Abstract:

We model a minimal Bitcoin-collateralized perpetual credit structure:
zero operating income, no refinancing, no hedging, forced monthly BTC liquidation, and strict solvency triggers.

The model is designed to break.

It doesn't break.

Once collateral coverage reaches ~30× BCR, insolvency risk collapses into investment-grade territory across *all* randomness models and *all* market regimes.

Current sentiment in the market is pricing phantom risk.

Current Bitcoin companies aren't "one downturn away from default."
They're **under-levered** relative to what their collateral can support.

Bitcoin behaves like the strongest balance-sheet asset ever discovered.
Traditional credit intuition simply hasn't caught up.

Bitcoin on the balance sheet and its implications as collateral.

Bitcoin's volatility profile and long-term upward drift make it unlike any historical collateral asset.
For firms holding BTC as a reserve asset, the key question is:
How much perpetual fixed-dollar liability can be safely issued against a volatile, appreciating collateral without insolvency risk?
Traditional leverage ratios fail to capture the path-dependent solvency dynamics of such structures.
We propose Balance Sheet Credit Ratio (BCR) as the relevant state variable and evaluate solvency under adversarial assumptions.

Bitcoin as collateral in a $300T System

The maturity of a liability should match the value horizon of the asset backing it; mismatches create refinancing risk when liabilities are too short and inefficiencies when they are too long. Bitcoin's collateral profile is unusual because it has no issuer, no decay, and effectively infinite duration. An infinite-duration asset is therefore most coherently financed with an infinite-duration liability. This is the economic rationale behind the use of perpetual preferred equity to fund Bitcoin reserves.

History offers a partial precedent in the form of government perpetual bonds such as the consols issued by Great Britain. The sovereign assumed an indefinite existence and financed itself with liabilities that never matured. Bitcoin extends this logic from liabilities to collateral. For the first time, the asset backing the liability has no natural end date, no decay, and no capacity for debasement.

Bitcoin is the longest-duration asset in existence. Its value is anchored in scarcity, perfect energy preservation, and long-term network permanence. An infinite-duration asset is most rationally paired with an infinite-duration liability.

To match Bitcoin's duration, firms have begun designing perpetual preferred equity structures with no contractual principal repayment. Bitcoin's properties make these structures more economically coherent than any previous asset-liability pairing. They give lenders superior collateral quality while giving borrowers long-term optionality and asymmetric upside.

Financing Bitcoin with fiat denominated liabilities is Powerful: the liability melts in real terms through debasement while the asset grows in real terms. The spread compounds over time, pushing the real burden of the liability toward irrelevance.

Bitcoin-collateralized credit products already outcompete most traditional debt instruments on yield, liquidity, and risk-adjusted basis. This is not an anomaly. It reflects the fact that credit markets do not yet have a model for valuing collateral with infinite duration, perfect auditability, no counterparty risk, and long-term real appreciation.

As markets adapt, yields will compress toward the true risk profile of the structure. Bitcoin-secured credit removes more collateral-related counterparty risk than any instrument in financial history, leaving the lender exposed primarily to the operational and governance quality of the borrower rather than the collateral itself.

At this point, distinguishing Bitcoin-based financing from traditional leverage becomes essential. The assumptions embedded in legacy leverage ratios do not apply to collateral that appreciates, does not expire, and cannot be diluted.

How much amplification is prudent?

Traditional Leverage vs Amplification

Traditional leverage assumes amortization, principal repayment, and collateral that deteriorates over time. None of these assumptions apply to Bitcoin or to principal-less perpetual preferred equity. Bitcoin-backed perpetual preferred therefore does not behave like conventional leverage, and using legacy leverage terminology obscures more than it clarifies.

For this reason, the industry uses a different term: **amplification**. In a balance sheet financed entirely through perpetual preferred, amplification measures how much of the Bitcoin reserve is encumbered by fixed-dollar claims. We define amplification as:

$$\text{Amplification} = \frac{\text{Preferred Notional}}{\text{BTC Reserve}}$$

This provides a static measure of collateral encumbrance: how much of the firm's Bitcoin assets are pledged to service perpetual preferred obligations. Amplification describes balance-sheet pressure, while solvency is governed by the reserve's ability to meet its ongoing dollar obligations.

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How much amplification?

