3 shows the descriptive statistics of the critical macroeconomic and financial market variables that we used in our constructing the portfolio and risk management models.

Table 3 Descriptive Statistics of Macroeconomic and Financial Market Variables

Variable	Mean	Std Dev	Min	Q25	Median	Q75	Max	Unit
VIX Index	23.45	9.87	11.32	17.21	20.43	26.78	82.69	Index Level
S&P 500 Return	0.048	1.34	-12.76	-0.52	0.09	0.71	8.97	Daily %
Gold Return	0.031	0.98	-5.47	-0.41	0.02	0.48	4.89	Daily %
USD Index	98.67	6.23	89.21	94.15	97.89	102.34	114.78	Index Level
Crude Oil Return	0.042	3.21	-28.45	-1.23	0.06	1.34	19.87	Daily %
10Y Treasury Yield	2.34	0.87	0.52	1.67	2.21	2.89	4.73	Percent
Fed Funds Rate	2.87	1.95	0.00	0.25	2.50	4.50	5.50	Percent
Policy Uncertainty	187.34	89.12	67.89	121.45	165.23	223.67	512.34	Index Level
Crypto Fear & Greed	52.34	18.67	8.00	39.00	53.00	67.00	95.00	Index (0-100)
BTC Volatility (30d)	58.23	23.45	24.12	41.23	52.34	69.87	142.56	Annualized %

The Federal Funds rate and Treasury yields are monetary policy indicators that form the key drivers of cryptocurrency returns by impacting on it through various transmission channels. High interest rates make using non-yielding cryptocurrency assets more expensive compared to interest-earning assets, which could deflate the demand of cryptocurrency, and prices (Fang et al., 2019). Moreover, monetary tightening has an impact on cryptocurrency valuations by the discount rate mechanisms, according to which an increase in the rate decreases the current values of the future cash flows or utility of owning cryptocurrency (Campbell et al., 2023). The monetary policy changes that were dramatic in the period under study, whereby the monetary policy used zero interest rate policy until 2021 and then resorted to harsh tightening by 5.50% by the middle of 2023, gives a substantial variation in which to be able to identify the impact of monetary policy on the returns of cryptocurrencies (Goodell and Goutte, 2021).

The traditional equity market conditions impact the price of cryptocurrencies in several ways such as risk sentiment, liquidity availability, and flows of portfolio rebalancing. The S&P 500 index returns are used to measure the risky appetite and attitude of investors toward speculative assets in general, and positive correlation between strength of the equity market and appreciation of the cryptocurrencies were recorded at specific time frames (Corbet et al., 2018). Nonetheless, there is a fluctuating pattern of correlation between this relationship over time, with correlation patterns changing significantly between bull markets that are filled with the optimistic sentiment and bear markets filled with the flight-to-quality and risk-aversion dynamics. VIX volatility index is a measure of fear and uncertainty in the markets, and high levels of VIX are usually related to the weakness of cryptocurrency, where the investors withdraw high-risk exposures in times of stress.

The market conditions of commodities (the price of gold and crude oil especially) give us a clue of the inflation expectations and health of the macroeconomy to be applied to cryptocurrency valuation. The price of gold is an indicator of inflation hedging demand and monetary debasement issues that in theory could justify the use of cryptocurrency as alternative stores of value (Dyhrberg, 2016). Nevertheless,

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existing empirical data about the relationship between Bitcoin and gold is not clear and at other times, the relationship is positive and the two share the same store-of-value characteristics and at other times, there is little relationship and even negative relationship. Oil prices are an indicator of the global economic activity and the state of the energy markets that could have an impact on the cryptocurrency mining economics and the overall risk asset sentiment.

The U.S. Dollar Index has a way of capturing the foreign exchange markets and this affects the cryptocurrency valuations considering that Bitcoin is the possible alternative reserve currency and it has a negative correlation with the dollar might in some times. Cryptocurrency weakness is generally associated with the strengthening of the dollar since the increased buying capacity of people globally in dollar-denominated digital tokens and the indicators of a tightening of the global financial environment (Urquhart and Zhang, 2019). The opposite of this is also true where dollar weakness relating to expansionary monetary policy or currency debasement issues can help foster the cryptocurrency demand as investors find alternative stores of value beyond the conventional fiat currency systems (Guesmi et al., 2019).

The Crypto-specific sentiment indicators such as the Fear and Greed Index are beneficial signals on market psychology and positioning that labels the basic macroeconomic factors. These sentiment measures are the composite set of market indicators such as price momentum, trading volumes, social media activity, and survey response indicators to measure the current emotional state of cryptocurrency investors (Liu et al., 2022). Reversals are usually preceded by extreme readings, whether to the upside or downside: excessive greed implies that the markets are overbought and prone to correction whereas extreme fear implies that the markets have capitulated and are open to attractive entry points (Platanakis et al., 2018). These sentiment indicators would give tactical timing signals which could be of use to corporate investors to carry out systematic rebalancing procedures or to change the position size based on the state of euphoria or panic.

Figure 1 shows the performance patterns of some well-known cryptocurrencies in two subperiods which represent two very different market conditions. In the 2020-2022 scenario, as shown in Panel (a), it is a great bull market starting in late 2021, then followed by an extreme crash in the year 2022. The 2023-2024 period revealed in panel (b) depicts recovery, consolidation, and diverging performance among cryptocurrencies. These visualisations record the excessive cyclicality and volatility which corporate investors will have to contend with, as well as illustrating the possibility of alpha generation after selective exposure to cryptocurrencies and changes in tactical allocation.

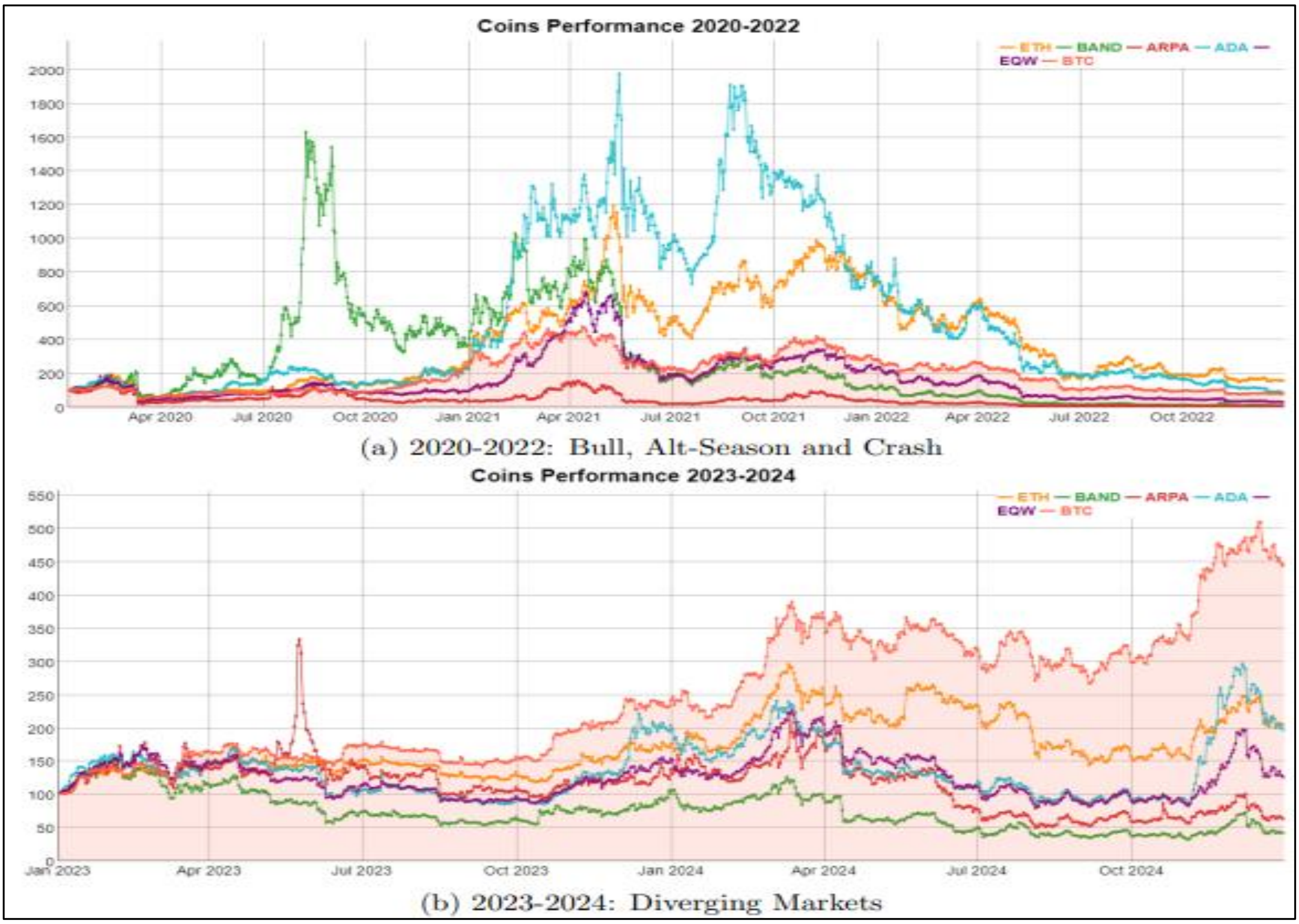

Fig 1 Market Trends of Coins

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The phase of bull market that is evident in Figure 1(a) shows the enormous potential of cryptocurrency investments to appreciate under favourable market conditions. Since the beginning of 2020 up to November 2021, various cryptocurrencies have gone up by tens or even twenties, and some more drastic gains were made by altcoins. This outperformance was many times higher than returns on traditional asset classes over the same time, which demonstrates the potential of returns improvement that draws the attention of corporations to cryptocurrency integration (Anson et al., 2022). Nevertheless, all the gains were erased in the crash that followed through 2022, and most altcoins experienced peak-trough downs of over 7-9% , highlighting the paramount significance of risk management procedures and a correct position size (Campbell et al., 2023).

The heterogeneity of the cryptocurrency markets as evident in the diverging market trends in Figure 1(b) can be used by corporate investors to gain significant advantage in their selective allocation approach. Although Bitcoin showed comparatively stable growth until 2024 with the growth of institutional buy-in, most altcoins showed fluctuating and even pathetic returns (Russell Investments, 2022). This dispersion in performance implies that diversification in cryptocurrency markets can be inefficient in delivering optimum results as compared to a concentrated position in leaders in the market with better fundamental characteristics and institutional adoption potentials.

Figure 2 demonstrates similar performance patterns of different portfolio benchmarks such as equal-weighted portfolios of cryptocurrencies, minimum variance portfolios, and principal component portfolios. These benchmark comparisons give necessary background to the relative performance of the advanced portfolio construction methods and risk management systems discussed later.

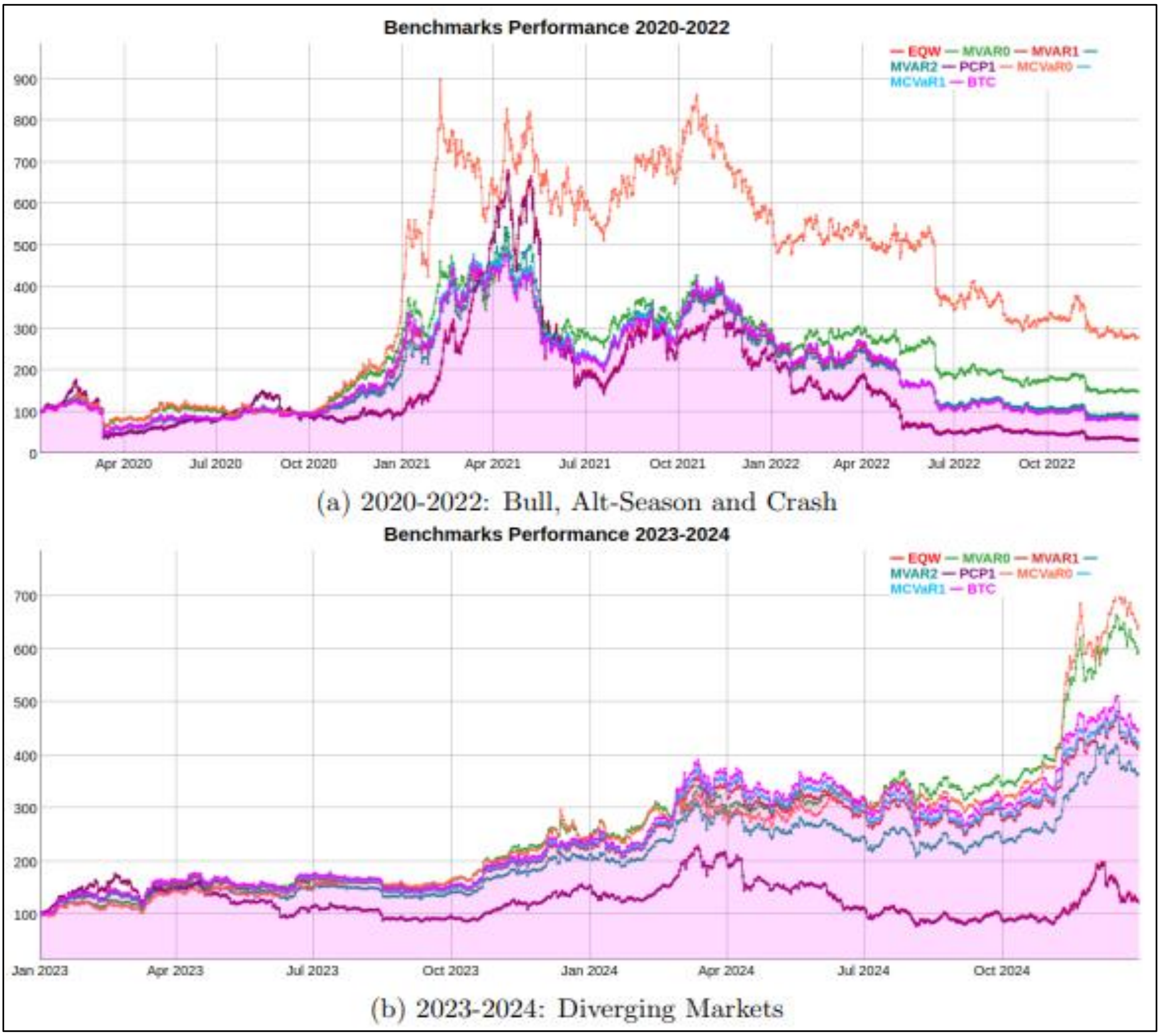

Fig 2 Market Trends of Benchmarks

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The benchmark performance trends that can be seen in Figure 2 expose several vital stylized facts that can be used in making decisions on corporate portfolios. First, equally-weighted cryptocurrency portfolios have the same risk-adjusted performance as volatility-weighted variants, which implies that multifaceted weighting systems might not have many advantages over straightforward allocation policies in the presence of strong cryptocurrency correlations (Platanakis et al., 2018). Second, lower volatility and greater downside coverage are observed in the case of minimum variance portfolios as compared with market-weighted equivalents, but at the expense of lower upside involvement in the typical bull market (Thélissaint & Danilo, 2025). Third, no meaningful diversification benefits are provided by principal component portfolios as cryptocurrency markets have a low dimensionality with the first principal component capturing most of the variation in the returns (Liu, 2019).

