Available Online: 27 August 2026 DOI: 10.54254/3049-5768/2026.36374

State-dependent Bitcoin risk: evidence from portfolio analysis and option-implied skew

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Abstract. Bitcoin has become an increasingly important asset for portfolio allocation, yet its diversification value and option-implied information remain difficult to evaluate. This paper examines Bitcoin risk from portfolio and option-implied perspectives. This study assesses whether Bitcoin improves the risk-return opportunity set with traditional assets and whether its diversification role remains stable during market stress. Option-implied measures, including the 25-delta Risk Reversal (RR25), smile curvature, and an at-the-money Implied-Volatility-minus-Realized-Volatility (IV-minus-RV) proxy, are then constructed to predict market conditions. Portfolio analysis shows that Bitcoin can improve risk-return tradeoffs but does not function as a stable minimum-variance asset or a reliable crisis hedge. Baseline regressions provide limited evidence that RR25 consistently predicts future realized volatility or returns. However, extreme negative short-dated RR25 is followed by higher future realized volatility, suggesting RR25 is more informative as a nonlinear stress-state indicator than as a continuous forecasting variable. Smile curvature captures the implied-volatility surface but provides weaker predictive information. Finally, the IV-minus-RV analysis shows that gradual RR25-based exposure scaling achieves a better risk-adjusted profile than a binary exposure rule. Overall, the findings indicate that Bitcoin's diversification benefits and option-implied information are state-dependent.

Keywords: Bitcoin, cryptocurrency, portfolio diversification, option-implied volatility, Risk Reversal (RR25), risk management

1. Introduction

Bitcoin has become one of the most visible assets in cryptocurrency markets and is now studied as an investable asset that may affect portfolio construction, risk management, and market pricing. Prior research shows that cryptocurrency returns have their own risk-return patterns. Crypto-specific factors such as momentum, investor attention, size, and market-wide crypto risk help explain these returns [1, 2]. At the same time, Bitcoin is very different from traditional assets. Its price history contains sharp drawdowns, high volatility, and strong boom-and-bust cycles. These features make Bitcoin attractive to some investors, but also difficult to evaluate using standard asset-pricing tools.

A natural first question is whether Bitcoin deserves a place in a traditional investment portfolio. Prior work from an investor perspective shows that crypto assets can have low correlation with traditional risky assets in normal periods, but that this correlation may rise during left-tail market conditions [3]. This suggests that

Bitcoin's diversification role is conditional rather than stable. In the first part of the analysis, this study compares Bitcoin with traditional assets such as SPY, QQQ, GLD, and DXY. The results show that Bitcoin has high return potential, but also much higher volatility and larger drawdowns than traditional assets. Small Bitcoin allocations can improve some portfolio risk-return tradeoffs, but Bitcoin does not behave like a stable minimum-variance asset. Its diversification benefit can also weaken during systemic stress.

These findings motivate a deeper question. If Bitcoin is highly volatile and its diversification role changes across market states, then spot return data alone may not be enough to understand its risk. The Bitcoin options market may provide additional information. Option prices are forward-looking. Their prices can reflect hedging demand, speculation, volatility compensation, and information about the underlying asset. Prior equity-option studies show that option volume, option-implied volatility, and option-stock market discrepancies can contain information about future underlying returns or price pressure, although the exact mechanism may differ across settings [4-7].

In this paper, this study examines whether Bitcoin option-implied variables contain useful information about future volatility, future returns, and volatility risk premia. The main option-implied measure is the 25-delta risk reversal, or RR25, defined as the implied volatility of a 25-delta call minus the implied volatility of a 25-delta put. A negative RR25 means that put implied volatility is higher than call implied volatility, which is consistent with stronger demand for downside protection. Smile slope and curvature are also examined using quadratic fits of the implied volatility smile. In addition, this study examines an IV-minus-RV volatility-premium proxy based on the gap between at-the-money implied volatility and subsequent realized volatility.

The empirical analysis begins with the construction of Bitcoin option-implied skew. The raw option data contain trade-level observations with contract information embedded in the instrument name. Call and put options are first matched by date, strike, and maturity to create a basic call-put implied volatility skew measure. This raw skew measure is useful, but it is limited because strike-based comparisons can mix options with different economic meanings across time. To improve the construction, a delta-based RR25 measure is adopted. This follows a commonly used option-market approach of comparing implied volatility at fixed delta levels rather than fixed strikes. RR25 is constructed across short-, medium-, and longer-dated maturities, and later refine the measure using synthetic constant-maturity interpolation.

The empirical analysis ultimately shows that option-implied information becomes substantially more informative in nonlinear stress regimes than under standard full-sample linear specifications. Standard full-sample regressions of future realized volatility and returns on RR25 provide limited and unstable predictive evidence. However, option-implied information becomes more useful once the market enters extreme downside-skew regimes. In particular, bottom-decile short-dated RR25 and large negative rolling deviations from RR25's recent distribution are followed by higher future realized volatility. This contrast motivates the empirical design: the analysis first tests standard continuous linear models and then turns to decile-based and rolling z-score stress-state analyses. Return predictability is weaker and less stable, although some results suggest that extreme stress conditions may be followed by rebound or squeeze-like price behavior.

The shape of the Bitcoin implied volatility smile is also examined. Smile curvature is important because RR25 captures directional asymmetry, while curvature captures the convexity or thickness of the wings. The results show that Bitcoin options often contain strong positive curvature, especially at short maturities. This finding suggests that the market prices tail risk not only through downside skew, but also through a broader convex smile shape. However, curvature is weaker than RR25 as a predictive signal in the current analysis. Joint RR25-curvature bucket analysis also shows that curvature does not clearly strengthen the RR25 stress signal. In this sample, RR25 remains the cleaner short-horizon volatility-stress indicator.

Finally, this study examines the information content and risk-management applications. Prior research on Bitcoin volatility indices shows that Bitcoin options can be used to construct implied volatility measures and study Bitcoin variance risk premia across maturities [8]. Building on this literature, the IV-minus-RV results show that at-the-money implied volatility tends to exceed subsequent realized volatility on average. This is consistent with a positive volatility premium in Bitcoin options. The IV-minus-RV proxy shows that RR25 stress days are associated not only with higher subsequent realized volatility, but also with larger premium-proxy observations. This makes a binary zero-exposure filter too blunt: it reduces exposure to stress but also removes too much of the proxy premium. Gradual RR25-based scaling provides a stronger risk-adjusted profile by reducing exposure as RR25 becomes more negative rather than fully exiting during stress.

This paper contributes to the study of cryptocurrency markets in three ways. First, this paper adds to the asset-pricing view of Bitcoin by showing that Bitcoin's risk is state-dependent and cannot be fully understood from spot returns alone. Second, the results show that Bitcoin option-implied skew contains more information in nonlinear stress regimes than in simple full-sample linear regressions. Third, this paper connects option-implied signals to conditional risk management by showing that RR25 is more useful as a dynamic exposure-scaling variable than as a simple binary exposure filter.

2. Literature review

This paper connects four strands of research: cryptocurrency asset pricing, cryptocurrency market structure and data quality, option-implied information, and Bitcoin implied volatility and variance risk premia. These literatures help motivate why Bitcoin options may contain useful information about future volatility, tail risk, and risk-management decisions.

2.1. Cryptocurrency asset pricing and portfolio risk

A growing literature studies whether cryptocurrencies behave like traditional financial assets or whether they require their own asset-pricing framework. Liu and Tsyvinski [1] provide one of the main empirical studies in this area. They show that cryptocurrency returns are not strongly explained by traditional asset classes such as stocks, currencies, or commodities. They also find that momentum and investor attention help predict future cryptocurrency returns. This suggests that cryptocurrency markets have their own pricing structure rather than simply behaving like another form of equity, currency, or commodity exposure.

Liu et al. [2] extend this view by studying the cross section of cryptocurrency returns. They find that a three-factor model based on the cryptocurrency market, size, and momentum captures much of the cross-sectional variation in expected cryptocurrency returns. This result is important for this study because it shows that crypto assets can be studied using standard empirical asset-pricing tools, but the relevant risk factors are often specific to the crypto market.

From an investor perspective, Harvey et al. [3] discuss cryptocurrency as an investable asset class. They emphasize that crypto assets have historically been highly volatile and have experienced large drawdowns. They also note that crypto assets can have low correlation with traditional risky assets in normal periods, but that these correlations may rise during left-tail market conditions. This point is particularly relevant to the present study. Bitcoin may offer diversification benefits in some periods, but its risk profile can change during market stress.

Together, these studies provide the motivation for this study. Bitcoin is not simply a high-volatility version of a traditional asset. Its return behavior, risk exposure, and portfolio role are state-dependent. For that reason, spot returns alone may not fully capture the market's expectations about future risk. This motivates the use of

Bitcoin options, which may contain forward-looking information about volatility, downside risk, and tail events.

2.2. Cryptocurrency market structure and data quality

A second related literature studies the structure and reliability of cryptocurrency markets. This is important because crypto markets are more fragmented and less regulated than traditional equity markets. Makarov and Schoar [9] show that cryptocurrency markets can have large and recurrent arbitrage opportunities across exchanges. These price deviations are especially large across countries, which they connect to capital controls and limits to arbitrage. They also show that common signed volume explains a large share of Bitcoin returns, suggesting that order flow and market segmentation are important for crypto price formation.

Griffin and Shams [10] provide another cautionary view of cryptocurrency markets. They study whether Tether influenced Bitcoin and other cryptocurrency prices during the 2017 boom. Their evidence suggests that Tether purchases were timed after market downturns and were followed by sizable increases in Bitcoin prices. Although this paper is not directly about options, it highlights a broader concern for empirical crypto research: observed crypto prices can be affected by market structure, exchange behavior, and large flows.

