Risk-On/Off in Volatile Markets: A Bitcoin Risk Model Case Study

Executive Summary

The Thesis Bitcoin Risk Model ("Thesis BTC Risk Model" or "Our Model") uses machine learning to identify when Bitcoin is in favorable versus risky regimes, systematically reducing exposure during overvalued periods. In live trading from October 29, 2024 through November 26, 2025, the Thesis BTC Risk Model delivered 83% annualized returns with a 1.65 Sharpe ratio versus Bitcoin's 22% annualized returns and 0.55 Sharpe ratio—outperforming by 61 percentage points. These results extend through the backtested period from September 15, 2021 to the live date, the model achieved 71% annualized returns (1.48 Sharpe) versus Bitcoin's 23% (0.51 Sharpe).

Table 1. Summary Results Table

Period	Strategy	Annualized Return %	Sharpe Ratio
Live Trading (Oct 29, 2024 – Nov 26, 2025)	**Thesis BTC Risk Model**	**83%**	**1.65**
	Bitcoin Buy and Hold	22%	0.55
Backtested (Sep 15, 2021 – Oct 28, 2024)	**Thesis BTC Risk Model**	**71%**	**1.48**
	Bitcoin Buy and Hold	23%	0.51

Why Bitcoin for our first model

Bitcoin is an ideal testing ground for systematic risk-regime identification. Unlike equities, which have widely accepted valuation frameworks (e.g., discounted cash flows and dividends), Bitcoin does not generate cash flows or pay dividends. As a result, Bitcoin's market value is less anchored to traditional fundamentals and more influenced by sentiment and adoption dynamics (e.g., network adoption, investor attention, macro liquidity, and speculative positioning[i]). The absence of traditional fundamental anchors creates a unique challenge: **how do you systematically assess when to de-risk one's Bitcoin position?**

The answer lies not in attempting to predict Bitcoin's intrinsic value, but in identifying regime shifts between accumulation (rational demand driven by adoption and scarcity) and speculation (irrational exuberance vulnerable to reversal). Bitcoin's 24/7 trading, transparent on-chain data, and extreme volatility, within the confines of an inefficient market[ii], create a ripe situation where information asymmetries enable alpha capture. These characteristics make Bitcoin an optimal first application for our machine learning-driven risk regime identification.

Our Approach: Systematic Regime Identification

We constructed the Thesis BTC Risk Model by building a machine learning architecture trained to classify daily Bitcoin return regimes as favorable or adverse for holding exposure. Our model integrates 55 features across on-chain activity, macro-conditions, and market conditions to predict- rather than react to- changes in risk regimes.

Rather than forecasting point returns, the model outputs class probabilities—overvalued, fairly valued, or undervalued—expressed on a bounded 0%–100% scale. This probabilistic classification framework is more robust than point forecasting for risk management because it produces interpretable, bounded signals that map directly to exposure decisions and better align with risk management objectives.

Table 2: Full Performance Comparison

Metric	Backtest	Live
Period Duration	788 days	269 days
Cumulative Return (Thesis)	313.21%	89.80%
Bitcoin Return	45.04%	23.94%
Excess Return	268.17%	65.86%
Sharpe Ratio - Thesis	1.379	1.689
Sharpe Ratio - Bitcoin	0.459	0.627
Information Ratio	0.548	1.734
Maximum Drawdown - Thesis	-34.32%	-23.53%
Maximum Drawdown - Bitcoin	-76.67%	-32.52%
Upside Capture	49.44%	79.10%
Downside Capture	36.75%	62.36%

Why Traditional Risk Management Approaches Are Insufficient

Traditional risk management models fail in cryptocurrency markets because they treat all volatility as equivalent risk. Three conventional approaches illustrate this limitation:

Volatility-Based Models: Volatility captures the magnitude of price fluctuations but does not differentiate between positive and negative returns: a +10% move and a –10% move contribute equally to realized volatility, even though they represent very different conditions for trend-following or return-seeking investors. In Bitcoin, where bull markets often produce sharp upside bursts, these volatility spikes can trigger defensive de-risking signals identical to those seen during crashes, forcing models to exit profitable trends prematurely.

