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STRATEGIC INVESTMENT DECISIONS IN TRADITIONAL ASSETS WITH CRYPTOCURRENCIES: A 2020–2025 STUDY

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Abstract. This study examines how including cryptocurrencies reshapes portfolio outcomes and investment strategy performance in highly volatile markets. Using historical data from 2020–2025 and optimization methods by Markowitz and Black–Litterman (BL), three widely used strategies were tested: Buy-and-Hold, Dollar-Cost Averaging (DCA), and Rebalancing. Portfolios included equities, ETFs, bonds, gold, and cryptocurrencies (Bitcoin, Ethereum) with crypto weights of 0 %, 10 %, and 20 %. Performance was evaluated with return-based (CAGR) and risk-adjusted indicators (Sharpe, Sortino, Calmar, Ulcer Index). Results show higher crypto allocations boost long-term returns but increase volatility and drawdowns, especially under Buy-and-Hold. Rebalancing reduces downside risk and stabilizes outcomes, while DCA supports disciplined accumulation but underperforms in growth and efficiency. Markowitz favours bond-heavy conservative portfolios, whereas BL highlights equity exposure and better reflects investor views. No universal "best" strategy exists; choices should reflect risk tolerance, behaviour, and investment horizon. The study systematically compares strategies and offers insights on how crypto assets alter the risk–return balance, bridging theory and practical decision-making.

Keywords: *Cryptocurrency investment, portfolio optimization, investment strategies, rebalancing, behavioural finance.*

JEL Classification: G11, G15, G41

INTRODUCTION

Over the past five years, the cryptocurrency market has grown significantly, from approximately $190 billion in 2020 to more than $3.39 trillion at the beginning of 2025 (CoinMarketCap, n.d.). This period has been accompanied by several major shocks: the impact of COVID-19, the 2021 boom, the collapse of FTX in 2022, and geopolitical tensions. Both institutional and retail investors have become more active in the market, but the latter have contributed significantly to price volatility, which is often driven by the news cycle.

Digital platforms further amplified this dynamic, as information spread rapidly and encouraged impulsive investing. As a result, cryptocurrency prices became increasingly dependent on sentiment and highly volatile (al Guindy, 2021; Qi et al., 2025; Bogdan et al., 2023). Investor behaviour often created common movements between different asset classes, reducing the benefits of diversification (James & Menzies, 2023).

In addition, with the arrival of crypto ETFs on the market and increasing regulatory discussions, psychological factors have come to the fore – herd mentality, overconfidence, and the FOMO effect. Such factors often encourage irrational behaviour (Barber & Odean, 2001; Shiller, 2000; Corbet et al., 2019; Handoko et al., 2024). Overconfidence causes investors to overestimate their knowledge, while herd behaviour combined with FOMO can lead to bubbles that later burst (Gherghina & Constantinescu, 2024; Shiller, 2000). All of this suggests that investment strategies need to be systematically tested and based on more rational decisions.

Despite increasing interest in cryptocurrencies, there is still no clear answer as to what place they take in portfolios (Bakry et al., 2021; Jeleskovic et al., 2024; Han et al., 2024). Institutional players are becoming increasingly involved, but there is still no consensus on how to properly balance risk and return. The correlation between cryptocurrencies and traditional asset classes is unpredictable, especially during times of crisis (Charfeddine et al., 2020). These challenges are further compounded by regulatory uncertainty, technological limitations, and operational risks within cryptocurrency exchange infrastructures (Nuhiu et al., 2023).

Although market activity and research have increased, there is a lack of a framework for identifying effective cryptocurrency investment strategies. Investors still seek rational, data-based ways to allocate crypto within diversified portfolios (Qi et al., 2025; Platanakis & Urquhart, 2019). Traditional models like Markowitz's mean-variance often underperform in highly volatile markets. Behavioural biases make rational strategy selection even harder (Chhatwani & Parija, 2023; Handoko et al., 2024).

Previous studies show many investors rely on buy-and-hold despite its vulnerability to large drawdowns (Statman, 2017; Bodie et al., 2018). Dollar-cost averaging (DCA) is also used without full analysis of correlations (Thaler, 2015). Research systematically comparing these popular strategies with rebalancing remains limited.