Alexander and Dakos [11] focus more directly on data quality. They argue that many empirical cryptocurrency studies rely on questionable data sources, non-concurrent time series, or non-traded prices. Their paper is especially relevant for the present analysis because the option-implied variables depend heavily on contract-level data construction. If option observations are noisy, non-comparable across maturities, or incorrectly aggregated, the resulting skew and curvature measures may be misleading.

These studies guide the interpretation of the empirical evidence. If Bitcoin option signals predict future volatility or returns, the source of predictability may not be only private information. It may also reflect liquidity, hedging demand, limits to arbitrage, market segmentation, or data construction. For this reason, the results are interpreted as evidence that option-implied variables are useful state variables, rather than as evidence that option traders always possess superior information.

2.3. Option-implied information

A third strand of literature studies whether options contain information about future movements in the underlying asset. Pan and Poteshman [4] show that option trading volume contains information about future stock prices. Using put-call ratios based on buyer-initiated opening volume, they find that stocks with low put-call ratios outperform stocks with high put-call ratios over the next day and week. They interpret this evidence as consistent with informed trading in the options market.

An et al. [5] study the joint cross section of stocks and options. They show that changes in call and put implied volatilities help predict future stock returns. Their paper is useful for the present analysis because it treats implied volatility itself as an informative option-market variable. It also emphasizes that options are not redundant assets in markets with frictions, incomplete information, transaction costs, and short-sale constraints.

Hu [6] studies another channel through which option markets may convey information. The paper shows that option-induced stock order imbalance predicts future stock returns, while order imbalance unrelated to options has more temporary price impact. This suggests that option order flow can affect the underlying market through hedging and trading-pressure channels.

Ryu and Yang [12] provide additional evidence from index options. They examine option trading volume by investor type and trade type, and find that foreign investment firms' option trades significantly predict next-day spot returns. Their evidence is useful because it shows that option-market information can appear not only in individual equity options, but also in broader index option markets.

Goncalves-Pinto et al. [7] provide an important caution. They argue that option-price-based predictability does not always have to come from informed trading in options. It may also reflect price pressure in the stock market that is not fully reflected in option prices. This distinction matters for this study because it should not be claimed that Bitcoin option signals always reveal private information. A safer interpretation is that option-implied variables may reflect a combination of hedging demand, risk compensation, trading pressure, and expectations about future volatility.

However, most of this option-implied information literature is based on equity or index options. These markets are relatively mature and operate within a different institutional environment from cryptocurrency markets. Bitcoin options are linked to a market with continuous trading, fragmented exchanges, large retail participation, high leverage, and liquidation-driven price pressure. Therefore, it is not obvious that option-implied signals documented in equity markets should behave in the same way for Bitcoin. This paper contributes to addressing this gap by studying whether option-implied skew, smile curvature, and volatility premia contain useful information in a crypto-native options market.

This paper builds on this option-implied information literature by applying its insights to Bitcoin options. Instead of using equity option volume or stock-option price gaps, this study focuses on the shape of the Bitcoin implied volatility surface. The main variables are delta-based RR25 and smile curvature. RR25 captures the relative pricing of downside versus upside volatility, while curvature captures the thickness of the smile wings. These variables are used to test whether Bitcoin options contain useful forward-looking information about future volatility and returns.

2.4. Bitcoin implied volatility and variance risk premia

The final related literature studies implied volatility and variance risk premia. In traditional markets, implied volatility indices summarize information from option prices and are often used to measure market expectations about future volatility. Alexander and Imeraj [8] bring this idea directly to Bitcoin. They use high-frequency Deribit Bitcoin option prices to construct Bitcoin implied volatility indices with maturities from one week to three months. They also study Bitcoin variance risk premia using realized volatility measured at different frequencies.

Their paper shows that Bitcoin options can be used to construct volatility indices and study variance risk premia. It also connects Bitcoin volatility measures to similar measures for traditional assets, including U.S. equities, oil, gold, foreign exchange, and Treasury markets. This study provides a benchmark for the present analysis of forward-looking volatility information in Bitcoin options. The empirical design, however, relies on simpler option-implied measures.

This paper differs from Alexander and Imeraj [8] in two main ways. First, instead of constructing a full Bitcoin VIX using the model-free variance swap formula, this study focuses on simpler option-implied measures that can be constructed from the available dataset: ATM implied volatility, RR25, and quadratic smile curvature. Second, these measures are used not only to study volatility risk premia, but also to test whether skew and smile-shape variables help identify nonlinear stress regimes. This approach connects Bitcoin implied volatility to both predictive analysis and practical risk management.

2.5. Position of this paper

Overall, this paper sits between cryptocurrency asset pricing and option-implied information. The crypto asset-pricing literature shows that Bitcoin and other cryptocurrencies have distinct risk-return behavior. The market structure and data-quality literature highlights the need to interpret crypto prices and signals carefully because of fragmentation, liquidity conditions, leverage, and data concerns. The option-implied information literature shows that option markets can contain information about the underlying asset, but most of this evidence comes from equity and index options. The Bitcoin volatility literature shows that Bitcoin options can be used to study implied volatility and variance risk premia, but there is still room to examine how skew, curvature, and IV-minus-RV measures behave as practical stress and risk-management variables in a crypto-native setting.

The contribution of this paper is to integrate these ideas within a simple empirical framework. This study constructs Bitcoin option-implied skew and smile-shape variables, tests their predictive power for future volatility and returns, and evaluates their use in managing exposure to an IV-minus-RV premium proxy. The key idea, developed from the preceding literatures, is that Bitcoin option signals may be more useful in nonlinear stress regimes than in simple full-sample linear regressions. Accordingly, this analysis focuses not only on average predictive regressions, but also on extreme RR25 regimes, rolling z-score deviations, smile curvature, joint RR25-curvature bucket analysis, and dynamic exposure scaling. In doing so, the results demonstrate how option-implied information can be adapted to a market where volatility, leverage, and liquidation risk are central features.

3. Data and variable construction

This section describes the data and variable construction used throughout the empirical analysis. The analysis combines three layers of data. The first layer uses Bitcoin and traditional asset price data to compare Bitcoin with SPY, QQQ, GLD, and DXY in a portfolio setting. The second layer uses daily return data to study extreme price-movement overlap, crisis-period behavior, and whether Bitcoin's diversification role weakens during systemic stress. The third layer uses Bitcoin options data to construct option-implied measures of skew, smile shape, and volatility premia.

Spot and benchmark asset data are first used to evaluate Bitcoin's portfolio role. Tail-event and crisis-window measures are then used to examine whether Bitcoin's diversification role changes across market states. Finally, Bitcoin options data are used to construct derivative-market variables, including RR25, smile curvature, and ATM implied volatility.

3.1. Data sources and sample construction

The empirical analysis combines Bitcoin price data, traditional asset price data, and Bitcoin options data. The spot-portfolio analysis uses Bitcoin together with SPY, QQQ, GLD, and DXY, which represent broad U.S. equities, technology-oriented equities, gold, and the U.S. dollar. The initial asset-comparison exercise uses daily returns from June 21, 2023, to June 21, 2024. These data provide the inputs for the asset-level comparison and mean-variance portfolio analysis. Fixed-weight SPY-BTC allocations are also examined as a transparent comparison alongside the optimized portfolio exercises.

The second data block extends the analysis to longer historical samples and crisis-state behavior. For the extreme-event analysis, daily data from December 1, 2018, to June 21, 2024 are used, and major price-movement days are defined using a 95% tail threshold. This provides a measure of how often Bitcoin tail events overlap with SPY and QQQ tail events. The COVID crisis window from February 1, 2020, to May 31, 2020 is also examined as a focused systemic-stress period. These tests provide the crisis-state measures used before the option-implied analysis. The portfolio-management block also uses monthly returns for the in-sample and walk-forward GMV analyses. Monthly returns are constructed from month-end prices, and walk-forward portfolio weights are estimated using only information available before each holding period.

The third data block consists of Bitcoin options data. The option dataset contains contract-level information such as trading date, option type, strike price, expiration date, implied volatility, and the underlying Bitcoin price. These fields are used to construct option-implied variables including delta-based RR25, at-the-money implied volatility, smile slope, smile curvature, and an IV-minus-RV volatility-premium proxy. This options block extends the spot and portfolio evidence by introducing derivative-market variables used in the later stress, tail-risk, and volatility-premium tests.

3.2. Spot return, portfolio, and benchmark variables

The first part of the empirical analysis uses spot price data to construct asset-level return and risk measures. For each asset, simple returns are computed from price changes. In the initial daily analysis, the sample runs from June 21, 2023, to June 21, 2024 and includes Bitcoin, SPY, QQQ, GLD, and DXY. These assets are used to compare Bitcoin with traditional market exposures and to evaluate whether Bitcoin changes the risk-return opportunity set when added to a traditional portfolio.

Each asset is summarized using annualized return, annualized volatility, Sharpe ratio, maximum drawdown, skewness, and kurtosis. These statistics provide a comparison of Bitcoin's standalone return potential with its standalone risk and place Bitcoin alongside traditional benchmark assets using the same performance measures. They also provide the baseline inputs for the portfolio analysis.

To study portfolio effects, the mean return vector and covariance matrix are constructed from the daily return series. These inputs summarize expected returns, volatility, and cross-asset comovement. These inputs are then used to construct mean-variance efficient frontiers. The efficient-frontier analysis compares portfolios with and without Bitcoin under long-only, fully invested constraints. This setup allows an assessment of whether adding Bitcoin changes the feasible risk-return set relative to portfolios constructed only from traditional benchmark assets.