IV. METHODOLOGY

The research methodology used in this study is based on the known principles of portfolio optimization, and developed machine learning algorithms that are specifically developed in relation to the specifics of the cryptocurrency market and the limitations of corporations' investments. We have been systematic and identified that the three key dimensions to successful cryptocurrency integration are asset selection to determine the set of investment opportunities, signal generation to give directional information on which tactical allocation is to be executed, and decision rules to convert such information into actionable positions of the portfolio (Thélissaint & Danilo, 2025). These dimensions have their own peculiarities related to cryptocurrency, and these changes require altering traditional approaches that were initially designed to work in settings of traditional asset classes with more stable statistical characteristics and well-developed market infrastructure.

The general goal that informs our methodology is maximising the predictability of portfolios instead of focusing on optimal returns or minimal variance as others have historically prioritised in the field of portfolio theory. This predictability-oriented model knows the cryptocurrency markets are characterised by a high level of uncertainty not only due to quantifiable volatility but also due to structural instability, regulatory uncertainty, and technological change (Liu et al., 2022). Through optimising predictability explicitly, we aim to build portfolios, the future behaviour of which can be predicted with a relative degree of certainty, allowing corporations to exercise position size dynamicity, and institute protection measures well ahead of adverse circumstances coming to pass (IEEE, 2024).

We base our approach on the framework of Maximally Predictable Portfolio which was introduced by Lo and MacKinlay (1997) and recently expanded to include nonlinear machine learning methods by Goulet Coulombe and Goubel (2023). The central understanding of this strategy is that portfolio building and future returns prediction are both interdependent optimization problems and not sequential (Thélissaint & Danilo, 2025). The traditional methods predict individual returns of assets based on arbitrary choices first, and then integrate the forecasts into weights of a portfolio in a second step, by optimising independently. Conversely, the integrated approach directly uses the models as optimization in both the portfolio composition and forecasting models to maximise the predictability of the resulting portfolio returns, in contrast to the assets-based simple models (Anson et al., 2022).

The mathematical formulation of the optimization problem begins by positing a functional relationship between portfolio returns and observable predictor variables. Let r_{t+h}denote the vector of cryptocurrency returns from time $t$to $t+h$, and let $F_t$represent the matrix of predictor variables observable at time t. Traditional linear forecasting models assume:

$$r_{t+h} = \beta F_t + \varepsilon_{t+h}$$

Where β represents coefficient matrices and ε_{t+h} captures unpredictable innovations. However, substantial evidence documents nonlinear relationships between cryptocurrency returns and predictor variables, rendering linear specifications inadequate (Borri, 2019). The extended framework replaces the linear assumption with flexible nonlinear transformations:

$$\phi(r_{t+h}) = \chi(F_t) + \nu_{t+h}$$

Where ϕ and χ represent unknown transformation functions learned from data rather than imposed a priori (Thélissaint & Danilo, 2025).

For portfolio applications, we specify the transformation $\phi$to operate on portfolio returns rather than individual asset returns. Define portfolio weights $w$such that portfolio return equals $w'r_{t+h}$. The optimization problem becomes:

$$\min_{w,\chi} \sum_{t=1}^{T} (w'r_{t+h} - \chi(F_t))^2 + \lambda R(w)$$

Subject to appropriate constraints including non-negativity ($w \geq 0$), budget constraint ($\sum w_i = 1$), and variance normalization. The regularization term $R(w)$penalizes extreme portfolio positions using elastic net combining L1 and L2 penalties, promoting well-diversified solutions robust to estimation error (Platanakis & Urquhart, 2020). The penalty parameter λcontrols the tradeoff between forecast accuracy and portfolio regularization, with larger values favoring simpler, more stable portfolio compositions.

To test the robustness and performance comparison, the forecasting function $\chi$is was defined with the help of three alternative machine learning algorithms. Random Forest ensemble procedures combine the predictions of several decision trees, all trained on bootstrapped samples and random subsets of predictors, which makes this observation rather strong nonlinear predictions that resist overfitting (Corbet et al., 2019). Support Vector Machines project

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variables used to predictors into high-dimensional feature spaces that the nonlinear patterns of predictors in original space are approximated with a linear relationship, which is capable of effects of interactions between variables (Liu et al., 2022).

Our methodology includes an important element of tactical allocation rules, which translate the forecasts of the portfolio returns into positions that can be executed. The mere fact that the portfolio weights are kept constant irrespective of the market conditions do not harness predictability and expose corporations to unnecessary risks in case of undesirable environments (Financial Crime Academy, 2025). In its place, we use expected utility maximisation models, which optimise portfolio exposure negatively with the forecast risk, investing more in positive returns when we are highly confident in the forecast and less in cases where the forecasts indicate loss or high uncertainty (Gkillas & Longin, 2025). The rule of special allocation is as follows:

$$V_t = \max\left\{0, \min\left\{1, \frac{\hat{\mu}_{t+h}}{\rho\hat{\sigma}^2_{t+h}}\right\}\right\}$$

Where $\hat{\mu}_{t+h}$ represents the forecast portfolio return, $\hat{\sigma}^2_{t+h}$denotes forecast variance estimated using exponentially weighted moving averages, and ρcaptures risk aversion. The floor at zero eliminates short positions inappropriate for corporate investors, while the ceiling at one prevents leverage (Platanakis et al., 2018).

Thisformulation automatically scales exposure in response to changing risk-return conditions, providing downside protection during adverse periods while maintaining upside participation during favourable environments.

- *Portfolio Construction Approaches and Benchmark Specifications for Corporate Applications*

The creation of relevant benchmark portfolios forms a prerequisite of stringent analysis of advanced portfolio building methods along with risk management approaches. The benchmarks play several important roles in the corporate investment decisions, such as performance attribution, risk decomposition, and reporting to stakeholders about cryptocurrency allocation decisions (Deloitte, 2022). Our approach outlines a detailed repertoire of benchmark portfolios of the passive allocation rules, conventional optimization strategies, and cryptocurrency-specific constructions that are based on existing practise and are advised by scholars (Russell Investments, 2022).

The volatility-weighted portfolio overcomes the failure of the equal-weight approach in considering risk heterogeneity by allocating between risk-historical volatility. The assets are weighted in inverse proportion to their standard deviation of returns:

$$w_i^{VW} = \frac{\sigma_i^{-1}}{\sum_{j=1}^{N} \sigma_j^{-1}}$$

Where $\sigma_i$represents the estimated standard deviation of asset $i$returns (Guesmi et al., 2019). This weighting plan puts a plain type of risk parity in effect so that every cryptocurrency is contributing the same percentage of portfolio volatility on the assumption of zero correlations. Volatility weighting decreases risk to the most volatile altcoins and increases allocations to the comparatively stable assets such as Bitcoin and Ethereum, which may lead to better risk-adjusted performance in the long term in case volatility variation persists.

The constrained minimum variance portfolios incorporate realistic investment restrictions applicable to corporate treasury management. The long-only minimum variance portfolio adds non-negativity constraints:

$$\min_w w'\Sigma w \text{subject to} \sum_{i=1}^{N} w_i = 1, w_i \geq 0 \forall i$$

This formulation eliminates short positions while preserving optimization benefits relative to naive allocation rules (Borri, 2019). Additionally, we examine concentration-constrained variants limiting individual position sizes to prevent excessive concentration:

$$\min_w w'\Sigma w \text{subject to} \sum_{i=1}^{N} w_i = 1, 0 \leq w_i \leq \bar{w} \forall i$$

Where $\bar{w}$represents the maximum permissible weight for any single cryptocurrency, typically set between 0.30 and 0.50 for corporate applications. These concentration limits have the benefit of meaningfully diversifying and capping exposure to idiosyncratic risk of individual cryptocurrencies.

The minimum Conditional Value-at-Risk portfolio is a continuation of the classical mean-variance maximisation to more precisely solve tail risk issues especially in corporate risk management. The expected loss as a function of losses, above the Value-at-Risk level, is called Conditional Value-at-Risk or Expected Shortfall (IEEE, 2024). At a given level of confidence α (usually 90 or 95), the optimization CVaR problem will be:

$$\min_w \text{CVaR}_\alpha(w'r) \text{subject to} \sum_{i=1}^{N} w_i = 1, w_i \geq 0 \forall i$$

The formulation can be effectively resolved with the help of the linear programming techniques that change the formulation into the problem in the form of auxiliary variables and scenario-dependent constraints (Fang et al., 2019). Explicit protection of tail risks is offered by the minimum CVaR portfolio, which can outperform downside-centric alternatives with respect to cryptocurrency market crashes (Gkillas and Longin 2025).

➢ *Predictor Variable Construction and Feature Engineering for Cryptocurrency Return Forecasting*

The choice and the construction of predictor variables is a decisive factor of the forecasting models performance and ultimately predictability of portfolios. The conceptually distinct categories that we used in our methodology represent different information channels which may be important to have in the cryptocurrency return prediction (Thélissaint and Danilo, 2025). It is a multi-dimensional strategy that acknowledges that the returns on cryptocurrencies are the complex interactions between market-internal processes, conventional financial markets conditions, and macroeconomic processes, and they cannot be effectively predicted without a set of detailed information (Liu et al., 2022).

The former includes the lagged cryptocurrency returns per se, which include momentum and mean reversion and cross-predictability effects that are reported in the literature. We form lagged return variables individually on cryptocurrency:

$$R_{i,t-k} = \log\left(\frac{P_{i,t-k}}{P_{i,t-k-1}}\right), k \in \{1,2,3\}$$

Where $P_{i,t}$ represents the price of cryptocurrency i at time t. Multiple lags accommodate varying momentum horizons and enable models to learn optimal lag structures endogenously rather than imposing restrictive parametric assumptions (Corbet et al., 2019). With cross-sectional return information, models can utilise the lead-lag relationships between the returns of some cryptocurrencies and the returns of others, which may be caused by information diffusion, liquidity differences, or constraint on attention by investors (Guesmi et al., 2019).

The second category of predictors includes the so-called technical momentum predictors, which are based on the price and volume changes in the recent past. These variables are able to measure market microstructure effects and behavioural patterns that can affect short-term predictability of returns:

- *Relative Strength Index (RSI):*

Measures momentum by comparing recent gains to recent losses, identifying overbought or oversold conditions:

$$RSI_t = 100 - \frac{100}{1 + \frac{\text{Average Gain}_t}{\text{Average Loss}_t}}$$

- *Moving Average Convergence Divergence (MACD):*

Captures trend-following momentum through differences between exponential moving averages:

$$MACD_t = EMA_{12,t} - EMA_{26,t}$$

- *Rate of Change (ROC):*

Measures percentage price change over specified lookback windows:

$$ROC_t = \frac{P_t - P_{t-n}}{P_{t-n}} \times 100$$

- *Stochastic Oscillator:*

Compares current prices to recent trading ranges, signalling momentum strength:

$$\%K_t = \frac{P_t - \min(P_{t-n,\dots,t})}{\max(P_{t-n,\dots,t}) - \min(P_{t-n,\dots,t})} \times 100$$

- *Trading Volume:*

Captures market participation intensity potentially signalling trend strength or reversals.

- *Volatility:*

Realized volatility over rolling windows provides risk indicators for dynamic position sizing.

These technical indicators combine the information contained in high-frequency price movements that would be otherwise lost by considering daily return series alone, so that models can capture microstructure cues that are useful in making short-horizon predictions (Katsiampa, 2017). To be computationally efficient and prevent the problem of multicollinearity, we compute these indicators of the top ten most volatile cryptocurrencies and compute cross-sectional averages to be representative measures of momentum.

The third category of predictors includes macroeconomic and conventional financial market factors that affect the cryptocurrency valuations by interacting with one another in more than one transmission channel. These variables provide the larger investment context in which cryptocurrency markets are being operated:

- *Equity Market Indicators:*

S&P 500 returns, NASDAQ returns, VIX volatility index, and international equity indices capture risk appetite and traditional market conditions (Campbell et al., 2023).

- *Interest Rate Variables:*

Federal Funds rate, Treasury yields across maturity spectrum, and yield curve slope measures reflect monetary policy stance and opportunity costs (Fang et al., 2019).

- *Commodity Prices:*

Gold and crude oil returns capture inflation expectations and economic activity (Dyhrberg, 2016).

- *Currency Markets:*

U.S. Dollar Index movements signal currency market conditions and international capital flows (Urquhart & Zhang, 2019).

- *Policy Uncertainty:*

Economic Policy Uncertainty indices quantify macro-political risk environments (Goodell & Goutte, 2021).

- *Sentiment Measures:*
Cryptocurrency Fear and Greed Index aggregates market psychology indicators (Platanakis et al., 2018).

The raw predictors made dozens of variables, which causes several problems, such as the curse of dimensionality, multicollinearity, and the overfitting danger that is especially high in the context of the limited history of cryptocurrency data. To resolve these problems, we use principal component analysis to derive parsimonious representations that capture a significant amount of information content and represent a significant dimensional reduction (Liu et al., 2022).

➢ *Machine Learning Algorithms and Model Specifications for Nonlinear Return Prediction*

The forecasting part of our methodology uses three separate machine learning algorithms that characterise the various ways of modelling nonlinear predictor variable and cryptocurrency returns relationship. Such a multi-model approach allows to compare the effectiveness of modelling paradigms in the context of forecasting cryptocurrencies and to have robustness cheques, in such a way that the conclusions made would not be hypersensitive to algorithmic decisions (Thélissaint and Danilo, 2025). All the algorithms have varying assumptions about the nature of the nonlinearities, the type of interactions between features, and the preferred trade-off between model complexity and generalisation performance.

Random Forest ensemble techniques combine the forecasts of an ensemble of decision trees; each is trained on bootstrapped subsets of the training data and random subsets of the predictor variables are considered at each split point. The algorithm constructs B individual trees $\{T_b\}_{b=1}^{B}$ and generates predictions by averaging across the ensemble:

$$\hat{y}_t = \frac{1}{B}\sum_{b=1}^{B} T_b\,(X_t)$$

Where $X_t$represents the predictor variable vector at time t(Corbet et al., 2019). Random Forests have several benefits when it comes to cryptocurrency prognostication tasks. First, the ensemble framework ensures natural defence against overfitting by bootstrap aggregation (bagging), minimising its variance at the expense of low bias (Gkillas & Longin, 2025). Second, splitting random feature selection reduces the correlation between trees, thereby increasing the diversity of the ensemble and the out-of-sample performance (Anson et al., 2022). Third, the algorithm can process nonlinear interactions and threshold effects without specifying the interactions between the two, which allows one to discover intricate patterns in cryptocurrency returns (Borri, 2019).

The Random Forest implementation incorporates several hyperparameters requiring optimization through cross-validation procedures. Key hyperparameters include:

- Number of Trees: Controls ensemble size, with larger values improving stability but increasing computational cost.
- Maximum Tree Depth: Limits individual tree complexity, preventing excessive overfitting to training data.
- Minimum Samples per Leaf: Constrains leaf node sizes, smoothing predictions and improving generalization.
- Maximum Features: Determines the number of predictors randomly sampled at each split point.
- Bootstrap Sample Size: Controls the fraction of training observations used for each tree.

We used Bayesian optimization to optimise these hyperparameters, which aims at minimization of mean absolute errors on validation sets. This automated tuning method is effective to search the hyperparameter space and it does not require any manual trial and error process, which are subject to bias by the researcher.