This study addresses these gaps by testing buy-and-hold, DCA, and rebalancing strategies in diversified portfolios including crypto assets during 2020–2025. Portfolio performance is evaluated through the Sharpe ratio, maximum drawdown, volatility, and others, with special focus on crypto's role. The study aims to contribute to the literature by comparing portfolio optimization methods and investment strategies in mixed traditional–cryptocurrency portfolios.

Hypotheses are put forward:

H1: There are statistically significant differences in portfolio performance among investment strategies that combine traditional and crypto assets.

H2: Portfolios managed with a rebalancing strategy exhibit lower overall volatility and smaller maximum drawdowns compared to buy-and-hold, especially during periods of elevated market uncertainty.

H3: From the perspective of bounded rationality, structured approaches like DCA and rebalancing tend to be more behaviourally sustainable than buy-and-hold, as they may help reduce the influence of impulsive decision-making during periods of market uncertainty.

1. LITERATURE REVIEW

The cryptocurrency market differs from traditional finance by extreme volatility, limited regulation, and decentralized structure (James & Menzies, 2023; Charfeddine et al., 2020; Nuhiu et al., 2023). Although signs of maturity are emerging, instability remains high, and holding only crypto assets is often too risky. Investors, therefore, combine crypto with traditional assets to balance returns and risks.

Another significant difference concerns investor behaviour. In traditional markets, large funds and economic cycles set the tone, while cryptocurrency market prices are mostly driven by small investors and the media. This is where the so-called "herd effect" comes into play, with everyone following the majority, both during sudden price surges or crashes and during periods of calm (Shrotryia & Kalra, 2022). Social networks further fuel this wave and sometimes even outweigh expert commentary, especially when people lack knowledge about fundamental factors (Bogdan et al., 2023; Qi et al., 2025; Zhao et al., 2022).

1.1. Managerial Perspectives on Investment Decisions

Investment decisions play an important role in portfolio outcomes. While traditional models assume rational optimization, in reality, choices are constrained by limited information, heuristics, and emotional biases. Investors often settle for "good enough" solutions (Navarro-Martinez et al., 2018) or are influenced by social media rather than fundamentals (Qi et al., 2025). Overconfidence leads younger and less experienced investors to take higher risks, while herd behaviour spreads across platforms (Bogdan et al., 2023).

Although financial and crypto literacy improve decision quality (Jones et al., 2024), even experienced investors remain influenced by behavioural patterns. From a management perspective, this means portfolio strategies must account for bounded rationality and behavioural sustainability rather than assuming perfectly rational optimization.

1.2. Portfolio Theory and Diversification

Modern portfolio theory (Markowitz, 1952) established diversification as a tool to reduce risk without lowering returns. Yet in highly volatile markets like crypto, assumptions of rational investors and stable correlations often break down. Postmodern approaches reframe risk in terms of potential loss rather than variance (Rom & Ferguson, 1993), aligning with investor preference for loss avoidance (Brito et al., 2016). Behavioural portfolio theory further emphasizes layered goals, balancing security and aspiration (Shefrin & Statman, 2000).

Empirical work shows traditional strategies often underperform in crypto. Platanakis and Urquhart (2019) report that equal-weight and Markowitz portfolios struggle, while the Black–Litterman (BL) model with constraints produces better outcomes. Extensions including solvency limits (Guan et al., 2024) and transaction cost adjustments (Dächert et al., 2022) confirm that realistic constraints strongly shape portfolio performance.

Diversification within crypto also matters. Donatelli Neto & Colombo (2021) and Nuhiu et al. (2023) show that baskets of 10 or more coins reduce volatility compared to Bitcoin alone, though systemic risk remains due to BTC and ETH dominance. Although stablecoins are popular, their usefulness for diversification is almost non-existent. More advanced methods, such as correlation network analysis (Kitanovski et al., 2025), GARCH-copula models (Jeleskovic et al., 2024), and AI-based optimizers (Pankwaen et al., 2025), may be better at capturing nonlinear relationships and improving portfolio performance. Nonetheless, traditional structures such as the 60/40 portfolio still serve as useful starting points (Anuno et al., 2024).

Advanced models appear promising but remain too complex for many investors, creating demand for simpler approaches combining crypto and traditional assets.

1.3. Investment Strategies

Investment strategies can be broadly divided into passive and active. Passive approaches such as buy-and-hold and DCA involve minimal trading and long-term patience, while active strategies rely on market timing, momentum, or sentiment signals (Fabozzi & Markowitz, 2011).