The global minimum-variance portfolio is also examined. This portfolio is useful because it focuses only on risk minimization rather than return maximization. Under the same long-only and fully invested constraints, the GMV exercise provides a test of whether Bitcoin contributes to the lowest-risk portfolio or whether its role is mainly outside the pure minimum-variance setting.

In addition to optimized portfolios, fixed-weight SPY-BTC allocation tests are used. These portfolios are fully invested and long-only, and they compare different Bitcoin allocations within a traditional equity portfolio. The reported performance metrics include annual return, annual volatility, Sharpe ratio, and maximum drawdown. This exercise provides a simple comparison alongside the optimized portfolio tests. It evaluates Bitcoin allocations without relying entirely on estimated optimal weights.

For the later portfolio-management analysis, monthly returns constructed from month-end prices are used. The in-sample GMV analysis covers December 1, 2018, to June 21, 2024 and uses 66 monthly return observations. Portfolio weights are chosen to minimize variance subject to full-investment and long-only constraints. This exercise provides a longer-horizon comparison of minimum-variance portfolio weights and performance using monthly data.

An out-of-sample walk-forward GMV test is also conducted using monthly asset returns from January 2019 to June 2024. The initial estimation window is 2019, and out-of-sample evaluation begins in January 2020. At each rebalance date, the covariance matrix is estimated using only historical data available up to the previous period end, the long-only GMV portfolio is constructed, and the optimized weights are applied to the next holding period. Yearly, quarterly, and monthly rebalancing frequencies are tested. This design helps evaluate whether the in-sample portfolio results translate into a more realistic out-of-sample setting.

These variables establish the paper's first empirical layer: Bitcoin's role in asset-level comparison, efficient-frontier analysis, fixed-weight allocations, and minimum-variance portfolios.

3.3. Extreme-event and crisis-state measures

After constructing the spot-return and portfolio variables, the analysis examines whether Bitcoin's diversification role changes during stress periods. This distinction is important because average correlations and portfolio statistics may hide state-dependent behavior. The analysis first examines extreme price-movement overlap between Bitcoin and equity benchmarks. The sample period for this analysis is December 1, 2018, to June 21, 2024. Extreme movement days are defined using a 95% tail threshold and Bitcoin's extreme days are then compared with the corresponding extreme days for SPY and QQQ. This construction allows an assessment of whether Bitcoin tail events are mostly idiosyncratic or whether they tend to overlap with equity-market stress.

The direction of overlapping extreme events is also examined. This step is important because overlap alone does not distinguish between hedging behavior and same-direction stress. If Bitcoin and equity benchmarks experience extreme movements on the same day, the sign of those movements helps indicate whether Bitcoin behaves more like a diversifier or more like a risk asset during tail periods.

The COVID crisis window from February 1, 2020, to May 31, 2020 is then examined. This window provides a focused stress-period setting for comparing Bitcoin with traditional assets during a major market-wide shock. This crisis window is used to examine whether Bitcoin behaves more like a diversifying asset or more like a risk asset when broader financial markets are under stress. These crisis-state measures connect the portfolio analysis to the option-implied analysis. They examine whether Bitcoin's portfolio role changes during stress before the paper turns to option-implied variables such as RR25, smile curvature, and ATM implied volatility.

3.4. Bitcoin options data and cleaning

The next part of the analysis uses Bitcoin options data to construct forward-looking measures of skew, smile shape, and volatility premia. The option dataset contains contract-level observations with information on trading date, option type, strike price, expiration date, implied volatility, and the underlying Bitcoin price. These fields allow each option contract to be identified by maturity, moneyness, and call or put status.

The first step is to aggregate raw option observations to the daily contract level. For each contract and trading date, the daily median implied volatility is computed. The median is used to reduce the influence of noisy or extreme intraday observations and to obtain a cleaner daily implied-volatility input for later skew and smile construction.

One central challenge is that Bitcoin option contracts are not directly comparable across strikes and expiration dates. On the same trading date, contracts may differ in time to expiration, moneyness, liquidity, and distance from the current Bitcoin price. A raw comparison of call and put implied volatility at the same strike may therefore mix several effects at once. For this reason, the analysis moves from a basic strike-based skew measure to a delta-based construction. Delta-based construction compares implied volatility at economically comparable points of the option surface, such as the 25-delta call, 25-delta put, and near-ATM option.

This data concern is also consistent with the broader cryptocurrency literature. Alexander and Dakos [11] emphasize that empirical cryptocurrency results can be sensitive to data sources and measurement choices. In the present setting, this issue is especially relevant because option-implied variables require additional construction beyond raw price returns. The reliability of the RR25 and curvature measures depends on careful aggregation, maturity matching, and delta-based interpolation.

3.5. Delta-based RR25 and synthetic tenor construction

The main option-implied skew variable in this paper is the 25-delta risk reversal, or RR25, defined in Equation (1) as the implied volatility of a 25-delta call minus the implied volatility of a 25-delta put:

$$RR25_{t,T} = IV_{t,T}^{25\Delta Call} - IV_{t,T}^{25\Delta Put} \tag{1}$$

where t denotes the trading date and T denotes the target maturity. $IV_{t,T}^{25\Delta Call}$ is the implied volatility of the 25-delta call, and $IV_{t,T}^{25\Delta Put}$ is the implied volatility of the 25-delta put. A negative RR25 means that put implied volatility exceeds call implied volatility, which is consistent with stronger relative pricing of downside protection. A positive RR25 means that call implied volatility exceeds put implied volatility, which is consistent with stronger relative pricing of upside exposure.

A delta-based measure is used because strike-based comparisons can be misleading when the Bitcoin price changes substantially over time. A fixed strike may be close to at-the-money on one date but far out-of-the-money on another date. Delta therefore provides a more comparable measure of option moneyness across dates. By comparing 25-delta calls and 25-delta puts, RR25 measures the relative pricing of upside and downside volatility at comparable points of the option surface.

To construct RR25, daily median implied volatility is first computed for each option contract. The strike-based option grid is then converted into a delta-based grid using Black-Scholes delta. For each trading date and maturity, implied volatility is interpolated at three points: the 25-delta call, the 25-delta put, and the near-at-the-money option. The RR25 measure is then constructed as the difference between the interpolated 25-delta call implied volatility and the interpolated 25-delta put implied volatility. This construction defines skew at constant delta rather than constant strike.

RR25 is constructed across three target maturities: 7 days, 30 days, and 90 days. These tenors capture short-, medium-, and longer-horizon option-market conditions. In the first maturity-specific construction, the nearest available expiry is selected for each target tenor on each trading date. This provides an approximate constant-maturity series.

Because nearest-expiry matching can introduce roll-related jumps, the maturity construction is later refined using synthetic constant-maturity interpolation. For each date, delta-based implied volatility is first constructed at each available expiry. Linear interpolation is then performed across the two nearest expiries to build synthetic 7-day, 30-day, and 90-day tenors. This produces smoother and more comparable RR25 series across time, while preserving the main term-structure pattern from the nearest-expiry construction.

The synthetic-tenor construction improves coverage, especially for the 30-day and 90-day series, and provides a standardized RR25 measure across time and maturities. The synthetic-tenor series is used in the refined predictive tests, nonlinear stress-regime analysis, and subsequent IV-minus-RV exposure analysis.

3.6. Realized volatility, future returns, smile curvature, and the IV-minus-RV proxy

After constructing RR25, the main outcome variables used in the predictive tests are defined. The first outcome is future Bitcoin return. Forward BTC returns are computed over short horizons, including 1-day, 5-day, and 10-day horizons. These forward returns are used to test whether option-implied skew contains information about subsequent directional price movements.

The second outcome is future realized volatility. Future realized volatility is used to measure the magnitude of subsequent Bitcoin price movement over short horizons. This variable is used to test whether option-implied skew is related to subsequent volatility conditions. In the empirical tests, future realized volatility is matched to the corresponding RR25 observation date and then compared across normal and stress-signal regimes.

In addition to RR25, the shape of the Bitcoin implied volatility smile is also examined. For each date with sufficient option coverage, log-moneyness is defined in Equation (2):

$$x = \ln\left(\frac{K}{S}\right) \tag{2}$$

where K is the option strike price, and S is the underlying Bitcoin price. The daily implied-volatility smile is then fitted according to Equation (3):

$$IV_t = a_t + b_t x + c_t x^2 \tag{3}$$

In this specification, b_t captures the slope of the smile, while c_t captures smile curvature. The slope measures directional asymmetry in the smile, while the curvature term measures the convexity of the smile wings. A larger positive curvature coefficient indicates a more convex implied-volatility smile. In the empirical analysis, these smile-shape variables are used to test whether curvature adds information beyond RR25.

The final option-implied variable is an IV-minus-RV volatility-premium proxy, defined in Equation (4) as the difference between at-the-money implied volatility and subsequent realized volatility:

$$VRP_{t,T} = ATMIV_{t,T} - RV_{t,T}^{future} \tag{4}$$

where $ATMIV_{t,T}$ is the at-the-money implied volatility on date t for tenor T, and $RV_{t,T}^{future}$ is the realized volatility over the matched future horizon. A positive value means that implied volatility exceeds subsequent realized volatility. In the first-pass comparison, the 7-day tenor is matched to 5-day future realized volatility, while the 30-day and 90-day tenors are matched to 10-day future realized volatility.

This IV-minus-RV measure should be interpreted carefully. It is an end-of-day implied-volatility-minus-realized-volatility proxy, not a full margin-aware option P&L backtest. It does not capture intraday margin spikes, liquidation risk, bid-ask spreads, contract rollover, collateral constraints, or full option-leg profits and losses. The purpose of the proxy is more limited: to compare implied volatility with subsequent realized volatility and to evaluate whether RR25-based stress signals affect the profile of a simple proxy exposure rule.