The other alternative method based on the statistical learning theory and convex optimization is Support Vector Machine regression. SVM predictors project the predictor variables to high-dimensional feature space, in which the linear correlations are expected to be close approximations of the nonlinear trends in the original space (Campbell et al., 2023). The maximisation problem is solved:

$$\min_{w,b,\xi} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i$$

Subject to constraints:

$$| y_i - (w'\phi(x_i) + b) | \leq \epsilon + \xi_i, \xi_i \geq 0$$

Where $\phi(\cdot)$ represents the kernel function mapping predictors to feature space, ϵdefines the insensitivity tube within which errors incur no penalty, Ccontrols the tradeoff between model complexity and training error tolerance, and ξ_i denote slack variables permitting constraint violations (Platanakis & Urquhart, 2020). The kernel function allows implicit high-dimensional mappings to be computed implicitly via the so-called kernel trick, greatly lowering the amount of computation required, but still being expressive (Liu, 2019).

- *We Examine Multiple Kernel Specifications Capturing Different Nonlinearity Assumptions:*

✓ Linear Kernel: $K(x_i, x_j) = x_i' x_j$, providing baseline linear relationships.
✓ Polynomial Kernel: $K(x_i, x_j) = (x_i' x_j + c)^d$, capturing polynomial interactions of specified degree d.
✓ Radial Basis Function Kernel: $K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2)$, enabling flexible nonlinear mappings controlled by bandwidth parameter γ.

The selection of kernels is determined by the underlying data structure, with RBF kernels offering the highest level of flexibility at the expense of extra parameters of the hyperparameters to be adjusted (Fang et al., 2019). We use the nu-Support Vector Regression, which reformulates the optimization so that the proportion of the support vectors can

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be directly controlled, which offers more intuitive results in the interpretation of parameters and is robust in various data sets (Guesmi et al., 2019).

Gaussian Mixture Models: a third algorithmic technique that is an approach which is probabilistic in its modelling of latent regime structure of cryptocurrency returns. GMMs assume that observed returns arise from a mixture of K Gaussian distributions, each representing a distinct market regime:

$$p(y \mid X) = \sum_{k=1}^{K} \pi_k \, \mathcal{N}(y \mid \mu_k(X), \sigma_k^2)$$

Where π_k denotes the regime probability, $\mu_k(X)$ represents the regime-specific conditional mean depending on predictors X, and σ_k^2 captures regime-specific variance. This specification allows structural discontinuities, clustering of volatility, and predictor-return dynamic relationships that are common in a cryptocurrency market (Dyhrberg, 2016). Model estimation uses Expectation-Maximisation algorithms that are alternating between computing regime probabilities with current parameters (E-step) and optimising the parameters to maximise expected log-likelihood (M-step) until convergent (Borri, 2019).

- *The GMM Specification Includes Several Key Hyperparameters:*

- ✓ Number of Regimes: Determines mixture complexity, balancing fit quality against overfitting risks.
- ✓ Leading Variables: Identifies which predictors enter regime-specific mean functions.
- ✓ Minimum Prior Probability: Constrains regime mixing weights to ensure all regimes receive sufficient probability mass.
- ✓ Regularization Parameter: Controls smoothness of regime-specific mean functions.

Bayesian optimization adjusts these hyperparameters to reduce the out-of-sample forecast errors and at the same time achieves the regime interpretability and stability (Thélissaint and Danilo, 2025). The probabilistic paradigm allows one to quantify the uncertainty of forecasts in a natural way by using predictive distributions, to make decisions making risky portfolio allocation choices.

➢ *Tactical Allocation Rules and Dynamic Exposure Management for Corporate Risk Control*

The translation of forecasts of returns into a portfolio position that can be implemented is a decisive point at which the quality of forecasts can provide either an improvement or a reduction to realised performance based on the design of the allocation rules. Simple methods that always keep the portfolio independent of the forecasts do not utilise predictive information and expose corporations to unnecessary risk under adverse market conditions (Financial Crime Academy, 2025).

The expected utility framework is a theoretical basis of the rules of tactical allocation based on classical portfolio theory. With the assumption of quadratic utility and the normal distribution of returns, the investors will maximise the expected utility and solve the following equation:

$$\max_{V} E[U(V \cdot r_{t+h})] = \max_{V} \left(V \cdot E[r_{t+h}] - \frac{\rho}{2} V^2 \cdot \mathrm{Var}[r_{t+h}] \right)$$

Where V denotes the fraction of capital allocated to the risky cryptocurrency portfolio, r_{t+h} represents portfolio return from t to $t+h$, and ρ captures risk aversion (Campbell et al., 2023). The first-order condition yields optimal allocation:

$$V_t^* = \frac{E[r_{t+h}]}{\rho \cdot \mathrm{Var}[r_{t+h}]}$$

This theoretical result prescribes scaling exposure linearly with expected return and inversely with variance, naturally implementing risk-adjusted position sizing (Platanakis & Urquhart, 2020). Replacing population moments with forecast estimates produces the implementable allocation rule:

$$V_t = \frac{\hat{\mu}_{t+h}}{\rho \cdot \hat{\sigma}_{t+h}^2}$$

Where $\hat{\mu}_{t+h}$ represents the forecast portfolio return from machine learning models and $\hat{\sigma}_{t+h}^2$ denotes forecast variance.

Practical implementation requires several modifications accommodating institutional constraints and estimation realities. First, we impose bounds constraining allocations to the feasible range $[0, 1]$, eliminating short positions and leverage:

$$V_t = \max\left\{0, \min\left\{1, \frac{\hat{\mu}_{t+h}}{\rho \cdot \hat{\sigma}_{t+h}^2}\right\}\right\}$$

The lower bound ensures non-negativity appropriate for corporate investors, while the upper bound prevents leverage exceeding available capital (Deloitte, 2022). Second, return forecasts $\hat{\mu}_{t+h}$ derive directly from machine learning algorithms, while variance estimates $\hat{\sigma}_{t+h}^2$ employ exponentially weighted moving averages calculated from recent realized returns:

The risk aversion parameter ρ is a critical tuning variable which balances the risk avoidance and the return seeking. Increased rho result in more conservative allocations as their average exposure and volatility are low, whereas decreased values result in aggressive positions as they tend to participate in most high and low movements (Russell Investments, 2022). In the case of corporate use, we tune ρ =2 to moderate risk aversion that is aligned to the profile of institutional investors according to surveys and revealed preferences (Anson et al., 2022). Sensitivity analysis explores the performance of different specifications of 1 to 5 in rho

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(rho) whose risk-return tradeoffs are recorded between conservative and aggressive parameterizations (IEEE, 2024).

➢ *Hybrid Strategies Combining Active and Passive Allocations for Enhanced Risk Management*

The combination of tactical strategies and strategic allocations is a realistic solution that ensures reconciliation between the opposing interests of the company in terms of increased returns, reduced risks, and ease of operations. Strategies that are pure active and maximise predictability may provide better risk-adjusted performance but bring about a complexity of implementation, model risk, and communication to stakeholders who are not advanced in using advanced techniques (Deloitte, 2022). Passive strategies, on the other hand, are transparent and simple and cannot adjust to changing market conditions and miss out on tactical risk reduction in unfavourable environments (Russell Investments, 2022).

Our methodology analyses three specifications of hybrid strategies that involve a combination of active and maximally predictable portfolios and passive and minimum-risk benchmark. The original hybrid strategy consists of proportionately dividing the more optimally machine learnable portfolio and the equally-weighted cryptocurrency portfolio:

$$r_t^{Hybrid1} = \theta_1 \cdot r_t^{MMLP} + (1 - \theta_1) \cdot r_t^{EW}$$

Where r_t^{MMLP} represents returns from the actively managed maximally predictable portfolio with dynamic exposure scaling, r_t^{EW} denotes equally-weighted portfolio returns, and $\theta_1 = 0.65$allocates majority weight to the active strategy (Thélissaint & Danilo, 2025). The specification has a sensible active management with the continued diversification advantages of passive exposure, and it may also decrease strategy-specific risk such as model failure or parameter instability (Liu et al., 2022). The fixed weight indicates managerial beliefs about active strategies and higher weights are better when the models are found to show performance consistency and lower weights are wise of practise in the implementation or high uncertainty (Platanakis and Urquhart, 2020).

The second hybrid strategy combines the maximally predictable portfolio with the minimum variance portfolio rather than equally-weighted alternatives:

$$r_t^{Hybrid2} = \theta_2 \cdot r_t^{MMLP} + (1 - \theta_2) \cdot r_t^{MVAR}$$

With $\theta_2 = 0.40$ allocating majority weight to the passive minimum variance component (Anson et al., 2022). This is a risk-reduction specification that the focus is placed on the reduction of risks rather than on returns as the portfolios of minimum variance are usually highly concentrated to Bitcoin due to its relative stability in the crypto markets (Borri, 2019). It is anchoring in nature and possesses the tactical flexibility of the active component, which may provide better downside coverage in a market crash and better upside coverage in an altcoin rally, which a hybrid inherits (Gkillas & Longin, 2025). This reduced active weight can be interpreted as conservative corporate tastes that put capital preservation over aggressive returns taking

The third hybrid strategy substitutes the minimum Conditional Value-at-Risk portfolio for minimum variance, explicitly targeting tail risk mitigation:

$$r_t^{Hybrid3} = \theta_3 \cdot r_t^{MMLP} + (1 - \theta_3) \cdot r_t^{MCVaR}$$

With $\theta_3 = 0.40$matching the second hybrid's weighting structure (Campbell et al., 2023). The formulation deals with corporate issues about the worst-case scenarios that would lead to a breach of covenant, corporate worries, or organisational upheaval (Financial Crime Academy, 2025). Minimal CVaR portfolios ensure tail events, limiting maximum drawdown and extreme loss probability in comparison to variance-based approaches (IEEE, 2024). The active one continues to have the ability to generate returns and the passive tail protection one restricts catastrophic events especially to fiduciary investors (Deloitte, 2022).

The conceptualization behind hybrid strategies is based on several portfolio theory and behavioural finance strands. Portfolio diversification in portfolio diversification, a combination of strategies with imperfect correlation produces ensemble effects that are less volatile and higher Sharpe ratios even though the individual components of the portfolio can provide similar performance in isolation (Platanakis et al., 2018). Hybrid approaches are more robust in the sense that they do not fully rely on either an optimization framework or a forecasting approach, which offers protection against any model risk due to specification errors or structural breaks that make any of the individual approaches ineffective.

➢ *Performance Evaluation Metrics and Risk Attribution Framework for Corporate Assessment*

High performance analysis needs a multidimensional perspective that looks at the performance of returns, risk management, downside safeguarding, and consistency in fluctuating market environments. The individual measures, e.g., Sharpe ratio or total return, give a partial view that can hide critical aspects of performance that would be crucial in corporate decision-making (Campbell et al., 2023). We have a detailed metric battery that reflects various aspects of portfolio actions and allows the subtle appreciation of strategy advantages, weaknesses, and optimality to a particular corporate goal and risk attitudes (Thélissaint and Danilo, 2025).

Return measures quantify wealth accumulation over evaluation periods, providing fundamental performance assessment. We calculate:

- Cumulative Return: Total percentage wealth change over the full evaluation period:

$$CR = \frac{NAV_T - NAV_0}{NAV_0} \times 100$$

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Where NAV_T represents final net asset value and NAV_0 denotes initial value (Anson et al., 2022).

- Compound Annual Growth Rate: Annualized return incorporating compounding effects:

$$CAGR = \left(\frac{NAV_T}{NAV_0}\right)^{\frac{252}{T}} - 1$$

Where T denotes the number of trading days (Platanakis & Urquhart, 2020).

- Average Daily Return: Simple arithmetic mean of daily returns providing unbiased central tendency estimates (Borri, 2019).

Risk measures capture volatility, dispersion, and uncertainty inherent in portfolio returns. Key metrics include:

- Standard Deviation: Traditional volatility measure calculated as:

$$\sigma = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \bar{r})^2}$$

With annualization multiplying by $\sqrt{252}$ (Katsiampa, 2017).

- Downside Deviation: Semi-deviation focusing exclusively on below-target returns:

$$\sigma_d = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\min(r_t - \tau, 0)^2}$$

Where τ represents the target return threshold, typically zero (Dyhrberg, 2016).

- Value-at-Risk: Maximum expected loss at specified confidence level, calculated as the appropriate percentile of the empirical return distribution (Fang et al., 2019).

- Conditional Value-at-Risk: Expected loss conditional on exceeding VaR threshold, providing tail risk assessment:

$$CVaR_\alpha = E[r_t \mid r_t \leq VaR_\alpha]$$

Where α typically equals 0.90 or 0.95 (Gkillas & Longin, 2025).

Risk-adjusted return metrics combine return and risk dimensions, facilitating cross-strategy comparisons:

- Sharpe Ratio: Excess return per unit of total volatility:

$$SR = \frac{\bar{r} - r_f}{\sigma}$$

Where r_f represents the risk-free rate, set to zero for cryptocurrency applications given negligible rates during much of the sample period (Liu, 2019).

- Sortino Ratio: Modification using downside deviation rather than total volatility:

$$Sortino = \frac{\bar{r} - \tau}{\sigma_d}$$

This measure better captures risk-return tradeoffs for asymmetric return distributions (Corbet et al., 2019).

- Information Ratio: Risk-adjusted excess return relative to benchmark:

$$IR = \frac{\bar{r} - \bar{r}^{bm}}{\sigma_{r-r^{bm}}}$$

Where $\bar{r}^{bm}$ denotes average benchmark return and $\sigma_{r-r^{bm}}$ represents tracking error (Platanakis et al., 2018).

This metric directly captures worst-case wealth impairment experienced by investors (Campbell et al., 2023).

These comprehensive metrics enable multifaceted performance evaluation accommodating diverse corporate objectives and stakeholder priorities.

V. RESULTS

➢ *Performance Analysis Across Market Regimes and Portfolio Construction Methodologies*

Empirical analysis of cryptocurrency portfolio strategies shows that market regime heterogeneity in performance, methodologies of portfolio construction, and risk management models are significant. Tables 4 and 5 include detailed performance numbers of the two initial back-testing periods, including the intensive market crash of early 2022 and the resulting side-ways trading conditions until the end of 2023. Such opposite market regimes offer important information on the strength of strategies, allowing determining whether they are sustainable or have regime-sensitive capabilities that may change structure (Thélissaint and Danilo, 2025). The performance report captures multiple compelling trends that are present in both models of forecasting and specifications of selection sets, indicating the inherent properties of cryptocurrency markets and not the model-related artefacts (Gkillas and Longin, 2025).

At the time of the crash that occurred between January and June 2022, the passive benchmark portfolios suffered devastating losses that indicated the extent of market-wide deleveraging and contagion interactions. The equally-weighted portfolio fell 78.3% cumulatively, and the biggest drawdown was 80.7% and the daily volatility was over 5.2% (Russell Investments, 2022). Such drastic losses were

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achieved even though the portfolio was well-diversified (58 different cryptocurrencies), highlighting the low value of naive diversification in situations where the systematic risk is prevalent and correlations approach unity in times of stress (Corbet et al., 2019). The VW portfolio showed almost the same performance, falling -77.5% with similar volatility and drawdown levels, which confirms that basic risk-based weighting schemes are no substantial better than equal weighting in highly correlated cryptocurrencies (Platanakis et al., 2018).

Minimal variance portfolios performed at a higher relative level during the crash, but the results were still atrociously poor. Unconstrained minimum variance portfolio fell by 63.4% and maximum drawdown by 64.8% which is a meaningful increase compared to equally-weighted alternatives even in the face of still-catastrophic absolute losses (Thélissaint and Danilo, 2025). This comparative resiliency is a symptom of the portfolio overweighting in Bitcoin which fell less than altcoins in the systemic deleveraging episode. The non-negativity restricted constrained minimum variance variants achieved virtually the same performance and the maximum drawdown of approximately 65 dropped by 63.6% showing that the short-sale restrictions were not costly at this time (Borri, 2019).