Complicating matters, volatility-based indicators are far less usable as investment decision tools than valuation-oriented scoring systems: even in equities, the VIX—though the calculation is methodologically standardized[iii]—has no inherent interpretation that maps a given value to a clear buy, sell, or risk-off threshold. In cryptocurrency, the problem is worse: with multiple crypto volatility indices but no clear market leader, there is a lack of both methodological uniformity and any widely accepted decision thresholds. As a result, volatility readings offer no consistent, interpretable framework for translating market conditions into actionable risk-on or risk-off decisions, unlike continuous, bounded scoring systems that explicitly encode valuation or risk asymmetry.

Signal Saturation: On-chain indicators, such as the market value to realized value ratio, attempt to assess aggregate holder profitability or cost basis relative to market price; historically, such metrics have sometimes been used to signal overvaluation or undervaluation. However, under the lens of an adaptive market framework, widely followed signals can degrade in effectiveness over time: as more investors monitor and trade around the same thresholds, market dynamics shift, reducing the predictive power of static threshold-based metrics[iv]. What once were robust ‘warning flags’ may become muted or obsolete as market ecology changes.

Active Management: Discretionary decision-making is inconsistent, emotionally influenced, and practically difficult to execute in a 24/7 market. Even professional traders struggle to maintain discipline across multiple Bitcoin market cycles, particularly during rallies or panic during crashes. Further, active management requires higher fees than passive strategies, reducing the net-of-fees returns for even the best active manager[v]s.

In our opinion, these approaches are either ineffective or too costly to return sufficient levels of performance for investors. We believe a more sophisticated, but cost-effective, approach in today’s market is necessary to outperform on a gross-of-fee basis.

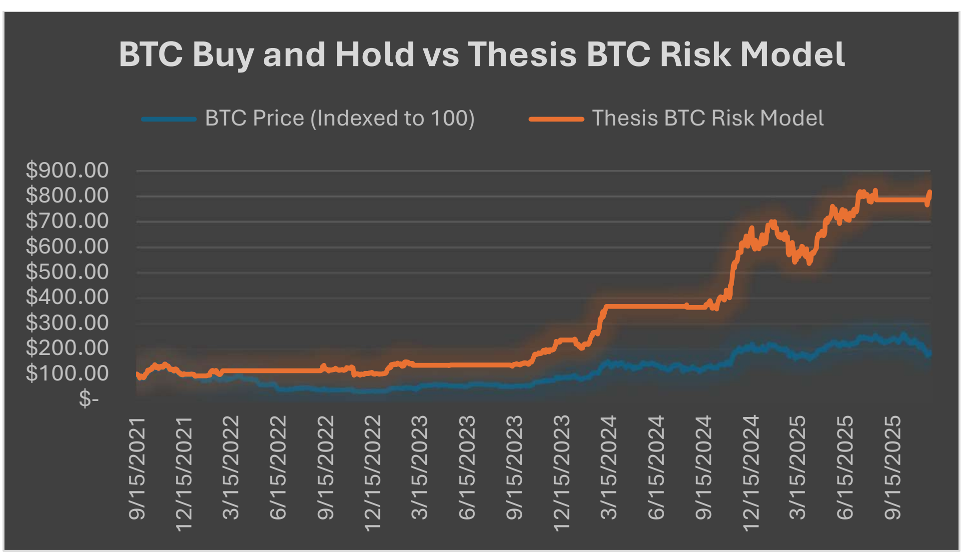
Thesis Bitcoin Risk Model

During the backtested period (09/15/2021 to 10/28/2024) and live period (10/29/2024 to 11/26/2025), the Thesis BTC Risk Model achieved **717% cumulative returns, compared to 87% for buy-and-hold exposure**, across four years of extreme volatility. The model's Sharpe ratio of 1.48 is nearly 3x higher than Bitcoin's 0.51, while its maximum drawdown of -34.3% represents less than half of Bitcoin's -76.6% peak-to-trough decline, over the entire period.

From the Live Date of 10/29/2024 through 11/26/2025, the Thesis BTC Risk Model delivered cumulative 90% returns versus 24% for buy-and-hold Bitcoin, a 6,600 BPS point outperformance in real-world deployment. This outperformance was driven by utilizing our proprietary C-Score criteria[1] to generate Bitcoin risk scores on a continuous range of -1(likely undervalued) to 1 (likely overvalued). We use these scores daily to reduce or liquidate our BTC positions on a timely basis using our dual scoring criteria:

- If daily risk score > 0.05[2] AND 10-day moving average of daily scores > 0.05[2] → Risk-off (reduce Bitcoin holdings exposure to 0%)
- If daily risk score ≤ 0.05[2] OR 10-day moving average ≤ 0.05[2] → Risk-on, with gross position of 100% less daily risk score.