4. Empirical results

This section presents the empirical results in three stages. The first stage evaluates Bitcoin's role in a traditional portfolio and examines whether its diversification properties remain stable during extreme events and systemic stress. The second stage turns to the forward-looking information contained in Bitcoin options, beginning with baseline RR25 predictive regressions and subsequently examining nonlinear stress regimes and smile curvature. Finally, the third stage evaluates the use of option-implied signals in a volatility-premium proxy risk-management framework.

4.1. Bitcoin in a traditional portfolio

Bitcoin is first compared with SPY, QQQ, GLD, and DXY over the daily sample from June 21, 2023, to June 21, 2024. Table 1 reports annualized return, annualized volatility, Sharpe ratio, skewness, kurtosis, and maximum drawdown for each asset.

Table 1. Asset-level summary statistics

Asset	Annualized Return	Annualized Volatility	Sharpe Ratio	Skewness	Kurtosis	Maximum Drawdown
SPY	0.2449	0.1121	2.19	-0.13	0.04	-0.0997
QQQ	0.3004	0.1564	1.92	-0.14	-0.07	-0.1078
GLD	0.1883	0.1328	1.42	-0.18	1.91	-0.0808
DXY	0.0376	0.0593	0.64	-0.28	1.16	-0.0562
BTC	0.8757	0.4831	1.81	0.58	1.67	-0.2027

Note: This table reports annualized return, annualized volatility, Sharpe ratio, skewness, kurtosis, and maximum drawdown based on daily returns from June 21, 2023, to June 21, 2024.

The summary statistics highlight the central tradeoff associated with Bitcoin. Bitcoin has the highest annualized return in the sample, at 87.57%, but it also has by far the highest annualized volatility, at 48.31%, and the largest maximum drawdown, at approximately 20.27%. In contrast, SPY has the highest standalone Sharpe ratio, while the traditional assets generally exhibit lower volatility and smaller drawdowns.

Bitcoin's return distribution also differs from that of traditional assets. BTC is the only asset in the sample with clearly positive skewness, which is consistent with greater upside asymmetry. Its positive excess kurtosis also indicates a return distribution with heavier tails than a normal distribution. These results suggest that Bitcoin's standalone attractiveness comes from high return potential rather than defensive characteristics. Its portfolio value must therefore depend on whether its imperfect comovement with traditional assets is sufficient to improve the broader risk-return opportunity set. Figure 1 compares long-only, fully invested mean-variance efficient frontiers constructed with and without Bitcoin.

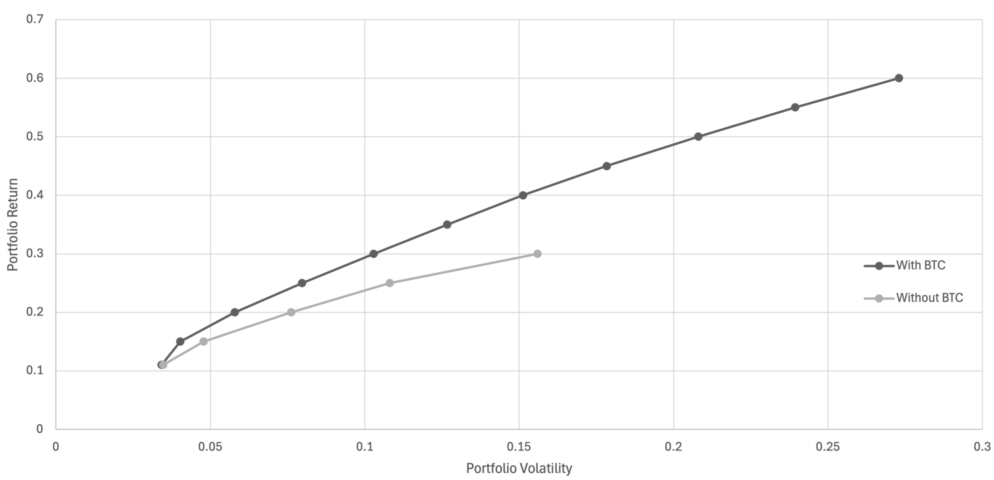

Figure 1. Mean-variance efficient frontiers with and without Bitcoin

Note: This figure compares long-only, fully invested mean-variance efficient frontiers constructed with and without Bitcoin using daily returns from June 21, 2023, to June 21, 2024. Portfolio volatility is shown on the horizontal axis, and expected portfolio return is shown on the vertical axis.

The efficient-frontier comparison shows that including Bitcoin expands the attainable risk-return opportunity set. Over much of the overlapping range, the portfolio universe with Bitcoin offers either a higher expected return for a given level of volatility or a lower level of volatility for a given target return. Under the long-only constraint, the portfolio without Bitcoin also becomes infeasible beyond approximately 30% expected return, while the portfolio including Bitcoin remains feasible at higher return levels.

However, the benefit is not uniform across the frontier. Near the minimum-variance region, the two frontiers are relatively close, indicating that Bitcoin contributes less when the objective is primarily to minimize volatility. Its main contribution appears at higher target-return levels, where Bitcoin allows investors to reach return combinations that are unavailable using only the traditional assets. The efficient-frontier evidence therefore suggests that Bitcoin broadens the investment opportunity set, but does not function as a conventional low-risk hedge.

This tradeoff is examined more directly in Table 2 by comparing a SPY-only portfolio with fixed-weight portfolios containing Bitcoin allocations ranging from 5% to 20%. Unlike the optimized frontier, this exercise does not rely on estimated optimal weights and therefore provides a more transparent assessment of how modest Bitcoin allocations affect portfolio performance.

Table 2. Fixed-weight SPY–BTC allocation results

Portfolio	SPY Weight	BTC Weight	Annualized Return	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
100% SPY	1.00	0.00	0.2449	0.1121	2.19	-0.0997
95% SPY 5% BTC	0.95	0.05	0.2765	0.1130	2.45	-0.0874
90% SPY 10% BTC	0.90	0.10	0.3080	0.1188	2.59	-0.0751
85% SPY 15% BTC	0.85	0.15	0.3395	0.1289	2.64	-0.0729
80% SPY 20% BTC	0.80	0.20	0.3711	0.1422	2.61	-0.0739

Note: This table reports the performance of fixed-weight SPY–BTC portfolios using daily returns from June 21, 2023, to June 21, 2024. All portfolios are fully invested and long-only.

The fixed-weight results provide a clearer view of how Bitcoin affects a conventional equity portfolio. Adding Bitcoin increases both annualized return and volatility, while the Sharpe ratio improves over most of the allocation range considered. The Sharpe ratio rises from 2.19 for the SPY-only portfolio to 2.64 at the 15% Bitcoin allocation, before declining slightly to 2.61 at the 20% allocation.

Maximum drawdown also improves relative to the SPY-only benchmark across all four Bitcoin allocations in this sample. The improvement is strongest around the 15% allocation, although the differences among the 10%, 15%, and 20% portfolios are relatively small. These results suggest that modest Bitcoin allocations can improve the risk-adjusted performance of a traditional equity portfolio, but the gains are not monotonic. As the

Bitcoin weight rises, portfolio volatility becomes more visible and the marginal improvement in the Sharpe ratio begins to diminish.

The fixed-weight evidence is therefore consistent with the efficient-frontier results. Bitcoin can improve the broader risk-return tradeoff, but its contribution depends on the size of the allocation and does not imply that Bitcoin is inherently a low-risk asset.

The analysis next examines whether Bitcoin is selected when the portfolio objective is restricted to variance minimization. In the initial daily-sample GMV exercise, Bitcoin receives a weight of only approximately 0.8%, suggesting that its contribution at the minimum-variance point is economically negligible. The analysis is therefore repeated using the longer monthly sample, with the results evaluated both in sample and through a walk-forward design. Table 3 presents the corresponding GMV results.

Table 3. Global minimum-variance portfolio results

Panel A. In-sample GMV portfolio weights					
Portfolio	SPY	QQQ	GLD	DXY	BTC
Traditional GMV	0.087	0.000	0.323	0.590	—
With-Bitcoin GMV	0.087	0.000	0.317	0.597	0.000

Panel B. Out-of-sample walk-forward GMV performance				
Strategy	Annualized Return	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
Traditional GMV—Yearly	0.0626	0.0415	1.508	-0.0423
With-Bitcoin GMV—Yearly	0.0594	0.0394	1.510	-0.0381
Traditional GMV—Quarterly	0.0584	0.0415	1.407	-0.0572
With-Bitcoin GMV—Quarterly	0.0577	0.0408	1.416	-0.0564
Traditional GMV—Monthly	0.0581	0.0411	1.412	-0.0533
With-Bitcoin GMV—Monthly	0.0578	0.0405	1.429	-0.0519

Note: Panel A reports long-only, fully invested GMV portfolio weights estimated from 66 monthly return observations between December 2018 and June 2024. Panel B reports out-of-sample performance from January 2020 to June 2024. At each rebalance date, the covariance matrix is estimated using only information available through the previous period.

The in-sample results reinforce the distinction between Bitcoin's broader portfolio value and its role at the minimum-variance point. In the longer monthly sample, Bitcoin receives zero weight in the long-only GMV portfolio. The optimized portfolios remain concentrated in DXY and GLD, while QQQ also receives zero weight. This suggests that, given Bitcoin's volatility and covariance with the other assets in this sample, it does not become a meaningful holding when the objective is limited to minimizing variance.