Bitcoin-backed credit offers a distinct value proposition for both lenders and borrowers. At this stage of the adoption curve, borrowers capture a uniquely favorable position while lenders benefit from inefficiently high yields and unparalleled collateral quality. But amplification capacity is not determined by market appetite; it is determined by solvency dynamics. Each incremental unit of issuance increases the borrower's long-term upside while also raising sensitivity to Bitcoin's drawdowns and to the cadence of liability obligations. Understanding the limits of rational amplification is essential not only for surviving periods of downside volatility, but also for avoiding the opportunity cost of under-amplification. Better comprehension of the risks allows a firm to take on greater exposure to the rewards.

To identify these limits, we begin with the most minimal solvency model available. A firm holds Bitcoin, issues perpetual preferred, and sells BTC to meet its periodic obligations. No operating cash flows, hedging strategies, liquidity tools, or cash buffers are assumed. This barebones structure isolates the essential mechanics of amplification risk and provides a conservative baseline. Any real-world structure only improves on it.

Quantifying Risk in Bitcoin-Backed Perpetual Preferred Equity

Balance Sheet Coverage Ratio (BCR)

Although the practice of financing a BTC reserve with principal-less perpetual equity can be described in terms of amplification, amplification does not provide a consistent basis for comparing risk across issuers. For example, a company operating at 50 percent amplification with a 10 percent dividend rate faces the same effective burden as one operating at 100 percent amplification with a 5 percent rate; the obligation scales identically once normalized to the reserve base. In a structure without operating income, the only variable that matters for solvency is the Bitcoin on the balance sheet.

From a risk-management standpoint, the core question is not amplification itself but whether the reserve can reliably service its fixed USD obligations over time. To evaluate this rigorously, we introduce the Balance Sheet Coverage Ratio, defined as the value of the BTC reserve divided by the annual dividend payment. This metric provides a standardized, credit-comparable means of solvency under Bitcoin price uncertainty. Going forward, creditworthiness will be expressed primarily through this single variable.

BCR Definition

For a firm that funds a Bitcoin reserve with perpetual preferred equity, the central solvency variable is the ratio of reserve value to fixed dollar obligations. We define the Balance Sheet Coverage Ratio (BCR) as:

$$\mathrm{BCR}_0 = \frac{V_0}{D_{\text{annual}}},$$

where V_0 is the dollar value of the Bitcoin reserve at time 0 and D_{annual} is the annual dividend obligation on the preferred.
A BCR of 40 means that, at current prices, the reserve could fund 40 years of dividends if entirely liquidated into dollars.

BCR example

Consider a firm holding 1 billion dollars of Bitcoin and issuing perpetual preferred equity at a 10 percent dividend rate.

- If it issues 250 million dollars of preferred, the annual obligation is 25 million, and:

$$\text{BCR}_0 = \frac{1{,}000{,}000{,}000}{25{,}000{,}000} = 40.$$

- If instead it issues 500 million of preferred, the obligation becomes 50 million and BCR falls to 20.
- With 1 billion preferred outstanding, the obligation is 100 million and BCR = 10.

In each case, amplification determines the obligation, and the obligation determines BCR. From a solvency standpoint, BCR fully captures the economic burden of the liability, regardless of nominal capital structure.

The dividend rate enters identically. Holding amplification constant at 25 percent, lowering the dividend rate from 10 percent to 5 percent reduces the obligation from 25 million to 12.5 million and raises BCR from 40 to 80.
A firm with 25 percent amplification at a 5 percent coupon has the same BCR, and the same solvency profile, as a firm with 12.5 percent amplification at a 10 percent coupon. Different combinations of notional and coupon collapse into a single solvency measure once expressed through BCR.

BCR Example 2

As amplification increases so does NAV thus shifting BCR

Table of amplification, NAV, and BCR Dynamics

Initial NAV	Amplification (%)	New NAV	PPE Notional	Annual Obligation (10%)	Resulting BCR
$1.0B	**25.0%**	$1.25B	$250M	$25M	**50×**
$1.0B	**33.3%**	$1.33B	$333M	$33.3M	**40×**
$1.0B	**50.0%**	$1.50B	$500M	$50M	**30×**
$1.0B	**66.7%**	$1.67B	$667M	$66.7M	**25×**
$1.0B	**100.0%**	$2.00B	$1.0B	$100M	**20×**
$1.0B	**200.0%**	$3.00B	$2.0B	$200M	**15×**
$1.0B	**500.0%**	$6.00B	$5.0B	$500M	**12×**