Table 3. Thesis BTC Risk Model Returns vs BTC Buy and Hold Strategy



[1] Please see our full whitepaper here for a full explanation of our proprietary C-Score design
[2] Or lower, based on adaptive threshold logic, based on calibration from testing period data

This dual-signal protocol reduces whipsaw trades: a single day's extreme reading must be confirmed by sustained elevated risk across 10 days before triggering a position change. The result of using this dual-signal protocol enabled Thesis BTC Risk model to avoid approximately 4,100 basis points of net losses (net of gains and losses missed) during the live period, with further drawdowns avoided in the backtest period:

Table 4. BTC Drawdown Events (Red) vs BTC Thesis Model Return (Blue)

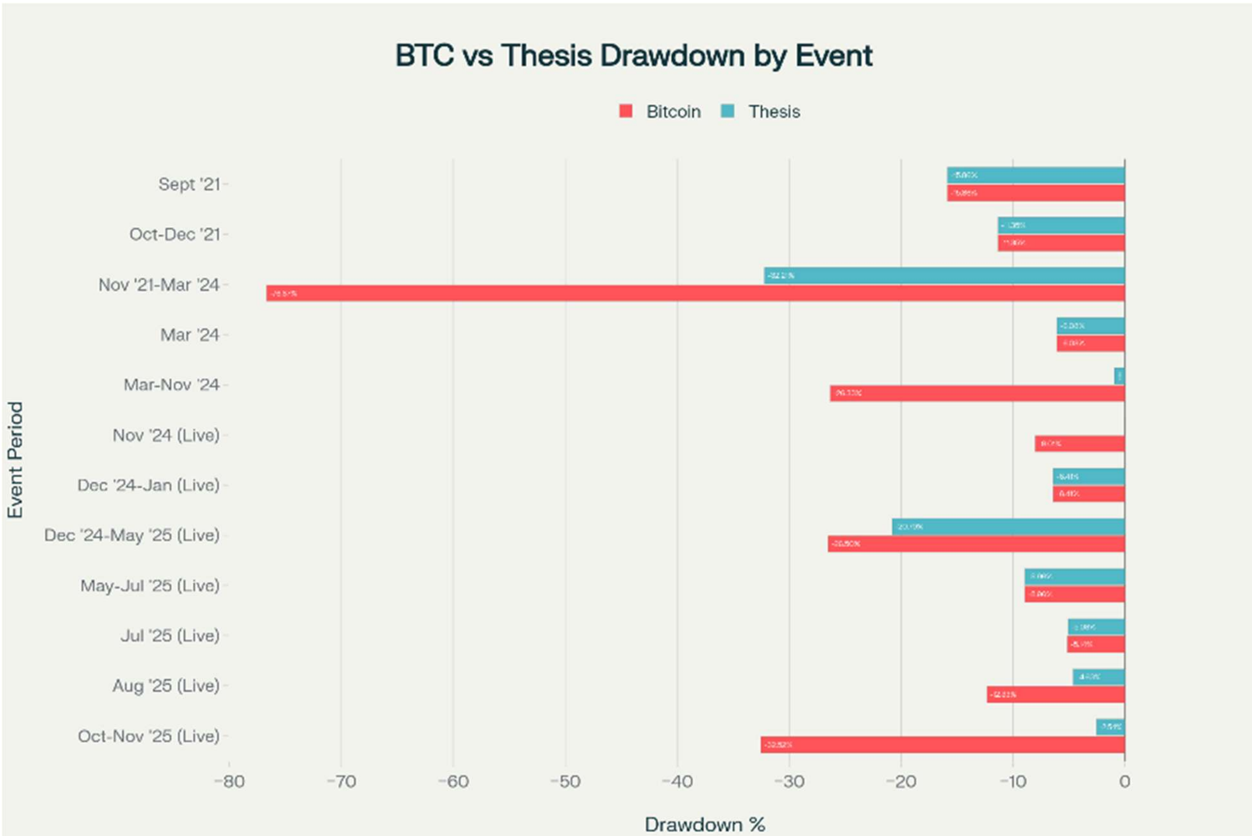
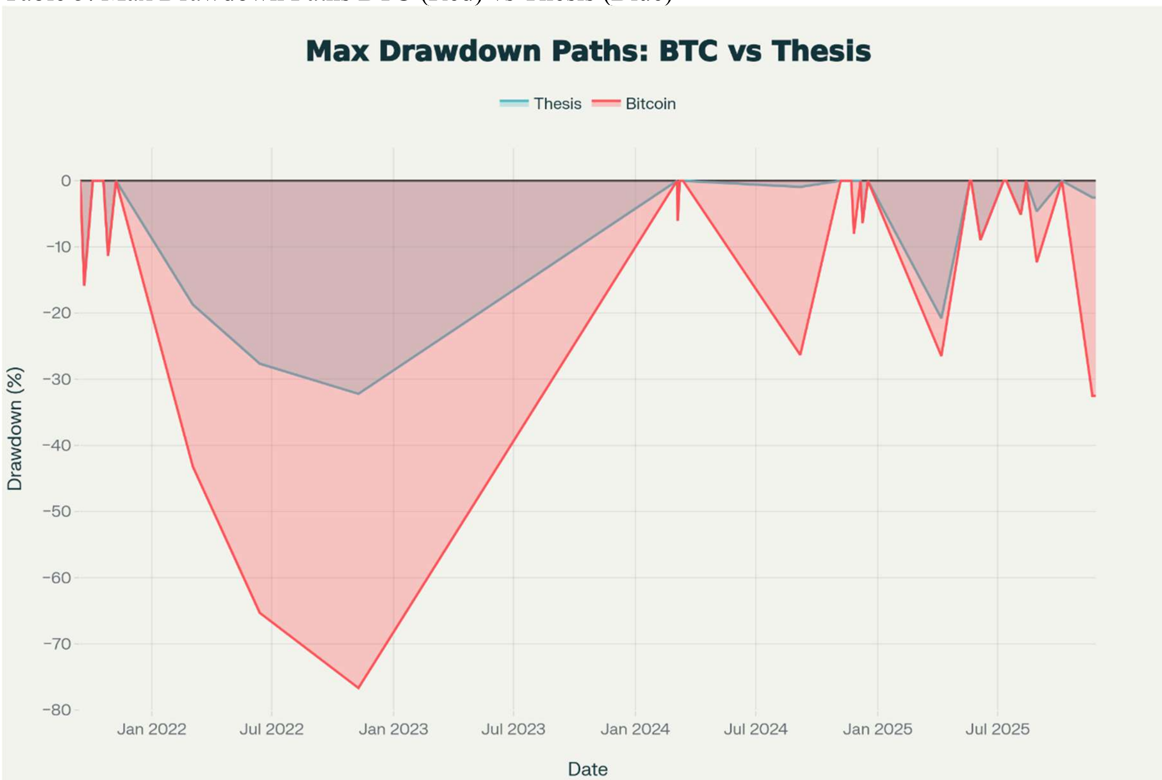