The walk-forward results are more nuanced. Allowing Bitcoin into the investment universe produces small improvements in volatility, Sharpe ratio, and maximum drawdown across the yearly, quarterly, and monthly specifications, although annualized returns are slightly lower. For example, under yearly rebalancing, the Sharpe ratio rises only marginally from 1.508 to 1.510, while maximum drawdown improves from 4.23% to 3.81%. The monthly specification shows a somewhat larger Sharpe-ratio improvement, from 1.412 to 1.429, but the economic magnitude remains modest.

More frequent portfolio re-estimation does not improve performance consistently. The yearly strategies achieve the strongest Sharpe ratios, suggesting that frequent covariance re-estimation may add noise rather than materially improve allocation decisions in this sample. Overall, the GMV evidence indicates that Bitcoin is not a dominant minimum-variance holding. Its contribution is small and appears mainly through modest diversification effects rather than through a substantial positive portfolio weight.

Taken together, the results in this subsection show that Bitcoin can expand the feasible opportunity set and improve selected fixed-weight portfolio outcomes, but it does not behave as a stable low-risk asset. This distinction motivates the next analysis, which examines whether Bitcoin's diversification role changes during extreme events and periods of systemic stress.

4.2. Tail events and crisis-state diversification

The portfolio evidence in Section 4.1 suggests that Bitcoin can improve selected risk-return tradeoffs, but these average portfolio results do not reveal whether its diversification role remains stable during periods of market stress. The analysis therefore examines the overlap between Bitcoin's extreme price movements and those of SPY and QQQ over the longer daily sample from December 1, 2018, to June 21, 2024.

Table 4 reports the frequency with which Bitcoin's extreme-movement days coincide with extreme-movement days in the two equity benchmarks. Extreme days are defined using the 95th percentile of absolute daily returns for each asset, which produces 70 extreme observations per asset over the sample.

Table 4. Extreme tail-event overlap between Bitcoin and equity benchmarks

Pair	BTC Extreme Days	Equity Extreme Days	Overlapping Extreme Days	Overlap Rate
BTC–SPY	70	70	13	18.6%
BTC–QQQ	70	70	13	18.6%

Note: Extreme-event days are defined using the top 5% of absolute daily returns for each asset over the sample from December 1, 2018, to June 21, 2024. The overlap rate is calculated as the number of overlapping extreme days divided by the number of Bitcoin extreme days.

The overlap results show that most extreme Bitcoin movements do not occur on the same days as extreme movements in the equity benchmarks. Only 13 of the 70 Bitcoin extreme days overlap with SPY extreme days, and the same number overlap with QQQ extreme days, producing an overlap rate of approximately 18.6% in both cases. These results indicate that the majority of Bitcoin's largest price movements are idiosyncratic rather than directly synchronized with equity-market tail events.

Table 5. Direction of overlapping Bitcoin–equity extreme events

Direction	Number of Days	Share of Overlapping Days
Same direction	11	84.6%
Opposite direction	2	15.4%
Total	13	100.0%

Note: The table summarizes the direction of returns on the 13 overlapping Bitcoin–equity extreme-event days identified using the 95% absolute-return threshold. "Same direction" indicates that Bitcoin and the equity benchmark involved in the overlapping event both increased or both decreased on that day.

On its own, this relatively low overlap is consistent with a diversification interpretation. Many of Bitcoin's extreme movements do not coincide with the largest movements in traditional equity markets, which is consistent with the importance of idiosyncratic or crypto-specific shocks. However, overlap frequency alone does not reveal whether Bitcoin hedges equity risk when common shocks do occur. To evaluate that question, the analysis next examines the direction of Bitcoin and equity returns on the overlapping extreme-event days. Table 5 reports whether Bitcoin and the equity benchmarks move in the same or opposite direction on the overlapping extreme-event days.

The directional evidence qualifies this diversification interpretation from Table 4. Although Bitcoin extreme events overlap with equity extreme events relatively infrequently, the overlapping episodes are overwhelmingly same-direction events. Eleven of the 13 overlapping days, or 84.6%, involve Bitcoin and the relevant equity benchmark moving in the same direction.

This suggests that Bitcoin's largest shocks are usually idiosyncratic, but when Bitcoin and equities experience extreme movements at the same time, Bitcoin rarely provides offsetting returns. Instead, it tends to participate in the broader risk-on or risk-off movement. The distinction is therefore important: low tail-event overlap may provide diversification across many episodes, but Bitcoin does not provide reliable downside protection when a common shock affects both markets.

To examine Bitcoin's behavior during a clearly systemic market shock, the analysis next focuses on the COVID crisis window from February 1, 2020, to May 31, 2020. Table 6 reports cumulative asset returns and crisis-period correlations.

Table 6. Bitcoin and traditional assets during the COVID crisis window

Panel A. Cumulative returns	
Asset	Cumulative Return
SPY	-0.0486
QQQ	0.0675
GLD	0.0909
DXY	0.0098
BTC	0.0089
Panel B. Bitcoin correlations with traditional assets	
Asset	Correlation with BTC
SPY	0.50
QQQ	0.50
GLD	0.29
DXY	0.10

Note: The table reports cumulative returns and daily-return correlations over the COVID crisis window from February 1, 2020, to May 31, 2020.

The COVID-window results provide a more direct test of Bitcoin's behavior during systemic stress. Over the full window, Bitcoin's cumulative return is approximately flat, while SPY records a negative cumulative return and QQQ and GLD record positive cumulative returns. However, the full-window cumulative results conceal substantial within-period volatility, including the sharp market decline in March and the subsequent recovery.

More importantly, Bitcoin's daily returns are moderately correlated with both SPY and QQQ during the crisis window, with correlations of approximately 0.50. Its correlations with GLD and DXY are considerably lower. This pattern indicates that Bitcoin behaves more like a risky asset than a defensive hedge during the COVID crisis window. Although its cumulative return had recovered by the end of the period, its contemporaneous comovement with equities reduces its diversification value during systemic stress.

Taken together, the tail-event and COVID evidence suggests that Bitcoin's diversification role is conditional. Most extreme Bitcoin price shocks do not coincide with equity tail events, but when systemic stress affects both markets, Bitcoin usually moves in the same direction as equities. Average portfolio statistics therefore do not fully capture how Bitcoin's risk characteristics change across market states.

Historical spot-return evidence shows that Bitcoin's diversification role changes during extreme and systemic events, but it does not provide a forward-looking measure of when these risk states are developing. This limitation motivates the use of Bitcoin options, whose implied-volatility surface may embed market expectations about future downside risk and volatility. The analysis therefore turns next to RR25 and tests whether option-implied skew predicts subsequent realized volatility and Bitcoin returns.

4.3. Baseline RR25 predictive tests

Table 7. Baseline RR25 predictive regression results

Panel A. RR25 and future realized volatility					
RR25 Tenor	Horizon	RR25 Coefficient	*t*-Statistic	*p*-Value	R^2
7-day	1-day	0.2201	0.47	0.635	0.001
7-day	5-day	-0.3355	-1.14	0.255	0.006
7-day	10-day	-0.1170	-0.52	0.606	0.001
30-day	1-day	0.0105	0.02	0.984	0.000
30-day	5-day	0.6642	0.91	0.364	0.014
30-day	10-day	0.9356	1.37	0.172	0.034
90-day	1-day	-0.1671	-0.17	0.866	0.000
90-day	5-day	1.2382	1.28	0.201	0.021
90-day	10-day	1.3839	1.48	0.140	0.036
Panel B. RR25 and future Bitcoin returns					
RR25 Tenor	Horizon	RR25 Coefficient	*t*-Statistic	*p*-Value	R^2
7-day	1-day	0.0334	1.14	0.255	0.006
7-day	5-day	0.0089	0.13	0.895	0.000
7-day	10-day	-0.1208	-1.16	0.247	0.006
30-day	1-day	0.0273	0.78	0.436	0.002
30-day	5-day	-0.0652	-0.55	0.581	0.002
30-day	10-day	-0.3213	-1.67	0.095	0.020
90-day	1-day	0.0793	1.33	0.184	0.008
90-day	5-day	0.1669	1.08	0.279	0.008
90-day	10-day	0.2630	0.93	0.354	0.010

Note: Panel A reports regressions of future realized volatility on current RR25, and Panel B reports regressions of future Bitcoin returns on current RR25. Regressions are estimated separately by tenor and forecast horizon using daily observations and HAC (Newey–West) standard errors. The detailed coefficients shown here are based on the baseline nearest-expiry RR25 construction.

The option analysis begins with a set of baseline full-sample predictive regressions. For each tenor, future realized volatility and future Bitcoin returns are separately regressed on the current RR25 level. The analysis considers 7-day, 30-day, and 90-day RR25, with future outcomes measured over 1-day, 5-day, and 10-day horizons. All regressions use daily observations and HAC (Newey–West) standard errors. Table 7 reports the estimated RR25 coefficient, *t*-statistic, *p*-value, and *R*-squared for each specification. The detailed baseline results obtained from the nearest-expiry construction are reported first, followed by an assessment of whether the conclusions change after moving to synthetic constant-maturity RR25.

The results in Table7, Panel A provide limited evidence that RR25 linearly predicts future realized volatility. The 7-day RR25 coefficients are negative at the 5-day and 10-day horizons, which is directionally consistent with the hypothesis that more negative short-dated skew is followed by higher future volatility. However, neither estimate is statistically significant. The 30-day and 90-day specifications produce mostly positive coefficients, and none of the volatility regressions is statistically significant at conventional levels. The low R-squared values further indicate that RR25 levels explain only a small fraction of the variation in subsequent realized volatility.