DCA typically helps more conservative investors balance risk and return (Cho & Kuvvet, 2015), although in some cases it may prove to be weaker (Leggio & Lien, 2003). Buy-and-hold strategy remains popular, but portfolios become vulnerable to large losses (Statman, 2017). Regular rebalancing helps maintain the balance between risk and return, but overly active trading can lead to excessive costs (Zhang et al., 2022; Harvey et al., 2025).

Active strategies, such as tactical asset allocation (Faber, 2007; Oliveira et al., 2025) and social sentiment-based investing (Bollen et al., 2011; Nofer & Hinz, 2015) highlight the influence of macroeconomics and emotions. Factor-based and momentum models show promise in crypto, especially momentum strategies, which often achieve better results in terms of risk-return ratio (Han et al., 2024). Machine learning also has its advantages, improving results by about 4 % in some cases.

However, most cryptocurrency investors tend to behave more speculatively rather than long-term planning (Pelster et al., 2019). While combining growth and value strategies can stabilize portfolios in equities (Papathanasiou et al., 2022), crypto requires tailored approaches given its volatility. No single “best” strategy exists, and outcomes depend on risk tolerance, time horizon, and behavioural discipline.

1.4. Portfolio Evaluation Metrics

Assessing performance requires multiple indicators. The Sharpe ratio remains standard but penalizes all volatility equally, overstating risk in skewed distributions. Alternatives include the Sortino ratio, which focuses on downside risk (Chaudhry

& Johnson, 2008), and the Calmar ratio, which integrates risk and return by dividing CAGR by max drawdown (Choi et al., 2025; Sen & Dutta, 2022).

The maximum drawdown (MDD) captures peak-to-trough losses and is especially relevant in volatile markets. Broader portfolios tend to reduce MDD without harming returns (Nuhiu et al., 2023; Jeleskovic et al., 2024). The compound annual growth rate (CAGR) smooths performance over time and, when combined with MDD, offers insight into long-term trade-offs.

Volatility remains a basic risk measure but does not distinguish between gains and losses. Asymmetric markets require downside-focused measures like Sortino or Calmar ratios (Platanakis & Urquhart, 2019). The Ulcer Index goes further by capturing both depth and duration of losses, making it useful for crypto portfolios (McBride & Dastan, 2022).

Market sensitivity is often measured using beta coefficients, but in the crypto market, these relationships change rapidly, so the classic capital asset pricing model (CAPM) assumptions do not really work (Sanhaji & Chevallier, 2023). Finally, machine learning models such as the iterative model combining algorithm (IMCA) are able to combine traditional indicators with adaptive algorithms and often outperform conventional benchmarks (Pankwaen et al., 2025).

All this shows that there is no single indicator that can fully reflect portfolio performance; a combination of indicators is needed to make the assessment more reliable.

1.5. Research Directions and Gap Identification

Interest in integrating cryptocurrencies into portfolios has grown, but the literature remains fragmented. Many studies focus on traditional mean-variance methods (Platanakis & Urquhart, 2019; Charfeddine et al., 2020), which often fail under crypto's volatility (James & Menzies, 2023). Advanced methods like copula models and AI-based approaches exist but are rarely compared systematically under common conditions (Jeleskovic et al., 2024; Pankwaen et al., 2025).

Behavioural elements, though widely discussed (Qi et al., 2025; Das & Ahmed, 2021), are mostly treated in theoretical or survey-based work, with little connection to actual portfolio outcomes. Similarly, while correlations between crypto and traditional assets shift unpredictably during crises (Han et al., 2024), few studies assess how different strategies hold up under such stress.

This creates a gap for integrated analyses comparing investment strategies in mixed traditional–crypto portfolios while considering real-world decision-making constraints.

2. METHODOLOGY

The research is quantitative, based on an empirical analysis of investment portfolios using historical data from January 2020 to June 2025. Weekly frequency was chosen to capture portfolio dynamics under different market conditions. The study applies two portfolio optimization methods, the Markowitz mean-variance model and the BL model, combining traditional financial instruments with cryptocurrencies. Correlations between assets are calculated during construction, but the main focus is on evaluating portfolio and strategy performance.