Table 5. Max Drawdown Paths BTC (Red) vs Thesis (Blue)



Statistical validation suggests the model's edge is not random noise. Over the full sample (2021-09-16 to 2025-11-26), on the 529 days when Bitcoin posted negative returns, the model averaged -0.98% versus Bitcoin's -2.30%, a 132 bps (1.32%) daily advantage on down days that is highly statistically significant ($p < 1e{-6}$) with a 95% confidence interval of 113 to 151 bps. This asymmetric payoff profile is also reflected in the capture metrics: the model delivers 56% upside capture while limiting exposure to 43% downside capture, which is a primary driver of the compounding advantage.

Table 6. Statistical Model Validation

Thesis BTC Model: Down-Day Advantage

Period	Trading Days (N)	Down Days (N)	Daily Adv (bps)	T-Stat	P-Value	95% CI Lower	95% CI Upper
Full Period	1058	529	131.91	13.67	<0.001	112.95	150.86
Backtest Only	788	395	150.07	12.37	<0.001	126.22	173.92
Live Only	269	134	78.37	6.5	<0.001	54.54	102.2

Importantly, the live trading results are consistent with what the backtest predicted. In the backtest window (2021-09-16 to 2024-10-28), across 395 Bitcoin down days, the model averaged -0.87% versus -2.37% for Bitcoin, a 150 bps daily advantage ($p < 1e{-6}$, 95% CI: 126 to 174 bps), with 49% upside capture and 37% downside capture. In the live window (2024-10-30 to 2025-11-26), across 134 Bitcoin down days, the model averaged -1.30% versus -2.08%, a 78 bps daily advantage that remains highly statistically significant ($p = 1.45e{-9}$, 95% CI: 55 to 102 bps), alongside stronger upside participation (79% upside capture) and controlled downside exposure (62% downside capture). The live results preserve the core asymmetry our backtest demonstrated, confirming the model is behaving in production as designed rather than reverting toward chance.