The return regressions in Table 7, Panel B are similarly weak. Most coefficient estimates are statistically insignificant and unstable in sign across maturities and horizons. The most notable result is the 30-day RR25 coefficient for the 10-day future return, which is negative and marginally significant at the 10% level. This estimate suggests that a more negative 30-day skew may be associated with higher subsequent returns given the RR25 sign convention. However, the relation is not robust across the other maturities or forecast horizons and should therefore be interpreted cautiously.

The synthetic constant-maturity refinement does not materially change the qualitative conclusion. Re-estimating the baseline relationships using synthetic 7-day, 30-day, and 90-day RR25 reduces roll-related noise and improves maturity comparability, but the full-sample linear relationships remain weak. Negative volatility coefficients continue to appear mainly in the short-dated series, while most return and volatility estimates remain statistically insignificant.

Overall, the baseline evidence does not support RR25 as a stable linear forecasting variable. This does not necessarily imply that option-implied skew is uninformative. Instead, its information content may be concentrated in unusually negative or unusually large deviations rather than operating uniformly across average market conditions. The analysis next examines bottom-decile RR25 regimes and large deviations from RR25's recent rolling distribution.

4.4. Nonlinear RR25 stress signals

The weak full-sample regressions in Section 4.3 suggest that the information content of RR25 may not operate continuously across average market conditions. The analysis therefore tests whether short-dated RR25 becomes most informative when downside skew reaches unusually extreme levels. The analysis focuses on the synthetic 7-day RR25 series because the baseline results in Table 7 show the strongest evidence that short-dated RR25 is the most informative candidate for nonlinear analysis.

An extreme negative-skew regime is first defined as days when 7-day RR25 falls within the bottom 10% of its sample distribution. The 10% threshold is intended to isolate sufficiently rare stress observations while retaining enough observations for reliable statistical comparisons. Table 8 compares future realized volatility and Bitcoin returns following these extreme-skew days with the corresponding outcomes during the rest of the sample.

The results in Table 8, Panel A show that future realized volatility is materially higher following extreme negative-skew days. The difference is positive and statistically significant at the 5% level across all three horizons. The effect is largest at the 1-day horizon, where future realized volatility is 0.2922 higher in the extreme regime, and remains economically and statistically meaningful over the 5-day and 10-day horizons.

Table 8. Extreme negative 7-day RR25 regime results

Panel A. Future realized volatility					
Horizon	Mean: Extreme Regime	Mean: Normal Regime	Difference	*t*-Statistic	*p*-Value
1-day	0.7544	0.4622	0.2922	3.45	< 0.001
5-day	0.7913	0.5647	0.2266	3.19	0.0014
10-day	0.7448	0.6015	0.1433	2.45	0.0144
Panel B. Future Bitcoin returns					
Horizon	Mean: Extreme Regime	Mean: Normal Regime	Difference	t-Statistic	*p*-Value
1-day	0.0078	-0.0007	0.0085	1.57	0.1166
5-day	0.0371	-0.0038	0.0409	2.20	0.0281
10-day	0.0587	0.0033	0.0554	1.85	0.0639

Note: The extreme regime is defined as observations in the bottom decile of the synthetic 7-day RR25 distribution. Future realized volatility is expressed in annualized decimal units, and future Bitcoin returns are expressed in decimal form. Differences are calculated as the extreme-regime mean minus the normal-regime mean. The reported t-statistics and p-values are based on dummy-regression comparisons between the two regimes. *p*-values below 0.001 are reported as < 0.001.

Economically, this pattern is consistent with short-dated option skew capturing stress-specific demand for downside protection. When leverage is concentrated and margin pressure rises, market participants may bid up near-term put implied volatility relative to call implied volatility. Extremely negative 7-day RR25 therefore identifies states in which downside hedging demand, liquidation risk, and near-term uncertainty are elevated. This may help explain why the bottom-decile signal predicts future realized volatility more clearly than the full-sample linear specification. Rather than providing a stable signal across the full RR25 distribution, short-dated skew becomes informative when it enters the lower tail. Extreme negative RR25 therefore behaves more like a nonlinear stress-state indicator than a constant forecasting variable.

The return results in Table 8, Panel B are more nuanced. Average future returns are higher following extreme negative-skew days at all three horizons, with the strongest evidence appearing at the 5-day horizon. The 10-day difference is only marginally significant, while the 1-day result is not statistically significant. These findings indicate that extreme downside skew does not function as a simple predictor of further price declines. Instead, the positive average return response is consistent with rebound or squeeze-like price dynamics in some episodes. The clearer result remains the link between extreme negative skew and subsequent volatility.

A fixed bottom-decile threshold identifies unusually low RR25 levels over the full sample, but it does not account for changes in the recent distribution of skew. A rolling deviation signal is therefore constructed using the 21-day mean and standard deviation of 7-day RR25. Negative-skew signals are defined at z-score thresholds of -1.5 and -2.0. Table 9 compares future realized volatility on signal and non-signal days.

The rolling-deviation comparisons provide descriptive evidence consistent with the bottom-decile result. Future realized volatility is higher following negative RR25 deviations at every horizon. Moreover, the stronger $z \leq -2.0$ threshold produces a larger volatility difference than the $z \leq -1.5$ threshold in all three cases. For example, the 5-day volatility difference rises from 0.1408 under the -1.5 threshold to 0.2218 under the -2.0 threshold. This relative-deviation design is economically useful because it treats skew stress as a change in market state rather than as a fixed level.

Table 9. Negative RR25 deviations and future realized volatility

Signal Threshold	Horizon	Mean: Signal Days	Mean: Normal Days	Difference
$z \leq -1.5$	1-day	0.5769	0.4855	0.0914
$z \leq -1.5$	5-day	0.7189	0.5781	0.1408
$z \leq -1.5$	10-day	0.6930	0.6104	0.0825
$z \leq -2.0$	1-day	0.7242	0.4834	0.2409
$z \leq -2.0$	5-day	0.8017	0.5798	0.2218
$z \leq -2.0$	10-day	0.7710	0.6104	0.1606

Note: The rolling z-score is calculated using the 21-day rolling mean and standard deviation of synthetic 7-day RR25. Signal days are defined as observations with $z \leq -1.5$ or $z \leq -2.0$. Differences are calculated as the signal-day mean minus the normal-day mean. The table reports descriptive mean comparisons; formal significance statistics are not reported for these specifications.

These results suggest that signal intensity matters. When short-dated RR25 falls substantially below its recent norm, the subsequent volatility response becomes stronger. Relative shocks to downside skew therefore display a stronger descriptive association with future volatility than the average RR25 level alone. This finding is consistent with the interpretation that option-implied skew is most useful for identifying unusually stressed market states.

Taken together, the bottom-decile and rolling-deviation results show that extreme negative 7-day RR25 is followed by higher future realized volatility, while directional return responses are less stable. RR25 is therefore interpreted as a short-horizon volatility-stress indicator rather than a directional trading signal. RR25 captures the directional asymmetry between call and put implied volatility, but it does not describe the full shape of the implied-volatility smile. The analysis next examines smile curvature and test whether broader wing convexity adds information beyond the RR25 stress signal.

4.5. Smile curvature and joint RR25-curvature evidence

The analysis is extended by examining the slope and curvature coefficients obtained from daily quadratic fits of the Bitcoin implied-volatility smile. Table 10 first compares the estimated smile characteristics of the 7-day and 30-day tenors and then reports the predictive relationship between 30-day curvature and future realized volatility.

The results in Table 10, Panel A show that positive smile curvature is a persistent feature of the Bitcoin options surface. Curvature is positive on more than 90% of fitted days for both tenors. Under the common fitting specification, the 7-day smile is more negatively sloped and substantially more curved than the 30-day smile. This pattern suggests stronger short-horizon asymmetry and convexity in the fitted Bitcoin volatility surface.

The baseline predictive regressions in Table 10, Panel B produce a small negative relationship between 30-day curvature and future realized volatility at the 1-day and 5-day horizons. Both coefficients are statistically significant, although the associated R-squared values are low. The relationship is no longer evident at the 10-day horizon. These results suggest that curvature contains some short-horizon information, but the estimated relationship differs from the simple interpretation that greater convexity necessarily predicts higher future volatility.

Table 10. Bitcoin smile curvature and future realized volatility

Panel A. Fitted smile characteristics by tenor		
Metric	7-Day Tenor	30-Day Tenor
Mean slope	-15.08	-7.48
Mean curvature	409.88	102.71
Share of positive curvature (%)	91.6%	93.1%
Mean R^2	0.768	0.740

Panel B. Baseline predictive regressions using 30-day curvature				
Horizon	Curvature Coefficient	t-Statistic	p-Value	R^2
1-day	-0.0006	-2.13	0.033	0.009
5-day	-0.0007	-2.63	0.009	0.013
10-day	-0.0003	-1.02	0.307	0.002

Panel C. Nonlinear 30-day curvature signals						
Signal Rule	Horizon	Mean: Signal	Mean: Normal	Difference	t-Statistic	p-Value
Top-decile curvature	5-day	0.6284	0.6399	-0.0115	-0.16	0.872
Top-decile curvature	10-day	0.7233	0.6707	0.0526	0.62	0.536
$z \geq 1.5$	10-day	0.8178	0.6681	0.1497	1.69	0.092
$z \geq 2.0$	10-day	0.7740	0.6742	0.0998	0.80	0.426

Note: Panel A reports the 7-day and 30-day smile coefficients estimated under the same fitted-smile specification and scaling, allowing direct comparison across tenors. Panel B reports regressions of future realized volatility on 30-day smile curvature. Panel C compares future realized volatility on unusually high-curvature days with the remainder of the sample.