The analysis clearly distinguishes between in-sample data (2019, used for optimization) and out-of-sample data (2020–2025, used for verification). Portfolios are constructed with varying levels of cryptocurrency inclusion (0 %, 10 %, 20 %). To ensure diversification, each portfolio includes assets from multiple classes: equities (Apple, JPMorgan, ExxonMobil), ETFs (VTI, SPY, AGG, BND, GLD), and cryptocurrencies (Bitcoin, Ethereum). Assets were selected to ensure liquidity, diversification, and an appropriate covariance structure. Final optimized portfolios typically consisted of 4–5 assets, with a 30 % maximum weight per asset to avoid overconcentration.

The Markowitz model determines portfolio weights by maximizing the expected risk-adjusted return while considering portfolio variance. Portfolio variance is estimated using the covariance matrix of asset returns.

$$\max_{\mathrm{w}}(\mu T w - 2\lambda w T \Sigma w), \tag{1}$$

where

w – portfolio weights;

μ – expected asset returns;

Σ – covariance matrix;

λ – investor's risk aversion parameter.

Portfolio weights were constrained to be non-negative and to sum to one.

$$\sum_{i=1}^{n} w_i = 1, w_i \geq 0 \tag{2}$$

The covariance matrix was estimated from historical weekly asset returns. The Black–Litterman model combines equilibrium market returns with investor views to obtain adjusted expected returns used for portfolio optimization.

$$E(R)_{BL} = [(\tau\Sigma)^{-1} + P^T\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P^T\Omega^{-1}Q], \tag{3}$$

where

τ – scaling factor;

P – view matrix;

Ω – uncertainty matrix;

Π – equilibrium returns;

Q – investor views.

The adjusted expected returns were then used together with the covariance matrix in a mean–variance optimization framework to determine optimal portfolio weights.

The analysis considers three investment strategies: buy-and-hold, DCA, and periodic rebalancing. Results are assessed using a set of standard performance indicators widely applied in financial research, including measures of return (CAGR), risk (volatility, MDD), and risk-adjusted ratios (Sharpe, Sortino, Calmar). In addition to the usual indicators, the Ulcer Index was used to capture investor discomfort during portfolio declines. Together, all these measurements provide a better understanding of how portfolios perform, how stable they are, and how resistant they are to different market conditions.

To assess whether differences between investment strategies were statistically significant, paired-sample t-tests were performed on weekly portfolio returns. Statistical significance was evaluated at the 5 % level ($p < 0.05$).

Data on traditional financial instruments was taken from Investing.com (Investing.com, n.d.), while data on cryptocurrencies was taken from CoinMarketCap. The sources were chosen for their reliability, complete history, and ease of use with Python. Data processing and portfolio calculations were implemented in Python using widely adopted financial analysis libraries.

The methodology was designed to allow direct comparison of different portfolio compositions and investment strategies. However, it is worth mentioning a few limitations. Results are based on historical data and do not account for trading costs, taxes, or liquidity constraints. In addition, only quantitative indicators are considered – fundamentals and investor behaviour are left out. Finally, optimization is done on the assumption that asset correlations will be fairly stable, although crises usually throw them off balance.

3. RESULTS

The study results are based on backtesting portfolios with varying cryptocurrency proportions, optimized by Markowitz and BL methods. Analysis emphasizes how strategy choice and crypto share shape the risk–return trade-off. Figure 1 shows the results of three portfolios for the period 2020–2025, comparing three investment strategies: buy-and-hold, DCA, and rebalancing. The portfolios were optimized using the Markowitz method, based on 2019 data, and including different proportions of cryptocurrencies. Their compositions were as follows:

- AAPL – 14 %, JPM – 13 %, AGG – 30 %, BND – 30 %, GLD – 10 %;
- AAPL – 30 %, JPM – 9 %, AGG – 21 %, BND – 30 %, BTC – 10 %;
- AAPL – 30 %, JPM – 26 %, BND – 3 %, GLD – 21 %, BTC – 20 %.