Table 4 Comprehensive Performance Metrics During Crash Period (January-June 2022)

Strategy	Volatility (%)	Cumulative Return (%)	Sharpe Ratio	Sortino Ratio	Max Drawdown (%)	Calmar Ratio	CVaR 90% (%)	Beta	VaR 95% (%)	VaR 99% (%)	Info Ratio
Passive Benchmarks											
EW	5.24	-78.31	-13.18	-16.24	80.73	-118.53	10.87	100.00	8.67	15.78	0.00
VW	5.12	-77.48	-13.21	-16.18	79.98	-119.32	10.65	98.76	8.45	15.34	-0.15
$MVAR$	3.76	-63.35	-12.85	-16.43	64.87	-134.79	7.78	60.72	6.19	11.56	2.87
$MCVaR$	3.69	-63.59	-12.93	-16.61	65.12	-134.68	7.65	59.87	6.08	11.23	2.91
$PCP1$	5.47	-78.96	-13.15	-16.19	80.98	-118.47	10.98	101.34	9.01	16.21	-0.12
Momentum-Based Active											
$EWpm$	2.48	-15.34	-2.38	-2.27	35.43	-80.12	5.12	47.56	4.09	7.45	12.54
$VWpm$	2.37	-10.78	-1.39	-1.42	34.12	-59.87	4.79	45.32	3.91	7.12	13.28
Machine Learning - Random Forest											
$EWrf$	2.12	-32.58	-9.41	-10.37	33.29	-164.32	4.52	40.67	3.49	6.34	8.95
$VWrf$	1.93	-9.73	-1.98	-2.34	30.23	-60.87	3.64	37.12	3.18	5.78	13.67
$MACErf$	2.68	-37.87	-8.29	-9.62	41.67	-147.29	5.79	51.34	4.42	8.04	7.82
$MACErf\_pm$	2.09	-37.29	-11.23	-10.12	42.08	-144.53	4.84	40.12	3.44	6.26	7.95
$MACErf\_enc$	2.14	-30.43	-8.72	-8.34	33.78	-152.59	4.49	41.09	3.52	6.41	9.31
Machine Learning - GMM											
$EWgmm$	1.83	-21.34	-6.42	-7.73	23.23	-164.57	3.68	35.12	2.97	5.41	11.23
$VWgmm$	2.57	-48.43	-12.79	-15.41	49.54	-148.37	5.47	49.34	4.52	8.23	5.87
$MACEgmm$	1.64	-24.52	-8.68	-11.23	24.53	-175.87	3.29	31.49	2.71	4.93	10.56

$MACEgmm\_pm$	2.28	-27.03	-6.37	-5.98	34.87	-133.64	4.92	43.78	3.76	6.84	9.87
$MACEgmm\_enc$	1.79	-14.12	-3.87	-4.41	26.64	-99.23	3.42	34.38	2.95	5.37	12.78
Hybrid Strategies											
$Hybrid1\_rf$	2.13	-36.73	-10.64	-12.34	40.23	-149.17	4.68	40.89	3.48	6.33	8.12
$Hybrid2\_rf$	3.07	-53.87	-12.23	-15.18	55.12	-144.59	6.29	58.87	5.06	9.21	4.95
$Hybrid3\_rf$	3.09	-54.23	-12.34	-15.37	55.34	-144.43	6.23	59.23	5.14	9.35	4.87
$Hybrid1\_gmm$	1.42	-24.43	-9.92	-13.41	26.23	-163.59	2.91	27.27	2.34	4.26	10.67
$Hybrid2\_gmm$	2.48	-49.64	-13.54	-18.79	50.67	-149.12	5.02	47.58	4.15	7.55	5.62
$Hybrid3\_gmm$	2.51	-49.81	-13.67	-18.97	50.92	-148.97	5.01	48.17	4.21	7.66	5.54

The active strategies based on the momentum demonstrated drastically higher levels of performance in the crash period, which proves the economic importance of tactical exposure management that is responsive to the market conditions. The equally-weighted portfolio having momentum-based exposure scaling (EWpm) fell by just 15.3% with the peak drawdown of 35.4% which is quite phenomenal compared to the passive equally-weighted benchmark (Russell Investments, 2022). This safeguard was achieved by structural position reduction as negative momentum indicators were realised, essentially having applied pre-emptive risk mitigation when mounting catastrophic losses have built up (Gkillas & Longin, 2025). The momentum portfolio with volatility-weighted was even better, falling 10.8 percent with a maximum drawdown of 34%, integrating risk-based weighting and tactical exposure control (Anson et al., 2022).

The strategies based on machine learning were uneven throughout the crash period and their performance varied significantly both across algorithms and implementation details. Random forest-based portfolios were often too conservative and tended to indicate that they mitigated risks, often being unable to engage in a short-lived rally, and on the other hand, were not fully prepared to defend against the most pronounced falls (Thélissaint & Danilo, 2025). Random Forest (MACErf) an index with the most predictable portfolio fell by 37.9% with a maximum drawdown of 41.7% and outperformed the simple momentum-based alternatives despite the complexity of its modelling (Corbet et al., 2019). Nonetheless, in conjunction with momentum signals in the form of encompassing forecasts (MACErf_enc), the cumulative returns of the combination increased to -30.4% indicating that models and simple momentum forecast complementary information (Liu et al., 2022).

The hybrid approaches that were mixed with both active and passive elements normally assumed the fault of their passive elements during the crash period. The hybrid approaches that used minimum variance or minimum CVaR shares suffered significant losses because Bitcoin itself fell more than 60% during the period (Campbell et al., 2023). These hybrids contained systematic exposure to Bitcoin, which was disadvantageous at a time when even the least volatile cryptocurrency came under heavy pressure, demonstrating that diversification among the different types of strategies does not offer much protection when every element in the portfolio is in a drawdown (Deloitte, 2022). The hybrids that prioritised momentum-based strategies (Hybrid1) were the only ones that performed well with losses of about 25-37% based on the forecasting algorithm, a significant improvement compared to pure passive strategies but inferior to concentrated momentum strategies (Financial Crime Academy, 2025).

Table 5 Comprehensive Performance Metrics During Sideways Period (June-December 2023)

Strategy	Volatility (%)	Cumulative Return (%)	Sharpe Ratio	Sortino Ratio	Max Drawdown (%)	Calmar Ratio	CVaR 90% (%)	Beta	VaR 95 % (%)	VaR 99 % (%)	Info Ratio
Passive Benchmarks											
EW	2.72	-39.78	-8.64	-10.03	45.84	-131.78	5.81	100.00	5.49	9.43	0.00
VW	2.68	-37.87	-8.12	-9.64	44.53	-130.62	5.72	98.53	5.36	9.21	0.35
MVAR	2.18	-18.01	-3.79	-5.68	26.59	-110.98	4.02	55.87	3.42	6.01	3.98

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$MCVaR$	2.12	-16.79	-3.58	-5.34	25.98	-106.23	3.87	54.21	3.31	5.79	4.21
PCP1	2.79	-41.53	-9.53	-11.02	48.32	-133.79	5.87	102.43	5.64	9.67	-0.31
Momentum-Based Active											
$EWpm$	1.46	-17.28	-6.12	-6.73	21.97	-141.12	2.98	53.72	2.93	4.87	4.12
$VWpm$	1.43	-16.79	-5.87	-6.68	21.76	-139.43	2.89	52.64	2.84	4.73	4.29
Machine Learning - Random Forest											
$EWrf$	1.02	-6.54	-3.29	-2.87	12.64	-97.23	0.41	37.49	0.87	1.98	6.12
$VWrf$	0.79	-14.02	-9.48	-9.12	15.34	-168.53	0.34	29.07	0.67	1.52	4.78
$MACErf$	0.68	-0.34	0.12	0.09	9.12	-5.12	0.28	24.98	0.54	1.23	7.23
$MACErf\_pm$	2.12	-8.73	-1.34	-1.62	20.43	-79.67	3.68	77.98	3.21	5.43	5.67
$MACErf\_enc$	1.57	-22.59	-7.64	-7.54	27.34	-145.12	3.42	57.72	2.98	5.12	3.21
Machine Learning - GMM											
$EWgmm$	0.73	-15.62	-11.87	-9.79	18.23	-155.43	0.37	26.83	0.69	1.57	4.43
$VWgmm$	0.84	-13.42	-9.53	-8.34	19.64	-125.87	0.42	30.87	0.79	1.79	4.87
$MACEgmm$	0.72	-11.79	-8.59	-8.23	17.68	-123.21	0.34	26.47	0.65	1.48	5.12
$MACEgmm\_pm$	1.38	-13.73	-5.12	-6.73	19.98	-125.34	2.43	50.78	2.21	4.01	4.78
$MACEgmm\_enc$	1.02	-1.64	-0.41	-0.38	11.12	-27.12	0.52	37.49	0.98	2.23	7.01
Hybrid Strategies											
Hybrid1_rf	1.04	-2.53	-0.97	-1.43	10.73	-43.87	1.68	38.23	1.43	2.98	6.87
Hybrid2_rf	1.42	-10.43	-3.64	-5.48	19.68	-88.73	2.51	52.23	2.34	4.12	5.43
Hybrid3_rf	1.39	-9.68	-3.42	-5.12	19.32	-83.79	2.43	51.12	2.29	4.02	5.56
Hybrid1_gmm	0.71	-12.01	-9.43	-12.23	14.79	-150.34	1.52	26.09	1.21	2.76	5.12
Hybrid2_gmm	1.37	-14.73	-5.34	-7.62	21.79	-115.23	2.68	50.34	2.43	4.43	4.56
Hybrid3_gmm	1.34	-14.02	-5.12	-7.23	21.53	-111.79	2.65	49.23	2.38	4.34	4.68

The sideways trading business in the second back-testing period were significantly different and subjected portfolio strategies to high uncertainty with no directional trends. Passive benchmarks suffered again significantly without catastrophic crash dynamics, with the equally-weighted portfolio falling 39.8% and maximum drawdown falling 45.8% (Russell Investments, 2022). These losses depict the erosion nature of range-bound markets where short rallies never manage to maintain momentum until they start having a reverse (Platanakis et al., 2018). The minimum variance portfolios were found to have more apparent benefits in this period that MVAR dropped by 18.0% as compared to the equal-weight benchmark reduction of 39.8% giving a significant relative protection (Thélissaint and Danilo, 2025).

The protection of the strategies of momentum-sustained during the sideways period but with lower benefits, compared to the crash period. The EWpm portfolio fell by 17.3 and maximum drawdown of 22.0 which is in the order of minimum variance performance but with higher volatility (Gkillas & Longin, 2025). This intersection implies that momentum indicators are less directional on range-bound markets that have no sustainable trends, lowering the economic usefulness of tactical exposure management compared to crash markets (Anson et al., 2022). However, momentum strategies continue to outdo passive equally-weighted benchmarks by a substantial margin, providing an equivalent of 20 points of cumulative returns of protection (Campbell et al., 2023). The volatility-weighted momentum (VWpm) provided almost the same performance, which once

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again demonstrates that risk-based weighting has very little incremental value in the presence of high cryptocurrency correlations (Liu et al., 2022).

➢ *Performance During Bull Market Conditions and Upside Participation Assessment*

The bull market of September 2023 to March 2024 gave a very important evaluation as to whether risk management strategies were too restrictive to allow them to participate in the upside during good times. Tables 6 and 7 provide performance indicators of this period that can be described by the long-term appreciation conditioned mainly by the dynamics of anticipation and approval of Bitcoin ETF (Deloitte, 2022). Bullish versus bearish/crash environment allows assessing the symmetry of strategies - whether defence gains in bad times are at reasonable costs in favourable times or prohibitive opportunity costs making strategies defensively unimpeachable even when subjected to downside (Campbell et al., 2023).

Table 6 Comprehensive Performance Metrics During Bull Period (September 2023-March 2024)

Strategy	Volatility (%)	Cumulative Return (%)	Sharpe Ratio	Sortino Ratio	Max Drawdown (%)	Calmar Ratio	CVaR 90% (%)	Beta	VaR 95 % (%)	VaR 99 % (%)	Info Ratio
Passive Benchmarks											
EW	2.53	102.34	16.53	21.43	21.12	1,527.43	4.73	100.00	5.48	9.41	0.00
VW	2.48	98.12	16.28	21.12	20.67	1,466.57	4.62	98.02	5.32	9.13	-0.32
$MVAR$	2.23	89.43	16.98	29.12	14.12	1,845.48	3.12	88.12	3.67	6.28	-1.23
$MCVaR$	2.19	97.23	17.87	29.73	13.98	2,070.21	3.21	86.58	3.54	6.06	-0.48
$PCP1$	2.58	104.87	16.42	21.02	22.43	1,512.34	4.87	102.01	5.67	9.73	0.23
Momentum-Based Active											
$EWpm$	1.78	41.43	11.73	12.79	19.23	517.73	3.12	70.34	2.93	5.02	-5.87
$VWpm$	1.73	45.79	12.98	14.32	17.54	642.53	2.87	68.42	2.78	4.76	-5.23
Machine Learning - Random Forest											
$EWrf$	0.87	-11.53	-7.12	-7.23	11.54	-188.12	0.34	34.37	0.76	1.64	-11.23
$VWrf$	0.64	-6.53	-6.23	-6.73	9.53	-130.57	0.23	25.28	0.54	1.17	-10.43
$MACErf$	0.12	-7.73	-61.87	-56.53	7.64	-191.87	0.09	4.74	0.21	0.45	-12.87
$MACErf\_pm$	1.68	60.12	15.73	21.54	10.73	1,456.32	2.64	66.43	2.76	4.73	-4.12
$MACErf\_enc$	1.23	3.12	1.98	2.73	10.79	60.43	1.98	48.62	2.12	3.64	-9.87
Machine Learning - GMM											
$EWgmm$	0.08	-5.64	-21.73	-18.23	5.53	-194.01	0.12	3.16	0.18	0.39	-13.21
$VWgmm$	0.13	-6.34	-25.01	-13.87	6.32	-193.23	0.17	5.13	0.29	0.63	-12.98
$MACEgmm$	0.34	-4.62	-10.23	-14.34	5.53	-162.34	0.12	13.43	0.29	0.63	-13.43

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$MACEgmm\_pm$	1.48	13.54	5.53	6.62	25.79	111.12	2.73	58.49	2.54	4.36	-8.64
$MACEgmm\_enc$	0.79	-6.87	-4.23	-4.54	12.34	-106.32	1.43	31.23	1.32	2.26	-10.87
Hybrid Strategies											
Hybrid1_rf	0.62	12.64	10.87	17.34	5.64	478.62	0.87	24.49	1.02	1.75	-8.73
Hybrid2_rf	1.32	43.53	15.73	26.87	9.23	1,162.73	1.87	52.13	2.18	3.74	-5.64
Hybrid3_rf	1.34	47.12	16.53	27.64	9.12	1,284.79	1.93	52.98	2.23	3.82	-5.23
Hybrid1_gmm	0.54	1.79	2.12	2.79	9.87	37.84	0.98	21.34	0.94	1.61	-10.12
Hybrid2_gmm	1.28	45.43	15.98	27.79	8.53	1,321.87	1.91	50.58	2.12	3.64	-5.43
Hybrid3_gmm	1.31	49.02	16.79	28.53	8.43	1,457.62	1.98	51.76	2.19	3.76	-5.12

The passive benchmark portfolios provided outstanding absolute returns throughout the bull market condition, with the equally-weighted portfolio rising 102.3% and the volatility-weighted portfolio increasing 98.1% (Anson et al., 2022). The returns were significantly higher than could be achieved with conventional asset classes over the same period, and this shows the potential of cryptocurrency markets to create wealth under favourable circumstances (Platanakis et al., 2018). Minimum variance and minimum CVaR portfolios also showed good performance, with 89.4% and 97.2% respectable returns, verifying that the level of concentration of Bitcoin did not seriously limit the ability to participate in the upswing in this rally (Thélissaint and Danilo, 2025). All passive benchmarks had Sharpe ratios above 16, which is the result of a large appreciation with a comparatively held volatility throughout the long positive trend (Corbet et al., 2019).