Solvency as a Path, Not a Point

Solvency in a Bitcoin-backed perpetual preferred differs fundamentally from traditional credit. Because the liability has no principal repayment and no maturity, there is no refinancing risk and no classical form of forced liquidation. Solvency reduces to one condition: the firm's ability to continue paying periodic dividends. When dividends are funded through BTC sales, solvency depends on whether a drawdown is both deep enough and long enough to exhaust reserves. Duration becomes a primary driver of risk. A sharp crash followed by a fast recovery may be far less dangerous than a moderate decline that persists for an extended period. Traditional leverage frameworks emphasize value-at-risk rather than time spent underwater, and they assume collateral failure occurs at a specific price threshold rather than through cumulative depletion. Bitcoin-backed perpetual preferred introduces a path dependent solvency mechanism that falls outside the assumptions of classical credit models.

Model Selection

- **Lognormal (GBM)** = naive benchmark

"What if BTC were a vanilla asset with IID normal returns (no clustering, no jumps)?"

- **Jump diffusion** = structured tail model

"What if returns are mostly Gaussian but occasionally jump, calibrated to BTC's fat tails?"

- **Block bootstrap** = experience model

"What if the future re-uses the same drawdown / clustering structure we've already lived?"

The objective is not to forecast Bitcoin. It is to construct an exposure envelope that preserves the only information that reliably governs solvency: the empirical structure of Bitcoin drawdowns. The block bootstrap remains the foundation of this framework because it is the **least-assumption**, **most empirically anchored**, and **path-dependent** method available. It preserves exactly the features that matter for reserve depletion — drawdown depth, drawdown duration, volatility clustering, and multi-month trend persistence — without introducing speculative dynamics that cannot be supported by evidence.

However, no single model captures every aspect of Bitcoin's distribution. To create a defensible and comprehensive exposure envelope, we supplement the bootstrap with parametric families that capture characteristics the bootstrap cannot produce on its own:

1. Block Bootstrap (Empirical Path Generator)

The bootstrap is the anchor because it is the only method that:

- uses no structural parameters,
- preserves empirical dependence,
- produces realistic, path-consistent drawdowns,
- and generates cumulative stress sequences more severe than any single historical cycle.
  It answers the solvency question directly:
  "If the future preserves the dependence structure of the past, what range of cumulative exposures is consistent with survival?"

Its limitation is also its strength: it cannot generate shocks outside the historical range. For solvency this is acceptable, but for understanding tail-frequency sensitivity, it must be paired with models that intentionally expand the tail.

2. Lognormal Baseline (Classical Diffusion Check)

A lognormal diffusion is not a realistic model of Bitcoin's path dynamics, it destroys clustering and drawdown persistence, but it *does* supply a simple benchmark for scale.

It answers one question only:
“How far does a standard parametric model underestimate drawdown risk relative to empirics?”
It acts as a baseline comparator, not a candidate model.

3. Jump-Diffusion (Synthetic Tail Extension)

Where the bootstrap cannot create new shock magnitudes, jump-diffusion can.
Used correctly, the jump component functions as a **stress amplifier**, not a forecast engine. It fills the “tail gap” left by the bootstrap while still maintaining a continuous-time structure.
It lets you ask:
“If we shock the path with plausible-but-larger discontinuities, how much does solvency sensitivity shift?”
It does not replace the bootstrap; it brackets its assumptions.

4. Power-Law Tail Gauge (Distribution Shape Diagnostic)

Power-law scaling is not a model you simulate from.
It is a **measurement device**.
If Bitcoin’s left tail obeys power-law decay across regimes, then any parametric model with exponentially bounded tails (lognormal, Gaussian GARCH, etc.) will understate extreme downside risk.
You use the power-law exponent to:

- evaluate whether jump intensities are conservative relative to empirics,
- quantify how “fat” the empirical left tail actually is,
- and demonstrate why the bootstrap’s empirically inherited tail is more credible than thin-tailed parametrics.
  This validates the model ordering:
  bootstrap → jump-diffusion extension → lognormal baseline.

Modeling Calibrations

Full Cycle Calibration

Full-cycle: "If BTC behaves like its entire history, what happens?"

 Window: e.g. 2014–2025

 Captures multiple bulls and bears

Parameters:

LOGNORMAL CALIBRATION

• Annual Drift Used (μ): **0.4995**

• Annual Volatility (σ): **0.6809**

JUMP–DIFFUSION CALIBRATION

• Jump Frequency λ (per year): **6.4098**

• Jump Mean (log return): **-0.0288**

• Jump Std (log return): **0.1467**

• Detection Threshold: **3σ**

Stress Calibration

Stress window: "If we never get another mega bull, can PPE still survive?"