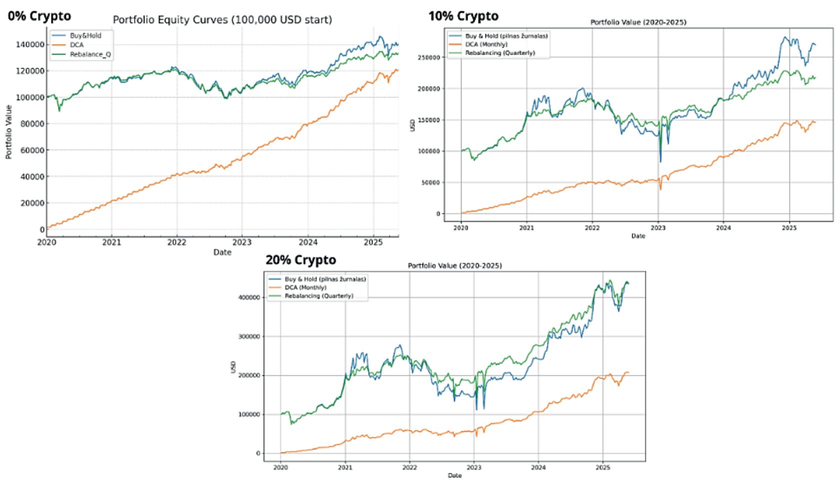

Fig. 1. Investment strategy results with portfolios optimized by Markowitz optimization.

Overall, buy-and-hold delivers the highest volatility and growth, rebalancing balances risk and stability, while DCA ensures steady but slower growth. Larger crypto shares boost returns but also deepen losses, especially under buy-and-hold, while rebalancing cushions volatility. This confirms the classic risk–return dilemma: higher profits require higher risk, becoming central in decision-making.

Figure 2 shows the same investment strategies in three portfolios constructed using BL optimization. The final portfolio compositions were as follows:

– AAPL – 30 %, JPM – 30 %, VTI – 30 %, SPY – 10 %;
– AAPL – 30 %, JPM – 30 %, VTI – 30 %, BTC – 10 %;
– AAPL – 30 %, JPM – 30 %, VTI – 20 %, BTC – 20 %.

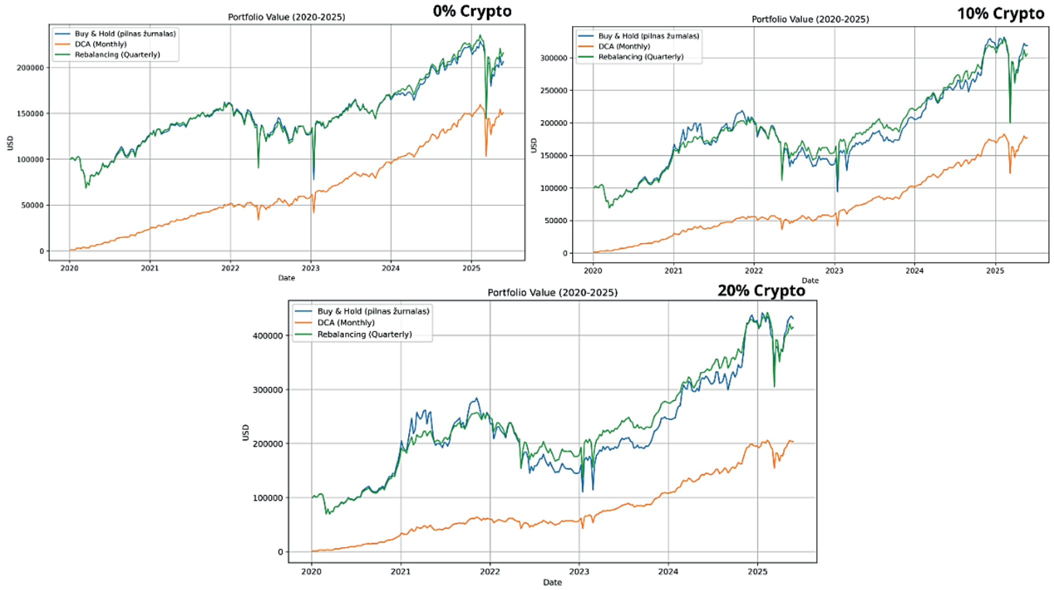

Fig. 2. Investment strategy results with portfolios optimized by BL optimization.

BL optimization produced different structures than Markowitz, emphasizing US stock ETFs (VTI, SPY). Portfolio dynamics show that balanced asset selection cushions some fluctuations. As crypto weight rises, return potential grows, but volatility escalates, most sharply with buy-and-hold. Compared to Markowitz, BL more clearly exposes the trade-off between diversification and crypto risk, underscoring the managerial need to weigh stability against higher but unstable returns. BL also incorporates subjective investor views, making its outcomes closer to real decision-making, where market data mixes with expectations.

In terms of quantitative results, the key portfolio performance indicators are presented below.