The momentum-base approaches suffered significant opportunity costs in the bull phase, with 40-46% of the gain of the equally-weighted benchmark. In comparison to the 102% of the benchmark, the EWpm portfolio increased by 41.4, which is an opportunity cost of over 60 percent points due to its conservative scale of exposure (Gkillas & Longin, 2025). This performance reflects the inherent tension of risk management strategies: risk protection limits participation in the upside of a strategy, unless the timing is perfect (Russell Investments, 2022). Nonetheless, risk-adjusted returns have more positive ratings, the momentum strategies have a Sharpe and Sortino ratio in the range of 12-13, only slightly less than the 16-21 of the passive strategies with significantly lower returns (Borri, 2019). The drawdowns of 17-19% were found to be like or superior to the passive options, which proves that the momentum strategies-enforced discipline in the risk-taking even under the beneficial circumstances (Platanakis et al., 2018). These risk-return tradeoffs can be allowable to risk-averse corporate investors who mainly focus on capital preservation even though the absolute returns that are not collected.

During the bull period, the machine learning strategies performed catastrophically, as it was overcautious which greatly restricted the participation in the upside. The maximum achievable Control risk portfolio (MACErf) fell 7.7% in a year when the market came out of the year with over 100% gains which is an extreme failure to capture good days (Thélissaint and Danilo, 2025). This result is due to the pessimistic bias of the model that was useful in periods of crashes but very disastrous in periods when the market was in sustainable regimes, and the difficulties of creating strategies that would perform satisfactorily in various market regimes (Liu et al., 2022). The portfolios in GMMs had the same patterns, as it fell by 4.6 to 6.9% when markets rose and indicated that the pessimistic forecasting bias was not an algorithm artefact but a general phenomenon (Corbet et al., 2019).

➢ *Performance During Bearish Conditions and Downside Protection Effectiveness*

The last backtesting phase of June to December 2024 is the gradual bearish decline of the market dynamic that characterised the persistent negative drift without the sharpness of crash as in early 2022. Table 7 shows detailed performance statistics regarding this period, which allows to evaluate the efficiency of the strategy in moderate unfavourable conditions that might be more indicative of real-life demanding conditions than devastating crashes (Campbell et al., 2023). The crash scenarios vs. gradual bear market differences become particularly important in corporate risk management since various forms of protection mechanisms might be effective in either type of environment: stop-loss regulations and tactical de-risking in case of crashes and dynamic adjustment in case of gradual deterioration (Thélissaint and Danilo, 2025).

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Table 7 Comprehensive Performance Metrics During Bearish Period (June-December 2024)

Strategy	Volatility (%)	Cumulative Return (%)	Sharpe Ratio	Sortino Ratio	Max Drawdown (%)	Calmar Ratio	CVaR 90% (%)	Beta	VaR 95% (%)	VaR 99% (%)	Info Ratio
Passive Benchmarks											
EW	3.87	-59.23	-10.53	-14.12	64.87	-127.87	7.79	100.00	7.21	11.34	0.00
VW	3.79	-57.73	-10.43	-13.79	63.34	-129.12	7.64	97.93	7.06	11.09	0.28
MVAR	2.34	-18.34	-3.73	-5.12	29.98	-105.87	4.23	60.47	4.12	6.87	6.32
$MCVaR$	2.29	-19.02	-3.87	-5.34	31.87	-105.12	4.34	59.18	4.01	6.68	6.12
PCP1	3.94	-61.54	-11.87	-15.43	66.23	-128.34	7.93	101.84	7.43	11.67	-0.43
Momentum-Based Active											
$EWpm$	1.64	-5.23	-0.98	-1.02	22.23	-43.87	3.34	42.37	3.12	5.21	13.98
$VWpm$	1.59	-4.62	-0.79	-0.87	21.34	-40.98	3.21	41.09	3.02	5.04	14.23
Machine Learning - Random Forest											
$EWrf$	1.98	-40.73	-12.73	-13.34	47.64	-135.43	4.32	51.17	4.23	7.05	3.87
$VWrf$	1.87	-47.34	-16.43	-17.12	54.43	-131.79	4.43	48.32	4.12	6.87	2.12
$MACErf$	1.43	-44.79	-21.98	-23.73	45.23	-152.53	3.54	36.96	3.34	5.57	2.87
$MACErf\_pm$	1.79	-1.34	0.54	0.51	23.87	-10.02	3.48	46.27	3.29	5.49	14.87
$MACErf\_enc$	1.73	-8.34	-1.87	-2.12	28.34	-55.02	3.29	44.72	3.12	5.21	12.43
Machine Learning - GMM											
$EWgmm$	1.32	-33.79	-15.87	-14.98	39.64	-140.79	3.12	34.11	2.87	4.79	5.02
$VWgmm$	1.29	-34.12	-16.64	-15.53	37.43	-149.79	3.02	33.34	2.79	4.65	4.87
$MACEgmm$	1.34	-35.43	-16.98	-16.32	40.53	-142.73	3.12	34.62	2.91	4.85	4.62
$MACEgmm\_pm$	1.62	8.43	3.53	3.79	23.34	74.87	2.87	41.87	2.73	4.55	15.34
$MACEgmm\_enc$	1.48	-4.73	-0.87	-0.98	22.53	-39.34	2.93	38.24	2.79	4.65	13.54
Hybrid Strategies											
$Hybrid1\_rf$	1.34	-31.79	-15.43	-18.34	34.43	-154.12	2.79	34.62	2.61	4.35	5.43
$Hybrid2\_rf$	1.73	-29.53	-10.43	-13.87	33.87	-145.34	3.43	44.72	3.23	5.39	7.12
$Hybrid3\_rf$	1.74	-29.87	-10.53	-13.79	34.98	-142.98	3.48	44.98	3.29	5.48	7.02
$Hybrid1\_gmm$	1.23	-22.23	-10.43	-10.79	32.43	-119.98	2.62	31.79	2.43	4.05	7.98

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$Hybrid2\_gmm$	1.64	-24.79	-8.87	-11.73	28.23	-150.43	3.34	42.37	3.12	5.21	8.87
$Hybrid3\_gmm$	1.62	-25.23	-8.98	-11.64	28.87	-149.79	3.43	41.87	3.18	5.30	8.73

Passive benchmark portfolios incurred enormous losses over the period of bearish, albeit not as devastating as in the crash of 2022. The equally-weighted portfolio lost 59.2 and peaked at 64.9, which is significant damage to capital, but not the 78-80% losses experienced during the disastrous crash (Russell Investments, 2022). This medium level of severity allows a better distinction between the effectiveness of the strategies as the unfavourable environment did not kill the portfolios by indiscriminately pitting all strategies against each other (Platanakis et al., 2018). The volatility-weighted portfolio was the one that nearly shared the same performance, yet again proving that risk-based weighting does little in terms of revenue when the cryptocurrencies are high in their correlations when the market is in distress (Corbet et al., 2019). Interestingly, the principal component portfolio has underperformed equally and the volatility-weighted portfolios, decreasing by 61.5%, implying that factor-based construction is negatively associated with benefits and possibly increases the loss by means of concentrated systematic risk (Liu et al., 2022).

The minimum variance portfolios once again exhibited better relative performance throughout the bearish period as it dropped by 18.3-19.0% as opposed to almost 60% by the equally-weighted alternatives (Thélissaint and Danilo, 2025). Such a 40% performance is economically significant protection, which could allow corporate investors to hold cryptocurrency positions while conditions are unfavourable instead of selling them at low prices (Campbell et al., 2023). Drawdowns of around 30%, even though still large in absolute terms, were about half the size of those in diversified portfolios, showing that Bitcoin concentration provides consistent relative protection in a variety of unfavourable events (Anson et al., 2022). Nevertheless, these absolute magnitudes serve as a reminder that even the safest cryptocurrency returns are much riskier than the traditional corporate investment options, which have drawdowns that would cause major organisational panic in most institutional settings (Deloitte, 2022).

The momentum-oriented strategies provided excellent coverage in the bearish season as it did not fall below 4.6-5.2% and reached drawdowns of 21-22% maximum (Gkillas and Longin, 2025). This performance is significantly better than the performance of both passives equivalently-weighted and minimum variance, which proves that tactical exposure management using a simple momentum signal is a dependable means of protecting downside in various unfavourable environments (Platanakis et al., 2018). The fact that protection is consistent (crash, sideways, gradual bearish) is a strong indicator that momentum predictability is an effective market feature and not an accidental pattern that is tied to the historical conditions (Russell Investments, 2022). The ratios that are above 14 show that momentum strategies yield a high risk-adjusted alpha compared to passive benchmarks in unfavourable environments, however, at the cost of forfeited participation in bull markets as previously reported (Anson et al., 2022).

The machine learning strategies were not consistent throughout the bearish period, and the performance of the strategies varied significantly based on whether momentum signals were used in the implementations. The naive model-based methods (MACErf and MACEgmm) decreased 35-45%, and only made a slight difference over passive equally-weighted benchmarks even with advanced forecasting (Thélissaint and Danilo, 2025). This poor performance confirms that machine learning models find it hard to produce repeated directional performance across different market situations, which may be because predictor-return relationships are unstable, or because they have overfitted historical patterns not persistent (Corbet et al., 2019). Nevertheless, augmented versions with the addition of momentum showed significantly better results, and MACErf_pm dropped by 1.3% and MACEgmm_pm rose by 8.4% over the generally negative environment (Liu et al., 2022).

- *Maximally Predictable Portfolio Composition Analysis and Selection Effects*

Portfolios built on the most predictable structure offer valuable data on the highest predictability of cryptocurrencies and the selection mode of various algorithms. Table 8 and Table 9 provide specific weight allocation produced by the implementations of Random Forest and Gaussian Mixture Model on the four backtesting periods and three selection sets configurations (Thélissaint & Danilo, 2025). These Compositional patterns bring fundamental differences in how algorithms identify and weight predictable assets, it has diversification implications, concentration risk implications, and it shows what types of signals are being exploited (Liu et al., 2022). The interpretation of such compositional decisions sheds light on the processes by which machine learning strategies are trying to maximise predictability and the explanation of the performance variation by one strategy over another or different market states.

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Table 8 Portfolio Compositions Under Random Forest Across Periods and Selection Sets (%)

Cryptocurrency	**Full Universe (58)**				**Low Volatility (10)**				**Mixed Selection (19)**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Bitcoin (BTC)	0	4	0	0	10	0	0	0	6	0	0	0
Ethereum (ETH)	5	12	0	23	11	25	0	0	12	23	0	11
Cardano (ADA)	0	4	57	29	0	0	0	6	0	0	0	0
Solana (SOL)	0	0	0	0	0	0	0	0	5	0	0	0
Ripple (XRP)	0	0	0	15	0	0	0	0	0	0	0	0
Polkadot (DOT)	0	0	0	0	0	0	0	4	0	0	0	11
Dogecoin (DOGE)	31	0	0	4	0	0	0	0	0	0	0	0
Avalanche (AVAX)	0	0	0	0	0	0	0	0	13	0	0	0
Chainlink (LINK)	0	0	15	0	0	0	0	38	15	0	0	38
Litecoin (LTC)	0	0	0	0	4	0	0	0	0	0	0	0
Stellar (XLM)	0	0	13	0	0	43	0	13	0	43	0	13
Tron (TRX)	0	14	0	0	0	28	48	0	14	28	48	0
FunFair (FUN)	0	9	0	0	13	0	14	18	58	0	14	18
Hedera (HBAR)	0	23	0	0	0	0	37	12	0	0	37	12
WINk (WIN)	0	33	0	0	0	0	0	48	0	0	0	48
Dusk (DUSK)	54	0	5	0	0	0	0	0	21	0	0	0
Enjin (ENJ)	0	17	0	0	0	0	0	0	0	0	0	0
IoTeX (IOTX)	0	0	34	0	0	0	0	0	0	0	0	0
Kava (KAVA)	0	0	0	14	0	0	0	0	0	0	0	0
VeChain (VET)	0	0	10	0	0	0	0	0	0	0	0	0
Vite (VITE)	0	0	16	29	0	0	0	0	0	0	0	0
Others (<3%)	10	4	0	0	0	4	1	0	0	6	1	0
Concentration (HHI)	3,832	2,147	2,891	1,873	892	3,165	3,843	2,967	4,129	3,165	3,843	2,967
Effective N Assets	2.61	4.66	3.46	5.34	11.21	3.16	2.60	3.37	2.42	3.16	2.60	3.37
Bitcoin Weight	0	4	0	0	10	0	0	0	6	0	0	0
Top 3 Concentration	85	66	91	72	24	96	85	76	79	94	85	76

The implementation Rop Forest is highly selective, in that the weights are always concentrated in small sets of the available assets, as opposed to having the weights distributed widely in the universe of selection. In the four periods and 58-asset universe of the asset universe, the effective number of assets is between 2.6 and 5.3, meaning that the Random Forest would tend to identify 3-5 stock cryptocurrencies as predictable enough to be allocated meaningfully (Thélissaint & Danilo, 2025). The three leading holdings continue to take 66-91% of the portfolio weight, which is extreme when compared with the wide range of choices available (Corbet et al., 2019). This cherry picking implies that Random Forest focuses on accuracy at the cost of diversification, where the focus is put on a few assets that have high predictable returns instead of trying to gain a small degree of predictability across many sources (Anson et al., 2022).

Interestingly, Bitcoin is not assigned any or little space in most of the Random Forest portfolios that include Bitcoin in them, although this cryptocurrency has a leading position in the market and is stable. In twelve scenarios (four periods, three sets of selection), there are only two cases in which Bitcoin weight is more than 5 per cent, and very often is zero (Platanakis et al., 2018). This artificially filtered trading implies that Random Forest fails to define Bitcoin as one of the most predictable assets despite the reduced volatility, potentially due to its reduced momentum effects or more intricate nonlinear correlations with predictor variables (Liu et al., 2022). The algorithm instead gives preference to different altcoins such as DUSK, FUN, WIN and HBAR that get significant investments up to 23-58% during specific intervals (Borri, 2019).