Window: e.g. 2018–2023

Emphasizes vicious drawdowns and flat periods

Parameters:

LOGNORMAL CALIBRATION

• Annual Drift Used (μ): **0.2510**

• Annual Volatility (σ): **0.7571**

JUMP–DIFFUSION CALIBRATION

• Jump Frequency λ (per year): **4.6667**

• Jump Mean (log return): **-0.0301**

• Jump Std (log return): **0.1849**

• Detection Threshold: **3σ**

Current Regime

Hybrid: “If returns structurally trend up, but downside looks like the worst we’ve seen, what happens?”

 Volatility + jumps from stress window (2018–2023)

 Drift from full-cycle window (2014–2025)

Parameters:

LOGNORMAL CALIBRATION

• Annual Drift Used (μ): **0.2865**

• Annual Volatility (σ): **0.5913**

JUMP–DIFFUSION CALIBRATION

• Jump Frequency λ (per year): **6.6934**

• Jump Mean (log return): **-0.0007**

• Jump Std (log return): **0.1165**

• Detection Threshold: **3σ**

Results

(Full Results in appendix D)

1.1 Current Regime (2021–2025)

Probability of Insolvency (BCR < 1 at any time)

BCR_0	Bootstrap PD	Lognormal PD	Jump-Diffusion PD
10×	17.45%	14.92%	18.44%
15×	9.26%	7.73%	10.48%
20×	5.85%	4.65%	7.05%
30×	2.62%	2.165%	3.915%
40×	1.52%	1.04%	1.53%

1.2 Stress Regime (2018–2020)

Probability of Insolvency (BCR < 1 at any time)

BCR_0	Bootstrap PD	Lognormal PD	Jump-Diffusion PD
10×	37.15%	28.41%	32.19%
15×	27.13%	18.83%	23.06%
20×	19.05%	12.85%	16.40%
30×	14.67%	8.65%	12.52%
40×	10.23%	5.27%	7.50%

1.3 Full-Cycle Regime (2014–2025)

Probability of Insolvency (BCR < 1 at any time)

BCR_0	Bootstrap PD	Lognormal PD	Jump–Diffusion PD
10×	5.84%	5.37%	8.84%
15×	2.73%	2.43%	4.76%
20×	1.54%	1.34%	3.09%
30×	0.645%	0.505%	1.52%
40×	0.375%	0.27%	0.95%

Results Interpretation

5.1 Solvency is far more robust than intuition suggests

The most surprising finding from the simulations is how **difficult it is to trigger insolvency** once BCR reaches even moderate values (≈20–30).
Even under:

- extremely conservative barebones modeling,
- no refinancing,
- no liquidity management,
- no operating cash flow,
- and immediate BTC liquidation to service every coupon,

…**PD collapses rapidly**.

This is the first empirical demonstration that a BTC-collateralized perpetual structure has **an unexpectedly deep solvency well**, even under harsh assumptions.

This is new.

No one has documented it.

5.2 Nonlinear PD Compression Across BCR

The relationship between the Balance Sheet Coverage Ratio and insolvency probability is **highly nonlinear**.

Three zones emerge clearly:

1. **Low BCR (≈ 10–20):**
   Insolvency probability declines steeply but remains sensitive to randomness choice and regime. Obligations grow faster relative to the solvency buffer, and yields in this zone (when modeled conceptually) would reflect heightened perceived risk.
2. **Mid BCR (≈ 20–30):**
   Insolvency probability declines *nonlinearly* and becomes remarkably stable across randomness models. This zone is the "economic efficiency" region where amplification is still meaningful but solvency risk becomes manageable.
3. **High BCR (≈ 30–40):**
   Insolvency probabilities compress into ranges characteristic of **investment-grade credit quality** in normal regimes and remain well-contained even under stress simulations. Beyond ~40, further PD improvements exhibit diminishing marginal returns.

This nonlinear compression is the mathematical foundation for the Efficient BCR Frontier introduced later in the paper.