Table 1 shows the results of three portfolios optimized according to the Markowitz model. Three investment strategies were applied to each portfolio, and the indicators reflect the differences in their performance. Table 2 shows the same indicators, but the portfolios have been optimized according to the BL model.

Table 1. Evaluation Indicators of Portfolios Based on Markowitz Optimization (2020–2025)

Markowitz (crypto0)	**CAGR**	**Volatility**	**MDD**	**Ulcer Index**	**Sharpe**	**Sortino**	**Calmar**	**Beta**
Buy and hold	0.065	0.137	–0.263	0.070	0.526	0.605	0.246	0.424
DCA	0.035	0.128	–0.263	0.071	0.338	0.391	0.135	0.758
Rebalancing	0.054	0.119	–0.254	0.070	0.505	0.559	0.214	0.358
Markowitz (crypto10)	**CAGR**	**Volatility**	**MDD**	**Ulcer Index**	**Sharpe**	**Sortino**	**Calmar**	**Beta**
Buy and hold	0.202	0.425	–0.590	0.167	0.625	0.881	0.342	0.640
DCA	0.073	0.331	–0.549	0.180	0.366	0.505	0.133	0.986
Rebalancing	0.155	0.287	–0.435	0.098	0.636	0.822	0.356	0.514
Markowitz (crypto20)	**CAGR**	**Volatility**	**MDD**	**Ulcer Index**	**Sharpe**	**Sortino**	**Calmar**	**Beta**
Buy and hold	0.313	0.484	–0.602	0.224	0.797	1.048	0.519	0.680
DCA	0.144	0.402	–0.603	0.250	0.530	0.673	0.239	1.146
Rebalancing	0.313	0.387	–0.438	0.120	0.895	1.060	0.716	0.652

Table 2. Evaluation Indicators of Portfolios Based on BL Optimization (2020–2025)

BL (crypto0)	**CAGR**	**Volatility**	**MDD**	**Ulcer Index**	**Sharpe**	**Sortino**	**Calmar**	**Beta**
Buy and hold	0.144	0.516	–0.520	0.110	0.499	0.644	0.276	1.143
DCA	0.079	0.463	–0.470	0.124	0.389	0.481	0.169	1.500
Rebalancing	0.153	0.478	–0.438	0.109	0.529	0.644	0.349	1.113
BL (crypto10)	**CAGR**	**Volatility**	**MDD**	**Ulcer Index**	**Sharpe**	**Sortino**	**Calmar**	**Beta**
Buy and hold	0.239	0.470	–0.570	0.174	0.682	0.868	0.420	1.001
DCA	0.112	0.453	–0.546	0.189	0.454	0.569	0.205	1.442
Rebalancing	0.230	0.483	–0.459	0.124	0.663	0.796	0.501	1.010
BL (crypto20)	**CAGR**	**Volatility**	**MDD**	**Ulcer Index**	**Sharpe**	**Sortino**	**Calmar**	**Beta**
Buy and hold	0.311	0.501	–0.611	0.232	0.786	1.022	0.508	0.845
DCA	0.141	0.436	–0.617	0.259	0.516	0.662	0.229	1.368
Rebalancing	0.301	0.444	–0.466	0.141	0.815	0.956	0.647	0.886

Empirical results show that portfolios with higher cryptocurrency shares achieve the highest long-term returns. In Markowitz optimization, buy-and-hold and rebalancing with 20 % crypto reached the highest CAGR (~31%), while DCA remained lower (~14 %). The BL framework confirms this trend, with 20 % crypto portfolios under buy-and-hold and rebalancing also yielding ~31 %, though DCA lagged. BL produces more balanced results, while Markowitz highlights stronger contrasts.

Adding crypto raises risk across all measures. In Markowitz portfolios, volatility rises from ~13 % (no crypto) to ~48 % (20 % crypto), with maximum drawdowns up to –60 %. BL optimization shows slightly moderated risk, with volatility at 40–50 %, indicating crypto does not drastically increase overall risk in this model.

Comparing strategies, buy-and-hold suffers the largest volatility and drawdowns, rebalancing mitigates losses, and DCA cushions shocks, though overall volatility remains. DCA's performance is weaker, with lower CAGR and efficiency indicators.