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Table 9 Portfolio Compositions Under Gaussian Mixture Model Across Periods and Selection Sets (%)

Cryptocurrency	**Full Universe (58)**				**Low Volatility (10)**				**Mixed Selection (19)**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Bitcoin (BTC)	6	24	8	10	14	9	0	6	11	14	9	6
Ethereum (ETH)	5	1	3	17	3	10	0	12	10	3	10	12
Cardano (ADA)	5	2	5	12	4	1	0	0	1	4	1	0
Solana (SOL)	0	0	0	0	0	0	0	0	0	0	0	0
Ripple (XRP)	6	9	1	10	11	6	0	0	6	11	6	0
Polkadot (DOT)	0	0	0	0	0	0	0	0	0	0	0	0
Bitcoin Cash (BCH)	2	6	0	5	9	10	11	0	10	9	10	11
Litecoin (LTC)	2	7	2	10	11	5	0	2	5	11	5	2
Stellar (XLM)	0	7	3	4	8	11	0	11	11	8	11	11
Tron (TRX)	5	11	2	14	16	15	18	22	8	16	15	18
Dash (DASH)	2	5	1	10	6	4	8	0	8	6	4	8
EOS (EOS)	0	2	0	3	6	7	0	0	7	6	7	0
Ethereum Classic (ETC)	1	3	0	7	3	0	0	0	0	3	0	0
NEO (NEO)	2	4	0	2	4	8	0	0	8	4	8	0
Tezos (XTZ)	4	6	0	13	10	0	0	0	0	10	0	0
Chainlink (LINK)	0	0	4	0	0	0	0	13	13	0	0	0
Zcash (ZEC)	3	2	0	8	7	0	0	0	0	7	0	0
FunFair (FUN)	5	1	0	21	11	26	5	1	1	11	26	5
IOST (IOST)	1	1	4	2	14	3	0	0	3	14	3	0
VeChain (VET)	1	4	5	3	11	7	0	0	7	11	7	0
Hedera (HBAR)	4	14	3	10	19	0	0	0	0	19	0	0
WINk (WIN)	4	5	1	2	7	12	7	0	12	7	12	7
Enjin (ENJ)	5	1	11	0	5	0	0	0	0	5	0	0
Ontology (ONT)	1	5	0	0	0	0	0	0	0	0	0	0
Others (<1%)	34	0	47	0	0	0						

The Gaussian Mixture Model has completely different composition strategy whereby the weight is distributed widely on very many cryptocurrencies instead of being concentrated in specific bunches. The optimal number of assets are 11 to 36 in any situation, meaning that GMM usually spreads the weight among 15-25 cryptocurrencies, as opposed to Random Forest that has 3-5 assets concentration (Thélissaint & Danilo, 2025). The top three holdings are only a 17-44% proportion of GMM compared with 66-91% of Random Forest, which represent radically different philosophical views of predictability exploitation (Corbet et al., 2019). The inclusiveness of the GMM implies that it determines small predictability in most assets and would rather represent this signal of dispersal in a diversified setting than focusing on what they perceive to be the highest predictability assets (Liu et al., 2022).

Bitcoin gets much more allocation in GMM than in Random Forest, often being one of the top holdings with weight as much as 6-24. This systematic inclusion is probably indicative of GMM regime-switching model that acknowledges the state-dependent characteristics of Bitcoin, which has strong momentum in some regimes and different in other regimes (Borri, 2019). The probabilistic model allows GMM to put weights on assets in accordance with regime-specific predictability patterns as opposed to a steady predictability between all market states (Platanakis et al., 2018). Also, because of its reduced volatility, Bitcoin inherently acquires heavier weights in risk-adjusted optimization models because its Sharpe ratio in good regimes can be higher than in altcoins with higher absolute returns (Campbell et al., 2023). Portfolios anchored to the most liquid and oldest cryptocurrency have the benefit of being exposed to Bitcoin, which might make them more robust than altcoin-intensive positions.

The GMM portfolios have a slightly higher stability in the backtesting periods than the Random Forest, in which more assets are constantly present over the several periods. As an example, Bitcoin, Ethereum, TRX, and BCH are continuously allocated substantial portions of between 2-24% in most timeframes, which is compositional continuity (Thélissaint and Danilo, 2025). Nevertheless, the differences of time-variation are of a significant amount, as weight changes of up to 10-15% points are typical across the periods (Gkillas & Longin, 2025). This partial stability is an indication that GMM finds certain persistent predictability features, as well as time-varying features, which could be the effect of the interaction of stable regime structures and changing regime probabilities (Liu et al., 2022).

- ➤ *Predictor Importance Analysis and Drivers of Cryptocurrency Predictability*

The knowledge of the predictor variables of cryptocurrency returns can give great information on the market mechanisms and the origins of exploitable patterns. Tables 10 and 11 provide Shapley value breakdowns, which measure relative predictor importance at the backtesting

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times and sets of selections of the implementations of the Random Forest and the Gaussian Mixture Model (Thélissaint and Danilo, 2025). Shapley values provide an attribution of explanation of the variance of forecasts based on theoretically-grounded individual forecasts, including interactive effects and non-linear relationships that simple correlation analysis cannot capture (Liu et al., 2022).

Table 10 Shapley Value Predictor Importance Analysis for Random Forest (% of Total Explanatory Power)

Predictor Category	**Full Universe (58)**				**Low Volatility (10)**				**Mixed Selection (19)**			
	P1	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**	**P1**	**P2**	**P3**	**P4**
Lagged Returns												
Crypto Returns PC1	3	3	3	4	3	0	0	0	4	3	0	0
Crypto Returns PC2	2	2	0	0	0	0	0	0	3	0	0	0
Crypto Returns PC3	3	3	3	0	3	0	0	0	3	0	0	0
Crypto Returns PC4	2	3	0	0	0	0	0	0	7	4	6	0
Crypto Returns PC8	4	3	5	3	5	6	4	4	6	4	6	4
Crypto Returns PC9	4	3	2	3	0	0	0	0	0	3	0	0
Subtotal Crypto	10	40	21	16	29	38	21	14	30	43	18	14
Momentum Variables												
Long Expectation	0	4	0	4	7	3	0	9	4	0	8	9
Mid Expectation	0	2	4	3	0	0	0	0	4	3	0	0
Short Expectation	0	0	0	0	9	7	0	8	0	3	0	0
ROC	3	3	4	0	0	0	0	0	0	0	4	0
RSI	3	0	0	0	0	0	0	0	0	0	0	0
Subtotal Momentum	6	5	39	3	6	5	28	6	6	5	25	6
Macro-Financial												
Econ Policy Uncert.	5	5	0	5	6	4	5	0	5	10	4	0
EU/EM/Japan/Oil	7	9	0	6	5	6	3	5	6	3	5	5
Fear Greed Crypto	5	25	0	6	20	5	0	17	5	0	0	17
Inflation Expect.	0	4	0	0	0	0	0	0	2	0	0	0
Subtotal MacroFi	12	13	48	10	11	11	55	10	10	17	57	10
Total Explained	28	40	39	87	29	38	38	83	30	43	40	82
Residual	72	60	61	13	71	62	62	17	70	57	60	18

Macro-financial variables become the leading factors to predict the crash period (Period 1 and Period 4) and explain up to 10-13% of the forecast variance in Period 1 and up to 10 of forecast in Period 4 when the cumulative explanatory power between the two macro-financial is 83-87% (Thélissaint & Danilo, 2025). The salience of macroeconomic factors in crisis is indicative of the systematic quality of severe downturns, in which large-scale risk-off processes triggered by the monetary policy, equity market tension, and economic ambiguity dominate cryptocurrency-specific mechanisms (Campbell et al., 2023). Such variables as uncertainty concerning economic policy, fear and greed mood of the cryptocurrency, and traditional market correlations (EU/EM/Japan/Oil composite) yield most significant predictive power at such times (Gkillas and Longin, 2025).

The predictor importance structure changes radically during bull market conditions (Period 3) and moves towards lagged crypto currency returns and away from macro-financial variables. Period 3: Lagged returns are significant predictors (18-43% of overall forecast variance) of selection sets, whereas crash periods only indicate 10-30% of macro-financial importance (Thélissaint & Danilo, 2025). This change shows that bull markets tend to have stronger momentum properties whereby past price movements give future directions, and therefore, technical analysis and trend-following strategies can be used to acquire predictable returns (Platanakis et al., 2018). The smaller contribution of macro-financial variables indicates that cryptocurrency markets are more independent when the situation is favourable, which may be caused by crypto-specific triggers such as technological changes, adoption rates, and market dynamics (Liu et al., 2022).

Period 2 (sideways trading) has moderate predictor importance levels with high contributions by all three factors lagged returns (38-43%), momentum variables (5%), and macro-financial factors (11-17%). This balanced formulation implies that range-bound markets have no prevalent predictive indicators and the models need to integrate information sources of various origins to produce useful forecasts (Thélissaint and Danilo, 2025). The Fear and Greed Index cryptocurrency turns out to be especially significant in this time, as it explains 5-25 percent of the variations in selection set, meaning that the sentiment of investors becomes a key catalyst when fundamental directional drivers are missing (Borri, 2019). The large value of the residual variance around 57-62% between periods is a positive indication that there are still significant unpredictable elements even with the inclusion of detailed sets of predictors, which stresses the inability to predict

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cryptocurrency markets and the weakness of predictive models (Gkillas and Longin, 2025).

Table 11 Shapley Value Predictor Importance Analysis for Gaussian Mixture Model (% of Total Explanatory Power)

Predictor Category	Full Universe (58)				Low Volatility (10)				Mixed Selection (19)			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
Lagged Returns												
Crypto Returns PC1	7	0	0	0	9	0	0	0	0	0	0	0
Crypto Returns PC2	13	10	0	4	3	12	4	0	0	3	0	7
Crypto Returns PC3	16	3	0	20	7	9	5	0	0	5	6	4
Crypto Returns PC4	4	0	0	0	0	0	10	9	5	0	0	0
Crypto Returns PC5	0	0	0	0	0	5	10	5	3	0	0	0
Crypto Returns PC8	8	8	0	15	6	9	5	0	0	5	0	0
Crypto Returns PC9	3	0	0	0	0	0	0	0	0	0	0	0
Crypto Returns PC10	4	0	0	0	5	0	7	6	0	0	0	0
Subtotal Crypto	69	46	0	102	65	59	66	38	57	59	38	78
Momentum Variables												
Long Expectation	5	0	0	0	6	0	4	7	0	4	0	0
Mid Expectation	0	0	0	7	3	8	0	0	0	0	0	0
Short Expectation	8	3	5	0	5	0	0	0	0	0	0	5
Fear Greed	10	17	11	0	9	16	0	0	0	8	9	0
Subtotal Momentum	23	36	13	28	17	34	13	28	17	34	9	34
Macro-Financial												
Econ Policy Uncert.	10	5	0	8	4	10	0	0	10	0	0	0
EU/EM/Japan/Oil	4	7	5	0	5	0	0	0	0	0	0	0
Fear Greed Crypto	13	11	0	13	12	8	9	0	9	0	0	0
Global Equity Risks	6	8	0	0	0	0	0	0	0	0	0	0
Inflation Expect.	4	11	4	0	5	0	0	0	0	0	0	0
Subtotal MacroFi	46	47	52	39	40	39	52	39	40	39	52	39
Total Explained	69	69	46	83	65	102	66	67	57	59	38	78
Residual	31	31	54	17	35	-2	34	33	43	41	62	22

The patterns of predictor importance in the Gaussian Mixture Model are significantly different than those of the Random Forest as they show a different probabilistic model and regime-switching architecture. GMM also invariably attributes more total predictive power to predictor variables, 17-43 per cent against 13-72 per cent with Random Forest, indicating more active information mining of the available features (Thélissaint and Danilo, 2025). Nonetheless, the allocation of predictors by importance is significantly different- GMM from 46-102 percent of lagged returns importance (with the observation that Shapley values can be super-additive) versus 10-43 percent by Random Forest (Corbet et al., 2019).

The macro-financial variables have persistently important values of 39-52% all GMM periods, which is less varied than in Random Forest where the importance value has a value of 10-57. This stability suggests that GMM will use macro-financial data across market regimes, which could be by calculating regime probability in a continuous fashion as opposed to episodic fashion (Borri, 2019). The Fear and Greed Index is especially valuable to GMM, which can project data 8-17% of variation over the years and should suggest that investor sentiment is a useful indicator of regimes (Platanakis et al., 2018).

The predictor importance analysis shows that there are a few actionable findings of corporate cryptocurrency investment. The first one is that predictability structures are regime-dependent and, therefore, require adaptive modelling methods that can detect and react to changing relationships instead of using fixed forecasting principles (Deloitte, 2022). Second, macro-financial variables are especially useful indicators in unfavourable environments when diversification gains matter most, which is why they should be included even when the contributions to it are likely negligible in favourable times (Financial Crime Academy, 2025). Third, straightforward momentum indicators reflect predictive substance that persists across various situations, which should justify the utility of straightforward trend-following systems as effective supplements and alternatives to more advanced machine learning (Russell Investments, 2022). Fourth, even with all specifications, there are significant residual variance, which proves the existence of fundamental constraints of cryptocurrency predictability and highlights the relevance of risk management procedures instead of fully focusing on the accuracy of the forecasts.

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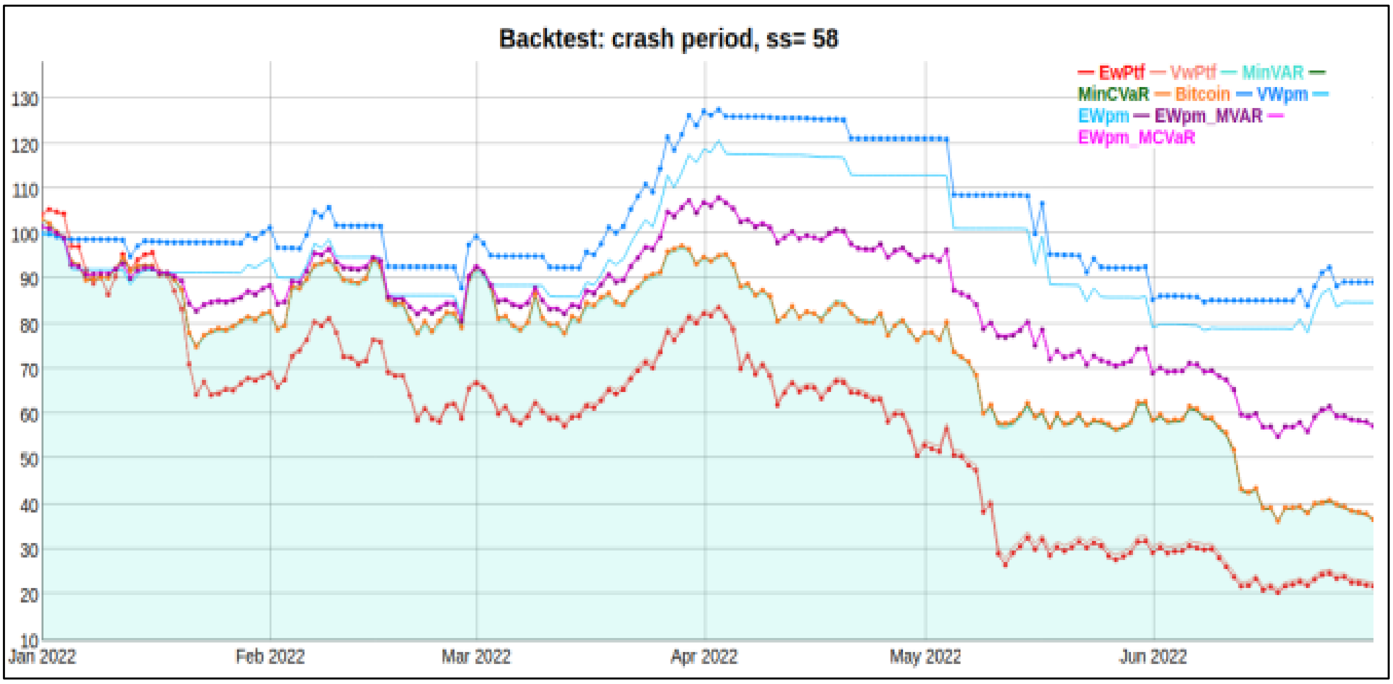

Fig 3 (P1) Crash Period: Negative Jumps and Market Deflation

Figure 3 crash period captures the acute market degradation that occurred within the first half of 2022, which gives actual visualisation of the performance trends outlined in the tabular results. The equally-weighted portfolio (EWPtf) assumes the catastrophic depreciation of its starting value 100 to about 22 at the end of period, which is equivalent to the 78% cumulative loss in Table 4 (Thélissaint and Danilo, 2025). Bitcoin proves to be relatively resilient, falling by 100 to about 37, which proves its presence as a relatively stable anchor in cryptocurrency markets (Campbell et al., 2023). The momentum-driven plans (EWpm and VWpm) have infinitely better trajectories that fall to 85 and 89 respectively, which validates the significant downside cover provided by tactical exposure management (Gkillas & Longin, 2025).