The nonlinear results in Table 10, Panel C are weaker than the nonlinear RR25 results reported in Table 8. Top-decile curvature days do not produce statistically significant increases in future realized volatility at either the 5-day or 10-day horizon. The rolling z-score signal at $z \geq 1.5$ is only marginally significant, and the stronger $z \geq 2.0$ threshold does not produce a larger or more reliable effect. Curvature is therefore an important descriptive feature of the smile, but its predictive content is less stable than the nonlinear RR25 results in Section 4.4. This weaker performance is economically intuitive because curvature captures broader two-sided wing pricing, whereas RR25 more directly isolates the asymmetry between upside and downside volatility demand.

Table 11. Mean 5-day future realized volatility by RR25 and curvature buckets

RR25 Bucket	Low Curvature	Middle Curvature	High Curvature
Low RR25 / Stress	0.8277	0.5929	0.5158
Middle RR25	0.6552	0.5537	0.4440
High RR25	0.7204	0.4545	0.5011

Note: Observations are independently sorted into three buckets based on RR25 and smile curvature. The low-RR25 row represents the downside-skew stress state. Each cell reports the mean 5-day future realized volatility.

To test whether curvature adds information beyond RR25, a joint bucket matrix is constructed by sorting observations into three RR25 buckets and three curvature buckets. Table 11 reports the mean 5-day future realized volatility across the resulting nine states.

The joint sort provides additional evidence that RR25 remains the clearer short-horizon stress indicator. The highest mean future realized volatility, 0.8277, appears in the low-RR25 and low-curvature state. More generally, the low-RR25 stress row contains relatively high future volatility compared with many of the middle- and high-RR25 states.

Curvature does not produce a monotonic pattern in future realized volatility. Within the low-RR25 row, future volatility declines as curvature moves from the low to the high bucket. A similar lack of monotonicity appears across the remaining rows. High-curvature states therefore do not consistently identify the highest subsequent volatility.

The interaction between RR25 and curvature does not appear to outperform the standalone RR25 stress signal. Curvature adds useful information about the shape and convexity of the Bitcoin volatility surface, but it does not materially strengthen short-horizon volatility prediction in this joint-sort specification.

Overall, smile curvature is a persistent and informative descriptive feature of Bitcoin option pricing, especially at short maturities. Its forecasting performance, however, is weaker and less robust than that of extreme negative RR25. RR25 remains the cleaner measure of directional downside stress, while curvature is more appropriately interpreted as a complementary description of broader tail-shape pricing.

4.6. Volatility-premium proxy and RR25-based risk management

Having identified RR25 as the stronger stress-state variable, the analysis next examines whether Bitcoin option-implied volatility contains a persistent volatility premium over subsequent realized volatility and whether RR25 can be used to manage exposure to that premium. A simple volatility-premium proxy is constructed as the difference between at-the-money implied volatility and subsequent realized volatility. The 7-day tenor is matched to 5-day future realized volatility, while the 30-day and 90-day tenors are matched to 10-day future realized volatility. Table 12 summarizes the implied-volatility level, subsequent realized volatility, and resulting IV-minus-RV gap across maturities.

Table 12. ATM implied volatility and subsequent realized volatility

Tenor	Matched Horizon	Mean ATM IV	Mean Future RV	Mean IV−RV	Share of Days IV > RV (%)	Corr. (IV, RV)
7-day	5-day	0.7537	0.5830	0.1707	80.1%	0.58
30-day	10-day	0.7645	0.6072	0.1573	77.5%	0.47
90-day	10-day	0.8021	0.6126	0.1895	78.0%	0.60

Note: ATM implied volatility is matched with subsequent realized volatility over the horizon shown in the second column. The IV-minus-RV proxy is defined as ATM implied volatility minus future realized volatility. All volatility measures are expressed in annualized decimal units.

Table 12 shows that ATM implied volatility exceeds subsequent realized volatility on average across all three maturities. The mean IV-minus-RV gap is positive for the 7-day, 30-day, and 90-day tenors, and implied volatility is greater than future realized volatility on approximately 78% to 80% of matched observations. The largest average IV-minus-RV gap appears in the 90-day tenor, while the 7-day tenor has the highest frequency of positive IV-minus-RV observations.

At the same time, implied volatility is positively correlated with subsequent realized volatility. ATM IV therefore contains useful information about future volatility conditions even though it exceeds realized volatility on average. The positive average gap is consistent with compensation for volatility risk, but it should be interpreted as an IV-minus-RV premium proxy rather than a directly tradable variance-risk-premium return.

The analysis next examines whether RR25 changes the risk profile of the IV-minus-RV proxy. The always-on specification records the proxy on every eligible observation. The binary exposure rule sets exposure to zero when 7-day RR25 enters its bottom-decile stress state. The dynamic specification instead reduces exposure gradually as the RR25 rolling z-score becomes more negative. Table 13 compares the performance of the IV-minus-RV proxy under these alternative exposure rules.

Table 13. IV-minus-RV proxy performance under alternative exposure rules

Exposure Rule	Mean Payoff	Payoff Volatility	Sharpe-Like Ratio	Hit Rate (%)	Cumulative Payoff	Maximum Drawdown
Always-on proxy	0.1707	0.3201	0.533	80.1%	74.75	-6.62
Binary RR25 rule, net cost 0.02	0.1437	0.3038	0.473	72.2%	62.96	-6.64
Linear RR25-scaled proxy, net cost 0.02	0.1552	0.2763	0.562	79.5%	67.99	-4.54
Linear curvature-scaled proxy, net cost 0.02	0.1556	0.2989	0.521	79.7%	68.15	-6.14

Note: The always-on specification maintains full exposure to the IV-minus-RV proxy. The binary RR25 rule sets exposure to zero when synthetic 7-day RR25 falls within its bottom decile, with a cost of 0.02 deducted whenever the exposure state changes. The scaled rules adjust exposure gradually using rolling RR25 or curvature z-scores and are reported net of the corresponding 0.02 cost assumption. The Sharpe-like ratio equals mean proxy payoff divided by its standard deviation. Cumulative payoff is the sum of proxy payoffs, and maximum drawdown is calculated from the cumulative proxy series.

The always-on specification produces the highest mean and cumulative proxy payoff, but it also experiences a larger drawdown than the linear RR25-scaled specification. The binary filter performs worse than the always-on benchmark in both mean proxy payoff and the Sharpe-like ratio, and it does not improve maximum drawdown. RR25 stress days are associated not only with higher subsequent realized volatility but also with larger IV-minus-RV gaps, on average. Setting exposure to zero on those days therefore removes some of the largest positive premium-proxy observations.

The dynamic RR25-scaled specification produces the strongest risk-adjusted proxy result. Its Sharpe-like ratio rises to 0.562, compared with 0.533 for the always-on specification and 0.473 for the binary filter. It also reduces payoff volatility and improves maximum drawdown from -6.62 to -4.54. Although cumulative proxy payoff is lower than under the always-on rule, the decline is smaller than under the binary filter. The economic intuition is that RR25 stress states are not pure exit signals in the IV-minus-RV proxy. These states combine higher realized-volatility risk with higher implied-volatility compensation. A binary zero-exposure rule discards both the risk and the compensation, while conditional scaling preserves part of the option-surface information and reduces exposure only when downside-skew stress becomes more severe.

The curvature-scaled specification provides a modest improvement over the binary filter but remains weaker than RR25-based scaling. Its Sharpe-like ratio is below those of both the always-on and RR25-scaled specifications, and its drawdown reduction is more limited. This result is consistent with Tables 10 and 11, which show that curvature describes the shape of the volatility surface but provides less stable predictive information than RR25.

These results should be interpreted as an information-content and conditional exposure-scaling exercise rather than as a fully executable option-strategy backtest. The proxy payoff measure is based on the end-of-day difference between implied and subsequent realized volatility. It does not represent the profit and loss of specific option contracts. It also excludes intraday margin requirements, liquidation risk, bid-ask spreads, contract rollover, collateral constraints, and contract-level execution costs. This analysis therefore evaluates whether RR25 improves the statistical profile of an IV-minus-RV proxy, not whether the reported payoffs could be earned directly in practice.

Overall, Bitcoin ATM implied volatility exceeds subsequent realized volatility on average, producing a positive IV-minus-RV premium proxy across maturities. RR25 stress periods combine higher subsequent realized volatility with larger average proxy gaps, making a binary zero-exposure rule too blunt in this exercise. Dynamic RR25 scaling provides a better risk-return balance by reducing exposure during stress without eliminating the proxy entirely. Among the specifications considered, it produces the highest Sharpe-like ratio and the smallest drawdown in the cumulative proxy series. These results reinforce the broader conclusion that RR25 is more useful as a nonlinear state variable and exposure-scaling variable than as a stable linear forecasting signal.

5. Discussion

The evidence supports a state-dependent interpretation of Bitcoin risk across both spot and options markets. Bitcoin can improve selected portfolio risk-return tradeoffs, but its diversification role is conditional rather than stable. Similarly, Bitcoin option-implied skew contains limited information in simple full-sample regressions but is most informative when the market enters unusually stressed states. Taken together, these findings suggest that average empirical relationships alone do not fully describe Bitcoin's portfolio behavior or the information embedded in its options market.

5.1. Conditional diversification and state-dependent Bitcoin risk

The portfolio results show that Bitcoin can expand the attainable investment opportunity set and improve the performance of selected fixed-weight SPY-BTC portfolios. These benefits, however, do not imply that Bitcoin functions as a conventional defensive asset. Bitcoin receives little or no weight in the minimum-variance portfolios, and its diversification value weakens during common stress episodes.