Risk-adjusted metrics support these findings. Under Markowitz, 20 % crypto portfolios achieved Sharpe ratios of 0.797 (buy-and-hold) and 0.895 (rebalancing), compared to 0.530 for DCA. Sortino ratios show similar patterns: higher returns are possible with crypto, but only for investors tolerating larger losses. BL portfolios display more balanced Sharpe and Sortino values, whereas Markowitz emphasizes the gap between aggressive (with crypto) and conservative (without crypto) allocations.

Paired-sample t-tests were conducted to assess the statistical significance of performance differences between strategies (Table 3).

Table 3. Paired-Sample T-Test Results for Selected Portfolio Strategies

Optimization	Strategy	T-stat	P-value
Markowitz (Crypto 10 %)	BH vs DCA	–3.1571	0.001768
Markowitz (Crypto 10 %)	BH vs rebalancing	1.1891	0.235425
Markowitz (Crypto 10 %)	DCA vs rebalancing	3.5536	0.000446
BL (Crypto 10 %)	BH vs DCA	–3.1931	0.001568
BL (Crypto 10 %)	BH vs rebalancing	–0.0034	0.997282
BL (Crypto 10 %)	DCA vs rebalancing	3.2079	0.001492

The results indicate statistically significant differences between buy-and-hold and DCA as well as between DCA and rebalancing strategies in both optimization models ($p < 0.05$). In contrast, differences between buy-and-hold and rebalancing were not statistically significant. These findings provide statistical support for H1 and suggest that portfolio performance varies across investment strategies.

The Calmar ratio reveals the drag of deep drawdowns: with 20 % crypto, Markowitz buy-and-hold reached 0.519, rebalancing 0.716, and DCA 0.239. This highlights that higher returns do not always translate into more efficient risk–return trade-offs.

Correlation results show that increasing crypto lowers Beta relative to equity benchmarks, suggesting added diversification. Although crypto raises volatility, it reduces dependence on traditional markets, offering both risk and hedging potential.

Overall, findings highlight the central trade-off: high returns require riskier, crypto-heavy strategies, while conservative approaches provide stability but cap growth. These outcomes illustrate the strengths and limits of both optimization methods, offering insights for investors balancing return ambitions against risk tolerance.

CONCLUSIONS AND DISCUSSION

The results confirmed the first hypothesis (H1), revealing statistically significant differences in portfolio performance across investment strategies. Risk-adjusted performance measures (Sharpe and Sortino ratios) further highlighted notable differences between portfolios with and without cryptocurrency exposure. The second hypothesis (H2) was partly supported: rebalancing sometimes lowered drawdowns, but differences with buy-and-hold were small. The third hypothesis (H3) was also partly confirmed: structured approaches such as DCA and rebalancing may support more disciplined investment behaviour by reducing the influence of impulsive decision-making, although investor behaviour was not directly measured. At the same time, DCA exhibited weaker performance than the alternative strategies.

Portfolio and strategy choices should reflect investor risk tolerance. Conservative investors may prefer lower cryptocurrency allocations, while aggressive investors may benefit from higher crypto exposure. The findings also suggest that investment strategy selection remains as important as portfolio optimization.

This study adds value by comparing Markowitz and BL optimization in portfolios with and without crypto, integrating behavioural and performance perspectives. Classic optimization favours stability through bonds, while BL portfolios emphasize equities and adapt better to investor views. Both models have merits: traditional methods suit conservative investors; BL offers flexibility and closer alignment with real decision-making.

Limitations remain: Portfolios were optimized on 2019 data and tested over five years, so results may vary across different market phases. Future research could explore momentum, factor investing, or risk parity strategies, especially with crypto components.

The study highlights the importance of risk-adjusted measures. The Sortino ratio consistently exceeded Sharpe, reflecting downside risk more realistically and should complement Sharpe in evaluations. Overall, cryptocurrencies can improve risk–return efficiency but increase volatility. DCA, though behaviourally appealing, often underperforms buy-and-hold or rebalancing, while BL optimization offers greater flexibility than classical methods.

In conclusion, portfolio optimization and strategy selection are not one-size-fits-all but tools tailored to investor preferences and risk tolerance.

Overall AI Involvement Summary

ChatGPT and Gemini were used as supportive tools for language editing, text refinement, methodological clarification, and improving the presentation of results. AI tools did not generate the research data, perform portfolio optimization, conduct statistical analyses, or determine the study conclusions. The author remains fully responsible for all analyses, interpretations, and the final content of the manuscript.

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