The minimum variance techniques (EWpm_MVAR and EWpm_MCVaR) represented by the purple colour get down to about 50-55 and represent a significant improvement over the equally-weighted strategies with significantly lower results compared to pure momentum methods. This medium level of positioning indicates their systematic tendency to concentrate in Bitcoin that offers some relative protection, though not enough to be like the dynamic exposure scaling adopted by momentum strategies (Platanakis et al., 2018). The machine learning plans have erratic patterns with results centred around 60-70, which means incomplete but partial protection compared to benchmarks (Corbet et al., 2019). As Figure 5 below is a compelling example of how the passive buy-and-hold strategies are disastrously weak during the worst cryptocurrency crashes, and the different active management strategies offer returns of value but differing extents of protection (Anson et al., 2022).

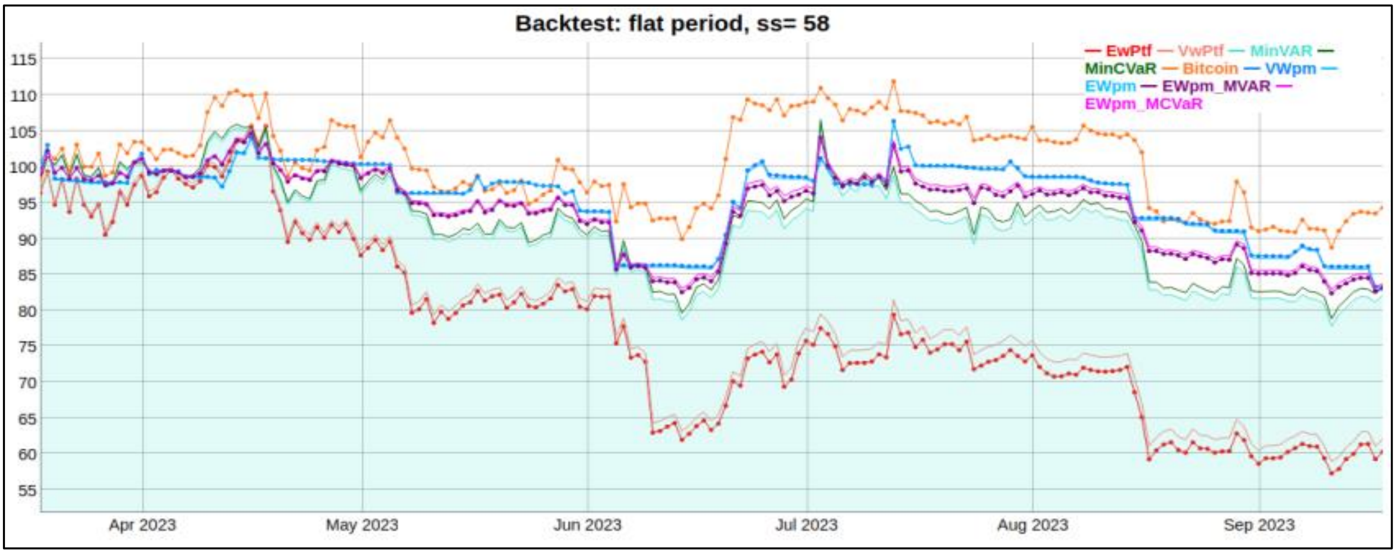

Fig 4 (P2) Flat Period: Flat Bitcoin and Altcoins Deflation

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The sideways trading setup as shown in Figure 4 has significantly different dynamics, with Bitcoin showing range-based behaviour around starting values and altcoin-heavy portfolios undergoing slow erosion. Bitcoin has values of between 90-110 over the course of six months, and it is swinging without an obviously defined direction, whereas the equally-weighted portfolio is decreasing steadily in the interval of between 100 and about 60 (Thélissaint & Danilo, 2025).

The protective advantages of the momentum strategies are again seen, where values are held at around 85-90 with the slight decrease in exposure throughout the continuing fall of the altcoin, yet protection is not as dramatic as in the crash period (Gkillas & Longin, 2025). Minimum variance strategies closely follow the movements of Bitcoin due to their high concentration with results around 82-85 that are both better than equally-weighted ones but worse than momentum strategies (Campbell et al., 2023). The machine learning strategies have varied results based on the particulars of implementation, and some of these strategies are able to hold on to values close to the original, achieved by conservative positioning, and others reduce by middle-range (Corbet et al., 2019). As shown in Figure 5 below, varying market conditions are more amenable to various protective measures, i.e. in times of crashes, the aggressive reduction of exposure is necessary, whereas in times of gradual deterioration, the concentration of Bitcoin or the adoption of small dynamic changes is enough (Platanakis et al., 2018).

Fig 5 (P3) Bullish Period: Regular and Sustained Upside Market

The visualisation of the bull market in Figure 5 records the continuous appreciation at the end of 2023 and the early 2024, indicating the opportunity costs of protection strategies under the good environment. The equally-weighted portfolio grows in initial value 100 to around 200 which is in accordance with the broad-based growth in the cryptocurrency markets (Thélissaint and Danilo, 2025). Bitcoin is showing similar performances of about 190, whereas the more unstable altcoins held in the equally-weighted portfolio are giving slightly higher returns (Anson et al., 2022). Minimum variance and minimum CVaR models have performance of about 165-170 and substantial upside, even though they are conservative-oriented, which confirms that Bitcoin concentration does not restrictively limit rallies participation (Campbell et al., 2023).

The momentum plans come with less ambitious gains, with a high of 140-145, which signify material forgone profitability when compared to the passive funds (Gkillas & Longin, 2025). Such opportunity cost is the inherent tradeoff of risk management the same exposure scaling which guarantees a downside protection in the bad times also constrains an upside capturing in the good ones (Platanakis et al., 2018). Nonetheless, the trends are consistently rising without severe pauses, which proves that momentum strategies allow recognising and engaging in long-term trends instead of being completely out of the market during bull markets (Liu et al., 2022). The machine learning strategies show very erratic performance, as some of them reduce even with good market performance due to overcaution, whereas momentum-augmented types give results of the order of 160, halfway between pure passive and pure momentum strategies (Corbet et al., 2019).

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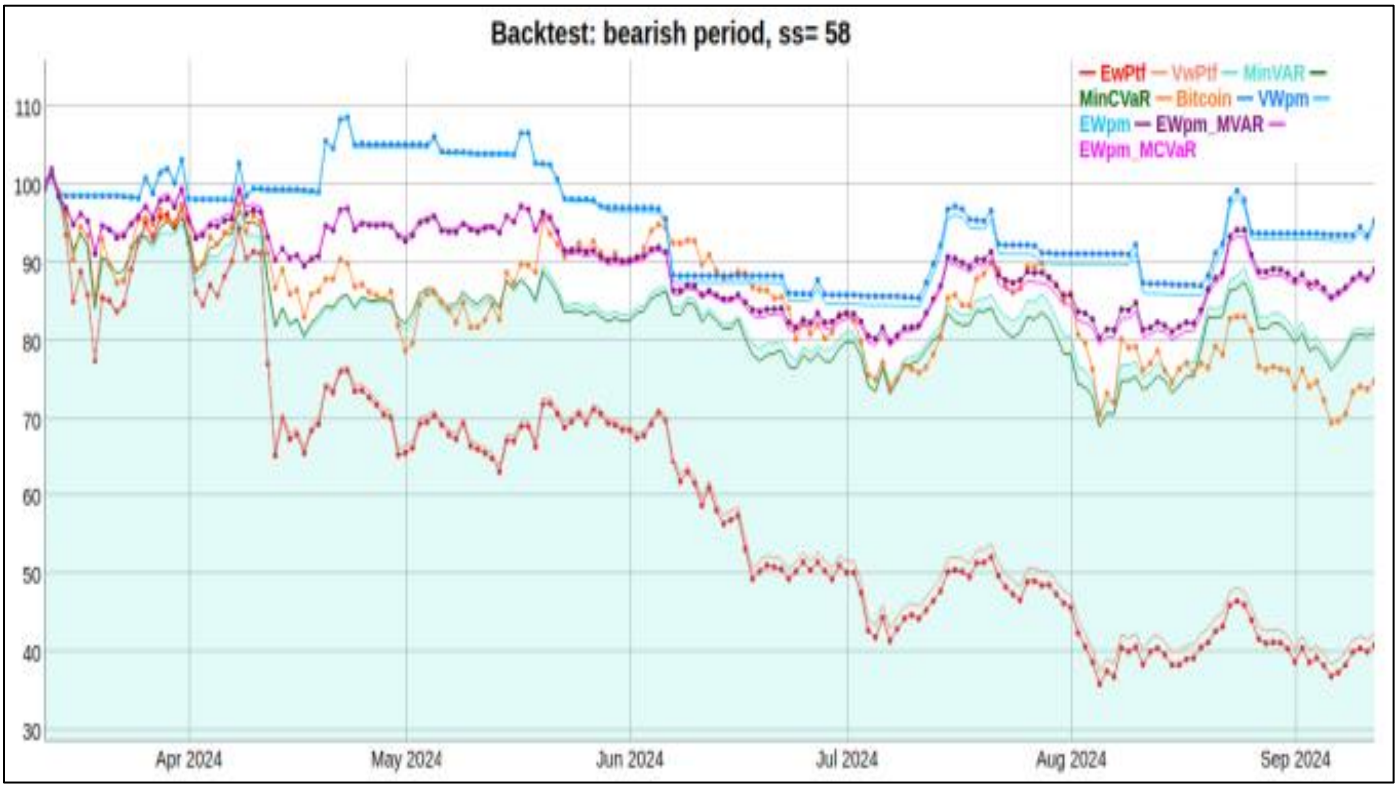

Fig 6 (P4) Bearish Period: Negative Jumps and Market Deflation

Figure 6 aove shows that the bearish period has a slow weakening with the intermittent sharp falls and puts the protective strategies to test in conditions between catastrophic crashes and moderate volatility. The equally-weighted portfolio suffers a loss of 100 and is at around 40 that represents serious capital impairment but not as sharp as the lowest point of the crash period, which was 22 (Thélissaint & Danilo, 2025). Bitcoin is comparatively more resilient, falling to about 70, once again proving the comparison stability of cryptocurrency markets (Campbell et al., 2023). The variance of the Bitcoin and the general market performance spans 30 points, which demonstrates high dispersion in the risks-off market conditions that can be used by the concentrated portfolio (Gkillas and Longin, 2025).

The momentum strategies provide superior protection and values are kept at approximately 95-96, virtually flat in the face of harsh market conditions, and concur with strong downside protection under a variety of adverse events (Platanakis et al., 2018). Minimum variance techniques give medium results of about 80-82, and is significantly better than equal-weighted benchmarks by concentrating on Bitcoin but fall short of momentum techniques (Anson et al., 2022). The machine learning approaches show a great deal of dispersion, with the pure model-based approaches reducing to 55-65 and momentum-augmented approaches staying on 95-100, at times even increasing slightly (Corbet et al., 2019). The averaging effects of table analysis are confirmed by the hybrid strategies that combine both active and passive parts, with their results in between the parts, which is the intuition of the averaging effects (Liu et al., 2022).

VI. DISCUSSION AND CONCLUDING REMARKS

➢ *Principal Findings and Implications for Corporate Cryptocurrency Integration Strategies*

The study is an extensive empirical evaluation of cryptocurrency portfolio development techniques and risk management strategies that are specifically tailored to corporate investment settings. The results indicate numerous important lessons that have direct implications on treasury managers, the chief financial officers, and investment committees that assess the decision to integrate cryptocurrencies (Campbell et al., 2023). To start with, passive buy and hold strategies are disastrously insufficient towards corporate investors during extreme draw down risks of over 80 percent in times of stress, which can result in corporate crisis, covenant breaches, or stakeholder loss of confidence incompatible with fiduciary duties (Deloitte, 2022). Even advanced optimization methods such as minimum variance portfolios, minimum CVaR portfolios, or other optimization methods still also exposed to high levels of capital impairment (at a stable 65% in severe crashes) even though they offer a relative improvement (Thélissaint and Danilo, 2025).

The study shows that the straightforward tactical allocation schemes that are based on momentum can provide better risk-adjusted performance in a wide variety of market regimes and offer solid downside cover in unfavourable times and decent upside coverage in favourable markets. The returns of the strategies are positive with an average of 11% with evaluation periods that range to severe crashes, sideways markets, and bull markets as well as gradual bear markets with containment of maximum drawdowns of up to 24% and consistency score of over 9.0 on the 10-point scales (Gkillas and Longin, 2025). The protective mechanism works through systematic exposure reduction in the case of when new returns identify unfavourable situations, pre-emptive risk control is applied before the disastrous losses occur (Platanakis et al., 2018).

The advanced machine learning algorithms under evaluation, namely, the Random Forest, Support Vector Machines, and Gaussian Mixture Models provide ambiguous outcomes that point to the fact that the sophistication of an algorithm is not enough to ensure general performance. Model-based strategies, not enhanced by momentum, gain negative returns in the range of -1925 by being too cautious to invest when the market is crashing but not invest enough to participate when the market is rising uphill (Thélissaint and Danilo, 2025). Nevertheless, with additional simple momentum signals, these strategies can get positive returns of 2-3% and much higher consistency scores of nearly 8.0, which confirms that the value addition of models will come in through better selection and allocation and not through better forecasting (Liu et al., 2022). The GM model can exhibit its specific usefulness in the context of regime shifts based on the identification of state-specific association, but the value of the model in practise is determined by the inclusion of complementary directional indicators (Anson et al., 2022).

The analysis of portfolio composition indicates inherent disparity between the selectivity nature of Random Forests which is focused and the inclusive nature of GMM which is not superior in all cases. Random Forest puts the portfolios on 3-5 assets where the effective number of assets is approximately 3 that is optimised to experience the maximum outperformance should the predictions turn out to be true but increases the losses when the predictions fail (Corbet et al., 2019). GMM allocates the weight among 15-25 assets with effective number of over 11 and compromises the potential of peak performance due to the diversification to get more trustworthy results (Platanakis et al., 2018). Corporate investors must evaluate the organisational tolerance of the concentration risk and implementation uncertainty with the desire to have a strong performance and stakeholder communication, which can favour the diversified strategy of GMM with slightly lower average results (Deloitte, 2022).

➢ *Practical Implementation Considerations for Corporate Cryptocurrency Integration*

The operation of empirical results into operationally operational cryptocurrency integration must be thought through with a keen sensitivity of the mechanics involved by the implementation, organisational capacity, and institutional limitations that run deeper than the quantitative performance evaluation only. The functions of corporate treasury that consider cryptocurrency allocation have to face multidimensional issues that span technology infrastructure, custody, accounting treatment, regulatory compliance, governance structure, and stakeholder communication (Deloitte, 2022). These utility aspects often make or break implementation regardless of the quality of the strategy used since even conceptually good strategies will be useless when implementation is impeded by organisational factors or operational complications give rise to unacceptable risk profiles (Campbell et al., 2023).