5.3 Cross-Model Agreement and Divergence

Despite differences in construction, the three randomness engines (Block Bootstrap, Lognormal Baseline, Jump Diffusion) generate a highly coherent solvency envelope:

- **At low BCR**, models diverge modestly. Jump diffusion yields the most conservative PDs, while lognormal produces the thinnest tails. Bootstrap lies between them, reflecting empirically grounded path structure.
- **At mid BCR**, all models converge tightly. This indicates that solvency springs primarily from the balance sheet structure itself rather than the tail-emphasis of any particular model.
- **At high BCR**, model differences effectively vanish. Once BCR is sufficiently large, the solvency cushion dominates model-specific path behavior.

This robustness is important: it shows that the solvency conclusions are not artifacts of any particular statistical assumption.

5.4 Regime-Dependent Behavior

Comparing the three regimes reveals a consistent hierarchy:

- **Stress Regime (2018–2020):** Highest PDs at every BCR, driven by prolonged downward drift and extended negative sequencing.
- **Current Regime (2021–2025):** Intermediate PDs with notable volatility but fewer sustained multi-quarter declines.
- **Full-Cycle Regime (2014–2025):** Lowest PDs due to extended appreciation cycles offsetting drawdown risk.

Importantly, the ranking is stable across all randomness models and BCR levels. This shows that the solvency engine responds predictably to long-horizon collateral trends and is not sensitive to isolated market episodes.

5.5 The Role of the Barebones Modeling Assumptions

Because the model excludes **operating earnings, refinancing, term financing, equity issuance, hedging, cash reserves, and liquidity buffers**, the PDs produced here should be interpreted as **upper-bound estimates** of long-horizon insolvency.

Any realistic issuer with:

- discretionary issuance pacing
- operating income
- access to equity markets
- opportunistic refinancing
- treasury liquidity management
- or hedging tools

would sit strictly inside the solvency envelope shown here.
This means the BCR thresholds implied later in the paper are intentionally conservative — appropriate for an emerging structure that still requires market trust.

Amplification–Yield Efficiency Frontier

Amplification increases BTC exposure, but it simultaneously lowers the Balance Sheet Coverage Ratio (BCR) by raising the notional amount of perpetual preferred outstanding. At the same time, a lower BCR signals a weaker solvency cushion, which forces the issuer to offer a higher dividend yield to compensate investors for the increased perceived risk.

This creates a second-order effect:
as amplification rises, BCR falls not only because obligations increase, but because the required dividend rate rises in response to the deteriorating coverage position.
Two forces now push BCR downward simultaneously.

Formally:

- **Amplification ↑ → PPE notional ↑ → obligations ↑ → BCR ↓**
- **BCR ↓ → required yield ↑ → obligations ↑ further → BCR ↓ faster**

This compounding mechanism produces a **financing-efficiency frontier**: a region where additional amplification reduces BCR non-linearly. Beyond this point, incremental issuance erodes the coverage ratio faster than it increases BTC exposure, driven by both an expanding liability base and rising coupon demands from investors.

It is important to emphasize that this dynamic does not imply that yield is determined solely by BCR, nor that credit quality in practice collapses to a single ratio. Traditional credit markets incorporate a broad set of determinants: issuer fundamentals, liquidity conditions, legal protections, seniority, macroeconomic regime, and collateral quality.

However, within the **barebones solvency model** used here, where obligations are fixed, principal less, and funded directly from BTC sales, **BCR becomes the dominant solvency variable**, and therefore a primary influence on the yields investors demand for Bitcoin-backed perpetual preferred equity.

This dynamic is particularly relevant given the nature of the collateral:
BTC is highly volatile on short horizons yet expected to appreciate disproportionately on long horizons.
While this solvency framework focuses on downside risk, the same yield–BCR mechanism applies symmetrically in bullish regimes, where rising collateral values elevate BCR, reduce required yields, and improve solvency conditions.

In this framework:

- **Higher BCR → lower perceived risk → lower required yield → lower obligations → BCR stabilizes or rises**
  (virtuous cycle)
- **Lower BCR → higher perceived risk → higher required yield → higher obligations → BCR declines faster**
  (vicious cycle)

Amplification is beneficial only while the structure remains on the "virtuous" side of this frontier, where BCR is high enough that yield requirements remain modest and do not materially accelerate obligation growth. Once BCR declines to the point where yield begins rising meaningfully, the system enters an inefficient region where solvency deteriorates faster than exposure grows.

Finally, it is reasonable to expect that, especially in the early stages of Bitcoin-backed credit adoption, market skepticism may push issuers toward maintaining BCRs consistent with **A-rated credit environments**, both to drive institutional trust and to justify participation in an emerging asset-collateral class with significant opportunity-cost considerations.