Live Trading Validation

From the Live Date through November 26, 2025, the Thesis BTC Risk Model delivered 90% returns versus 24% for buy-and-hold Bitcoin, a 6,600 BPS outperformance in slightly over a calendar year. This live performance demonstrates that the model's patterns, derived from historical data, remain applicable to forward-looking market conditions.

Table 7: Upside and Downside Capture

Period	Upside Capture	Downside Capture	Risk Ratio (Up/Down)	Interpretation
Full Period	56.48%	42.62%	1.32x	Capture majority of upside, limit to ~40% downside
Backtest Only	49.44%	36.75%	1.34x	Conservative positioning, strong downside protection
Live Only	79.1%	62.36%	1.27x	Improved upside capture in bull market, reasonable downside

Since the Live Date, the model continued to behave as designed: occasionally conservative during the early stages of rallies, but consistently effective at minimizing downside exposure. While the strategy did not capture every upswing in full, participating in about 79% of Bitcoin's upside days, this modest opportunity cost was outweighed by the model's superior performance during declines. On Bitcoin's down days, the model absorbed only 62% of the losses and generated an average advantage of roughly 78 basis points per day, a result that is highly statistically significant ($p < 1e\text{-}12$, 95% confidence interval 55 to 102 bps). The live data therefore confirms the same asymmetry observed in the backtest: occasional missed upside, but meaningfully reduced participation in drawdowns, resulting in a positive net timing effect throughout the live period.

Implementation and Model Governance

The Thesis BTC Risk Model is offered as a systematic, rules-based methodology that can be licensed by institutional investors. The model recalibrates daily using 55 data inputs, running inference on a 15-minute delay from NYSE market close. Practitioners should account for trading costs specific to their platform spot exchanges, futures venues, or ETF mechanisms.

Model Governance: Since the model's initial deployment in October 2024 through November 2025, no material changes have been made to model parameters (including backtested periods). This frozen-parameter approach ensures consistency and prevents overfitting to recent data. The model operates under a transparent change management protocol: material parameter changes will be data quality issues or accessibility issues affecting 5%+ of input features for 10+ consecutive days, or structural market changes requiring reassessment. Any parameter change will trigger full re-optimization, cross-validation, publication of updated methodology, and 30-day notice to all licensees before changes take effect.

The model is designed for integration by institutional investors seeking a systematic approach to Bitcoin exposure management. For licensing inquiries or technical integration support, please contact ben@thesisfunds.com.

Risk Disclosures

Past Performance: Historical returns do not guarantee future results. The Thesis BTC Risk Model's outperformance may not persist under different market regimes, correlation structures, or macroeconomic conditions. Backtested results are hypothetical based on the methodology described in our whitepaper.

Model Risk: The model relies on machine learning pattern recognition. Performance depends on the assumption that historical relationships between input features and Bitcoin return regimes remain relevant. Model robustness has been tested across multiple market cycles, but extreme tail events or unprecedented macro conditions could produce suboptimal results.

Data Dependencies: The model's efficacy depends on the availability and accuracy of real-time on-chain and derivatives data. Data delays or quality issues could impair signal generation.

Cryptocurrency Volatility: Bitcoin is highly volatile and can experience sudden, severe price movements. Drawdowns exceeding 30% are common and drawdowns exceeding 70% have occurred historically. No risk management model eliminates this risk.

Regime Dependency: The model utilizes data during a specific historical period that includes multiple bull and bear cycles. Future market regimes that differ materially from this training window may produce different results. Specific limitations include potential impacts from Bitcoin ETF adoption, monetary policy regime changes, and evolving leverage dynamics.

Execution Considerations: Model implementation assumes execution at close-of-day prices or equivalent pricing. Real-world execution slippage, order-filling dynamics, and trading cost allocation may affect realized returns compared to model-level calculations.

Publication Status: This case study does not represent a published methodology and analytical framework. It does not constitute investment advice, a regulated investment product, or discretionary asset management. Institutional investors must conduct their own due diligence and suitability assessment before licensing or implementing this model.

Document prepared November 2025. For licensing inquiries or technical integration questions, please contact ben@thesisfunds.com.

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