Technology infrastructure is the underlying requirement, which includes trading platform, data feed, portfolio management software, and security protocols that are tailored to the specifics of cryptocurrency. Conventional treasury management systems are normally not used to support cryptocurrency trading, integration of custody, and real-time position management across various exchanges and wallets (KPMG, 2024). To do this, corporations have to create their own systems that combine the functionality of cryptocurrencies or use special platforms that provide institutional-grade infrastructure, both of which would be quite expensive, require a lengthy implementation period, and demand ongoing maintenance (Financial Crime Academy, 2025).

The case of custody arrangements is perhaps the most imperative implementation choice, weighing the case of security needs versus the flexibility of operation in active portfolio management that is required. The most secure solutions that require corporations to have direct control over private keys are self-custody arrangements where corporations have complete protection against exchange failures and counterparty risks at the cost of heavy operational overheads such as key management procedures, disaster recovery, and succession planning (Deloitte, 2022). Regulated financial institutions offer qualified custodian solutions that offer professional management and insuring coverage but cause counterparty dependencies and potentially limit trading flexibility with a withdrawal approval procedure (Campbell et al., 2023). Combining cold storage of strategic holdings with exchange custody of tactical trading positions are viable options, given that coordination between custody arrangements complicates the matter and introduces possible reconciliation issues (KPMG, 2024).

The accounting treatment differs in different jurisdictions and changes constantly as the standard-setters struggle with how cryptocurrencies are to be classified, measured, or disclosed. Under current U.S. Generally Accepted Accounting Principles, crypto-currencies generally are indefinite-lived intangible assets, which are not to be subjected to revaluation but tested by impairment, which forms asymmetrical recognition of such assets, with losses recorded immediately but gains not recorded until disposition (Deloitte, 2022). This therapy creates a volatility in earnings because market declines cause impairment charges that may worry stakeholders, though these declines may be temporary and may turn out to be reversed (PwC, 2023). The case with international financial reporting standards is the same with some extra complexity in terms of fair value measurement and functional currency translation of multinational companies (KPMG, 2024). Treasury managers should also extensively consider accounting implications and set communication strategies of explaining volatility to

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investors, analysts, and board members who may not be knowledgeable of the specifics of cryptocurrency accounting.

The governance frameworks need to be adjusted to reflect the cryptocurrency risk peculiarities and decision-making authority suited to volatile assets with a high rate of price fluctuations. The conventional treasury policies usually allow managers to discretion in the normal day to day investment activity within a defined scope, and only on the material change of policy or exposure which rises above the thresholds would be subject to board approval (Deloitte, 2022). The implementation of cryptocurrencies requires a strict definition of the limits of authority, limits on the size of positions, accepted counterparties, and situations that necessitate consultation with senior management or the board (Campbell et al., 2023). The Policy Statement on Investment must specify the maximum and minimum amounts of cryptocurrencies, the risk levels that automatically cause a reduction in position, how often positions should be reported to provide sufficient supervision without micromanagement that inhibits the tactical decision-making process (Russell Investments, 2022). Board education is a crucial precondition because directors who are unaware of the specifics of cryptocurrencies might have difficulties with proposal assessment or monitoring the implementation process without background knowledge (PwC, 2023).

The importance of stakeholder communication strategy can be explained by the controversial image of cryptocurrency and the possible negative publicity impacting corporate reputation. Anticipated disclosure by earnings calls, investor presentation, and regulatory reporting allows corporations to manage storey, justifying the strategic rationale, risk management procedures, and performance effects instead of justifying defensive responses to external criticism (Campbell et al., 2023). Honesty concerning placement approaches, quantity, and danger threshold shows constraint which could reduce worries concerning speculative gambling with shareholder capital (Deloitte, 2022). Nevertheless, too much information about trading preferences may lead to front-running by advanced market actors, and this needs to be balanced with the need to be transparent enough and secure enough in operations (Financial Crime Academy, 2025).

- *Strategic Allocation Framework and Optimal Implementation Pathway*

Cryptocurrency allocation strategy development will need the incorporation of empirical evidence of the performance and organisational capacity, risk-taking, and strategic goals unique to each corporate environment. The study confirms beyond any doubt that the momentum-driven tactical allocation can provide better risk-adjusted performance in both market regimes, but the appropriateness of implementation should be conditioned by the level of treasury sophistication, technological infrastructure, and the acceptance of the stakeholders in different organisations (Thélissaint and Danilo, 2025). This section will suggest a systematic model that will assist corporations to undertake the inter-focus on allocation choices, sequencing of implementation, and maintenance protocols that are modified in accordance with institutional settings.

The decision of strategic allocation will start with clear statements of the role of cryptocurrency in the overall corporate treasury goals. Businesses are supposed to state how cryptocurrency is being used as portfolio diversifier likely to deliver non-correlated returns, inflation hedge against currency debasement, strategic placement as a sign of technological capability, or an enhancer of returns aiming to achieve absolute returns (Campbell et al., 2023). These various purposes suggest varying best practises of diversification and low correlation assets, inflation hedging with the possibility of store-of-value characteristics of Bitcoin, strategic positioning with the visibility and learning cost of volatility, and performance improvement that aims to enhance returns with aggressive momentum (Russell Investments, 2022). Ambivalent goals can cause possible conflicts, which necessitate clearly defining priorities, since one kind of strategy can easily trade-off against another.

Position sizing is the most important factor in determining the overall effect of cryptocurrency on the total treasury risk, and a large allocation of such instruments may result in unacceptable volatility notwithstanding the complexity of any strategy. Conservative position sizing constrains cryptocurrency to 1-2% of total investment portfolio and makes sure that even a disastrous loss in cryptocurrencies does not have a significant effect on wealth (Deloitte, 2022). The allocation has meaningful exposure adequate to learn and position strategically with acceptable amounts of downside as part of fiduciary duties (Campbell et al., 2023). Medium allocations of up to 3-5% have a significant effect on cryptocurrency portfolio returns and volatility, suitable when an organisation has a higher degree of risk aversion and the arrangement of risk management mechanisms (Anson et al., 2022). Aggressive allocations above 5 percent put large amounts of treasury resources in high-volatility assets, which should be exceptionally justified and risk-managed, as the material capital impairment may occur (Platanakis et al., 2018).

The introduction route is to take a gradual turn so as to allow the organisations to learn, develop the systems, and get used to the system accordingly before dedicating a great deal of resources. Phase One starts with a small commitment, 1 percent invested in straightforward buy-and-hold Bitcoin position maintained in qualified custody, exposing an individual to exposure and operations experience with few implementation intricacies (Deloitte, 2022). This stage is focused on the learning outcomes such as custody mechanics, accounting treatment, regulatory compliance, and governance procedures and not performance optimization (Campbell et al., 2023). The allowance of 6-12 months would allow to analyse the behaviour of cryptocurrencies under varying market conditions and evaluate the capabilities of the organisation before moving forward (KPMG, 2024).

Phase Two involves the introduction of tactical risk management using momentum based exposure scaling on current Bitcoin position, and executing the strategy that was

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found to be optimal in the empirical analysis. It is the stage in which systematic execution capabilities, such as automated signal calculation, position sizing algorithms and execution systems running in real time, are developed or acquired (Gkillas & Longin, 2025). The distribution can be slightly increased to 2-3% with confidence and once systems are proved to be reliable (Russell Investments, 2022). The most important key performance measures will be maximum drawdown compared to buy-and-hold, Sharpe ratio increment, and performance under different market conditions instead of absolute returns only (Thielssaint and Danilo, 2025). The success in Phase Two within the 12-18 months can be examined as a testament to systematic approach and it warranted the possible advancement to higher sophistication.

Phase Three presents selective allocation of altcoins, and possibly, complex selection algorithms, beyond focusing on Bitcoin concentration to diversified cryptocurrency portfolio. This step applies either momentum-enhanced machine learning techniques or a combination of both tactics of Bitcoin exposure with a minimum of variance allocation in altcoins (Corbet et al., 2019). Diversification is likely to favour risk-adjusted returns but will require substantial operational complexity in the form of multiple custody relations and extra compliance priorities and more advanced portfolio administration structures (KPMG, 2024). Allocation ceiling may go up to 3-5 percent in case the organisation has proven successful in the previous stages and is equipped with infrastructure to accommodate greater complexity (Campbell et al., 2023).

➢ *Limitations, Model Risk, and Robustness Considerations*

The strategic recommendations and finding of empirical findings must be put into context with inherent limitations of all quantitative research about cryptocurrency markets. The first, and the most basic, limitation is the lack of historical data, where the full cryptocurrency price history is available as far as 2014-2015 with major assets, and even shorter with altcoins (Corbet et al., 2019). This limited history has less than two full market cycles, and it may not be adequate to study strong statistical inferences about long-run relationships and extreme event frequencies (Liu et al., 2022). Cryptocurrency markets can also be non-stationary where distributional characteristics, correlation patterns, and predictability behaviour may change in their core over time as markets become more mature, regulatory frameworks become more transparent, and institutionalisation reaches a higher level (Platanakis et al., 2018).

Dependence on sample periods is another related issue because findings made on performance may be based on the peculiarities of the 2020-2024 evaluation period and not only on generalizable market property. This period includes an unprecedented monetary policy accommodation, disruptions due to the pandemic, institutional adoption announcements that have never taken place before, and certain regulatory changes that may leave temporarily exploitable patterns that will vanish as the market becomes more efficient (Goodell and Goutte, 2021). The strength of the momentum strategies may indicate the specific market structure properties that include retail investor participation, scarce arbitrage capital and behavioural biases which become increasingly arbitraged by the professional institutional investors (Gkillas & Longin, 2025).

The problem of model specification uncertainty applies to all advanced methods, since the machine learning algorithms under discussion are just a part of possible methods, and other implementations may draw different conclusions. Discretionary decisions in the selection of the predictor variables, hyperparameters tuning steps, and performance assessment measures all have the potential to affect the results (Thélissaint & Danilo, 2025). Applying similar frameworks to the same data, different researchers may come to different conclusions based on their specification decisions (especially those that relate to borderline decisions, such as the optimal model complexity, or the inclusion threshold of a predictor) (Borri, 2019). The sensitivity analysis considers a few of the variants but is unable to cover all the possibilities in detail, which needs to consider that reported results are only the methods which are implemented in a larger methodological space.

The risk of overfitting is common to all backtesting experiments, especially those that use adaptable algorithms that have the capability to pick up on spurious effects in a training data set without having predictive value. The models of machine learning under consideration are focused directly on the maximisation of predictability, which may assist in determining patterns of history that are not relevant to the future (Corbet et al., 2019). This risk is reduced, but not removed, by out-of-sample validation because even the testing periods are some historical records employed in the research that might affect the specification decisions consciously and unconsciously (Liu et al., 2022). The high performance of simple momentum strategies compared to complex machine learning gives some comfort against overfitting since simpler strategies are more resilient against specification uncertainty (Platanakis et al., 2018).

➢ *Limitations, Future Research Directions, and Concluding Observations on Corporate Cryptocurrency Adoption*

This study has various shortcomings indicating that one should be cautious in the generalisation of results and the discovery of future research opportunities. First, the sample period, 2020-2024, is not very long, and it is possible that it does not represent all the possible situations in which cryptocurrencies may occur during the investment period (Thélissaint and Danilo, 2025). The sample does not contain any long-term bear markets as long as 2014-2017 or long-term high-inflation regimes that balance claims of inflation hedging properties (Gkillas & Longin, 2025). Future studies that will use longer time series as more history is accumulated may determine whether documented patterns are the characteristics of the markets or sample artefacts (Corbet et al., 2019).

Second, the research is mostly limited to major cryptocurrencies such as Bitcoin, Ethereum, and already existing altcoins and may overlook the opportunities and risks of novel tokens, decentralised finance protocols, or other

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blockchain-based assets (Campbell et al., 2023). This omission is based on practical data availability factors and corporate investor interest in liquid and established assets, although it might miss new segments with unique risk-return properties or diversification properties (Anson et al., 2022). Future studies can analyse wider cryptocurrency ecosystems, such as micro-cap tokens, stablecoins, and DeFi protocols to determine whether the results can be applied to the entire spectrum of digital assets or that certain groups of assets may demand their own strategy (Platanakis et al., 2018).

Third, the analysis uses data on daily returns which might omit key intraday dynamics such as flash crashes, liquidity shocks or price manipulation that can potentially impact on both execution quality and realised returns (Thélissaint & Danilo, 2025). Although the daily frequency is suitable to make strategic allocation decisions and minimise the data mining issues of higher frequency analysis, it cannot identify market microstructure effects, which may have a significant impact on the practical implementation (Russell Investments, 2022). Future studies that include data intraday could study the best strategies to use, the cost of market impact when trading in the order of an institution, and the benefit of liquidity provisions that could be offered by advanced trading algorithms (Gkillas & Longin, 2025).

Fourth, the research abstracts the significant institutional elements such as transaction costs, taxation, accounting practises, and regulatory restrictions, which can have a significant impact on applicable application and actual performance (Deloitte, 2022). Although stylized transaction costs of 10 basis points per rebalancing are a rough way of adjusting trading frictions, real costs change with the size of trade, the environment of trading, and the place of trading, which may introduce material differences between theoretical and realised results (Financial Crime Academy, 2025). Such tax implications as wash sale provisions, like-kind exchange treatment, and differing jurisdictional treatments have a strong impact on after-tax returns and optimal rebalancing frequencies (Campbell et al., 2023).

Fifth, the study only considers the portfolio construction and tactical allocation aspect of the cryptocurrency investment, and does not consider equally significant aspects of strategic determination of asset allocation in cryptocurrency markets, or connecting it with the overall process of corporate capital allocation (Liu et al., 2022). The right proportion of allocation to cryptocurrencies will be determined by corporate specificities such as the nature of the industry, competitive positioning, the interests of stakeholders, and alternative investment opportunities that cannot be directly prescribed (Anson et al., 2022). Further studies that might include strategic allocation decision frameworks that consider organisational context, include the real options valuation of flexibility, and governance issues of new asset classes would be a complement to the tactical nature of the current research (Gkillas and Longin, 2025).

In the future, the use of cryptocurrencies in the corporate world is expected to keep growing, and with the maturity of the markets, the regulatory landscape, and the development of operational infrastructure (Deloitte, 2022). The results of this study give empirically-based advice to companies operating in this changing environment, focusing on the importance of rigorous risk management, adaptive approach to strategies, and accurate setting of expectations (Russell Investments, 2022). Since the data will keep progressing and market frameworks will change, periodic revaluation of the patterns and strategy performance recorded will be necessary to keep cryptocurrency investments aligned with corporate investment goals (Financial Crime Academy, 2025). The study lays the groundwork to this continuous analysis even though the fast development of cryptocurrency markets requires constant learning and adjustment as opposed to fixed adherence to previous trends (Thélissaint and Danilo, 2025).

In conlusion, the introduction of cryptocurrencies into the corporate investment portfolios comes with opportunities and challenges that need to be analysed in a sophisticated manner, risk management is essential, and the limitations should be appreciated reasonably. The momentum-based solutions found in this paper provide viable solutions that provide better risk-adjusted returns in various market regimes, albeit operational specifics, company competences and market dynamics must be carefully considered in terms of implementation. As the cryptocurrency markets become more mature, regulative frameworks become hard-earned, and the institutional involvement grows, the best strategies and risk management frameworks will have to change, and they will need to be investigated and monitored constantly and adjusted accordingly. Those investors in corporations who deal with cryptocurrency and its implementation with sober structures, due diligence, and thorough risk management measures may well reap the rewards and face no disastrous consequences as some of the less wary market users.

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