The tail-event evidence illustrates this distinction. Most extreme Bitcoin movements do not coincide with extreme equity-market movements, suggesting that many large Bitcoin price shocks are idiosyncratic or crypto-specific. However, when Bitcoin and equity tail events overlap, they usually occur in the same direction. The COVID crisis evidence also shows moderate positive correlations between Bitcoin and both SPY and QQQ. This pattern is consistent with prior evidence that cryptocurrency correlations with traditional risky assets may be relatively low in normal periods but rise during left-tail market conditions [3].

These findings help reconcile the apparently conflicting views of Bitcoin as both a diversifying asset and a risk-sensitive asset. Its imperfect average comovement with traditional assets can improve portfolio outcomes in some periods, while its same-direction tail behavior during common shocks limits its usefulness as a crisis hedge. The key issue is therefore not simply whether Bitcoin is correlated with traditional assets on average, but whether its correlations and joint tail exposures change across market states.

5.2. Interpreting limited linear RR25 predictability

The baseline RR25 regressions provide little evidence of stable linear predictability for either future realized volatility or Bitcoin returns. This result is not necessarily evidence that the options market is uninformative. Option-implied variables may reflect several forces simultaneously, including hedging demand, speculative positioning, volatility compensation, liquidity conditions, informed trading, and temporary price pressure.

Prior option-market research identifies several possible sources of predictive information. Option volume and implied-volatility changes may reflect informed trading or investor expectations, while option-related order flow and stock-market price pressure may also generate predictive relationships [4-7]. Because these mechanisms can vary across time and market conditions, a single full-sample coefficient may average across economically different regimes.

The weak linear results therefore suggest that RR25 should not be interpreted as a continuous forecasting variable whose marginal effect remains constant across all observations. A moderately negative RR25 reading during a calm market may have a different economic meaning from a sharp negative movement during a rapid repricing of downside risk. This distinction is especially relevant in Bitcoin markets, where leverage, liquidations, fragmented trading, and rapid shifts in sentiment can produce abrupt changes in option demand and risk pricing.

5.3. RR25 as a nonlinear stress-state indicator

The nonlinear results provide the clearest evidence on the information content of RR25. Extreme negative synthetic 7-day RR25 observations are followed by materially higher future realized volatility, and the rolling-deviation analysis shows that larger negative departures from RR25's recent distribution are associated with larger subsequent volatility increases. This pattern suggests that RR25 becomes most informative when downside skew reaches an unusually stressed level. During such periods, relatively high put implied volatility may reflect stronger demand for downside protection, heightened concern about near-term jump risk, or a broader repricing of short-horizon uncertainty. In Bitcoin markets, where leverage, liquidation risk, and rapid sentiment shifts are central features, short-dated skew can therefore become informative precisely when the market moves away from normal conditions.

The short maturity of the signal is also economically meaningful. One possible interpretation is that seven-day options respond more strongly to immediate event risk, rapid leverage adjustments, and liquidation-driven market conditions than longer-dated options, which incorporate a wider range of future states. This may explain why the strongest nonlinear results appear at the front end of the implied-volatility surface.

The return response is less consistent. Extreme negative RR25 is not followed by consistently negative future returns, and some specifications show positive average returns after stress signals. This pattern is consistent with rebound or squeeze-like dynamics in some episodes, although the evidence does not establish a unique return mechanism. The more robust conclusion is that RR25 contains clearer information about the magnitude of future price movements than about their direction.

RR25 is therefore better interpreted as a short-horizon volatility-state variable than as a directional trading signal. Its value lies in identifying conditions under which future uncertainty is elevated, rather than in providing a constant forecast of positive or negative returns.

5.4. Smile curvature as a complementary measure

The smile-curvature results show that positive convexity is a persistent feature of Bitcoin option pricing, particularly at short maturities. The 7-day smile is both more negatively sloped and more strongly curved than the 30-day smile, suggesting that near-term Bitcoin options price not only directional downside asymmetry but also substantial wing risk and tail convexity.

Curvature, however, is less reliable than RR25 as a predictive variable. The baseline curvature coefficients are small, the estimated relationship does not support a simple interpretation in which greater convexity always predicts higher future volatility, and the nonlinear curvature signals are not consistently significant. The joint bucket analysis also fails to produce a monotonic increase in subsequent realized volatility as curvature rises.

One interpretation is that RR25 and curvature capture different dimensions of the implied-volatility surface. RR25 directly measures the relative pricing of downside and upside volatility and is therefore more closely connected to directional asymmetry. Curvature measures the broader convexity of both wings and may reflect two-sided jump risk, general uncertainty, or demand for convexity that is not specifically linked to downside stress.

The joint results do not imply that curvature is unimportant. Rather, curvature appears more useful as a descriptive measure of tail-shape pricing than as a standalone short-horizon forecasting signal. In this sample, it complements RR25 by describing the broader structure of the volatility smile, while RR25 remains the cleaner indicator of downside-skew stress.

5.5. Implications for volatility-premium risk management

The IV-minus-RV results show that Bitcoin at-the-money implied volatility exceeds subsequent realized volatility on average across maturities. This is consistent with the broader evidence that Bitcoin options embed a positive volatility or variance-risk premium, although the measure used in this paper is a volatility-level proxy rather than a model-free variance-risk-premium return [8].

This distinction matters for the exposure-scaling exercise. RR25 stress periods are associated with higher subsequent realized volatility, but they are also associated with larger average IV-minus-RV gaps. A binary rule that fully removes exposure during such periods reduces participation in high-risk states, but it also removes some of the largest positive premium-proxy observations. This helps explain why the binary filter lowers average payoff without producing a comparable improvement in risk-adjusted performance.

The dynamic scaling rule produces a stronger risk-adjusted profile because it recognizes that stress periods can contain both greater risk and greater compensation. Rather than treating exposure as an all-or-nothing decision, the rule reduces exposure gradually as downside-skew stress intensifies. This preserves part of the premium while lowering proxy volatility and drawdown. However, the always-on specification continues to produce the highest mean and cumulative proxy payoff.

The broader implication is that option-implied stress signals may be more useful for adjusting exposure than for determining whether it should be eliminated entirely. Because RR25 identifies changes in market state rather than a deterministic loss event, continuous scaling is economically more consistent with the signal than a binary exit rule. This result should not be interpreted as evidence that the reported proxy payoffs can be earned directly through a specific option strategy. The exercise instead shows how information from the option surface can support conditional exposure scaling in a volatility-premium proxy.

5.6. Limitations and directions for future research

Several limitations should be considered when interpreting the results. First, the IV-minus-RV measure is an end-of-day information proxy and does not represent the realized profit and loss of a specific option portfolio. A full implementation study would require contract-level option data, bid-ask spreads, rollover assumptions, margin requirements, collateral management, and liquidation-risk controls.

Second, the empirical analysis relies on transparent methods such as linear regressions, percentile-based regimes, rolling z-scores, and bucket sorts. These approaches make the results easy to interpret, but they may not capture more complex nonlinear interactions among maturity, skew, curvature, spot volatility, liquidity, and market leverage. Future research could examine threshold regressions, regime-switching models, or other nonlinear forecasting methods.

Third, the construction of option-implied variables depends on data availability, contract coverage, maturity interpolation, and filtering choices. Cryptocurrency research can be particularly sensitive to data quality and measurement design because market data may be fragmented, non-concurrent, or based on contracts with uneven liquidity [11]. Although the synthetic-tenor construction improves comparability, further work could test alternative interpolation methods and liquidity filters.

Fourth, the analysis focuses primarily on Bitcoin. Extending the framework to Ethereum or other liquid cryptocurrency option markets would help determine whether the nonlinear RR25 result is specific to Bitcoin or reflects a broader feature of crypto options.

Finally, the sample spans periods of substantial change in cryptocurrency market structure, including shifts in institutional participation, liquidity, leverage, and exchange behavior. Future research could examine whether the strength of the RR25 signal changes across subperiods, market-development stages, or different volatility regimes.

Overall, the evidence supports a state-dependent interpretation of Bitcoin option-implied information. RR25 is weak as a stable linear forecasting variable but informative when downside skew becomes unusually extreme. Its primary value lies in identifying elevated near-term volatility and supporting gradual risk adjustment rather than generating a simple directional forecast or binary trading rule.

6. Conclusion

This paper examines Bitcoin risk from both portfolio and option-implied perspectives. It evaluates whether Bitcoin improves the investment opportunity set when combined with traditional assets and whether option-implied variables, particularly RR25 and smile curvature, contain useful information about future volatility, returns, and volatility-premium risk management. The portfolio results show that Bitcoin can improve selected risk-return tradeoffs, but its diversification benefit is conditional. Bitcoin does not behave as a stable minimum-variance asset or a reliable defensive hedge, and its diversification value weakens during common stress episodes.

The main option-implied finding is the contrast between weak linear predictability and stronger nonlinear predictive information. Full-sample regressions provide limited evidence that RR25 consistently predicts future realized volatility or returns. In contrast, extreme negative synthetic 7-day RR25 is followed by materially higher future realized volatility, while large negative rolling deviations show a similar pattern. RR25 is therefore better interpreted as a nonlinear stress-state indicator than as a stable continuous forecasting variable. Smile curvature is a persistent feature of the Bitcoin implied-volatility surface but provides weaker predictive information.

The volatility-premium analysis further shows that at-the-money implied volatility exceeds subsequent realized volatility on average. A binary RR25 rule removes too much premium during stress, while gradual RR25-based scaling produces a stronger risk-adjusted profile by reducing exposure without eliminating it entirely. Overall, the results show that Bitcoin risk and option-implied information are strongly state-dependent. The analysis remains a proxy-based information-content and conditional risk-scaling exercise rather than a fully executable option-strategy backtest. Contract-level implementation and applications to broader cryptocurrency option markets are left for future research.

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