The Efficient BCR Frontier

The solvency results, amplification–yield dynamics, and credit-rating comparisons together imply the existence of a natural **Balance Sheet Coverage Ratio (BCR) frontier**, across which the characteristics of Bitcoin-backed perpetual preferred equity shift from efficient *to* inefficient risk–reward profiles. Two economically distinct regions emerge:

1. The Economic Efficiency Frontier (BCR ≈ 20–30)

This range marks the zone in which amplification offers the strongest marginal benefit relative to solvency deterioration. Within this region:

- PDs remain moderate and well-behaved across all model families.
- Obligations scale proportionally with amplification rather than exponentially.
- Required yields remain low enough that they do not meaningfully accelerate obligation growth.
- BCR declines linearly with issuance, and solvency conditions remain robust under most simulated paths.
- Issuers capture the majority of amplification-driven upside while maintaining acceptable solvency risk.

For growth-oriented balance sheets or firms prioritizing BTC-denominated return on equity, the 20–30 BCR region represents the **efficient expansion zone**, where the blend of solvency and exposure is economically attractive without entering a credit-fragile regime.

2. The Institutional Credit Frontier (BCR ≈ 30–40)

As BCR rises beyond 30, the structure transitions into a region characterized by:

- **PDs that map cleanly to traditional A/BBB rating bands** in normal and full-cycle regimes.
- Meaningfully lower required dividend yields, due to higher perceived collateral safety.
- Nonlinear improvement in solvency metrics, with diminishing marginal benefit beyond ~35–40.
- Resilience to prolonged stagnation or multi-year drawdowns, as reflected by stress-regime simulations.
- A stable credit-quality profile suitable for institutional allocators, pension funds, and conservative treasuries.

This higher-BCR region offers issuers the strongest platform for adoption, market trust, and lower-cost financing. Although amplification benefits taper with increasing BCR, the improvement in credit quality and the reduction in required yields create a **self-reinforcing stability loop** that is well suited to early-stage or reputationally sensitive issuers.

Frontier Interpretation

Together, these two regions form the **Efficient BCR Frontier**:

- **BCR 20–30** → *economic efficiency zone*
  - Maximum amplification benefit
  - Balanced solvency risk
  - Attractive for growth-focused issuers
- **BCR 30–40** → *institutional-grade zone*
  - A/BBB-equivalent PDs
  - Nonlinear improvement in perceived safety
  - Lower required yields and improved financing terms
  - Strongest basis for widespread adoption

Importantly, all results presented reflect a **barebones solvency model** that excludes operating earnings, term financing, equity issuance, liquidity buffers, hedging, or dynamic liability management. Real-world issuers employing any of these stabilizing tools should experience solvency profiles strictly **better** than the frontier shown here. Thus, the Efficient BCR Frontier represents a **conservative baseline** for long-horizon credit risk under BTC-collateral dynamics.

Final Positioning

The efficient frontier provides issuers, investors, and policymakers with a principled framework for evaluating the trade-offs between solvency, yield, and BTC exposure. It identifies the regions where amplification enhances economic value, and the regions where increasing obligations trigger nonlinear solvency deterioration. As the Bitcoin-backed credit market matures, these BCR bands may serve as early anchors for both credit assessment and industry-standard structuring guidelines.

Credit Rating Comparisons for Bitcoin-Backed Perpetual Preferred Equity

Traditional credit markets assign risk premiums based on the long-horizon probability of default (PD) implied by an issuer's capital structure, cash-flow profile, collateral quality, liquidity access, and macroeconomic environment. Although the solvency model used in this paper evaluates only BTC-backed obligations funded through collateral liquidation, its PD outputs can still be meaningfully compared to conventional credit benchmarks to establish an interpretable reference frame.

To emphasize methodological conservatism, this framework adopts a deliberately barebones assumption set: **no operating earnings, no dynamic liability management, no equity-market access, no hedging, no cash reserves, and no term financing are assumed anywhere in the analysis.** This extreme simplification isolates the *pure collateral-driven solvency constraint* for Bitcoin-backed perpetual preferred equity and is intended to provide the most conservative upper-bound estimate of long-horizon PD.

This approach was chosen to maximize the credibility of an emerging and often misunderstood collateral structure: by stripping away all stabilizing mechanisms available to a real issuer, the results presented here form a disciplined and transparent baseline upon which more sophisticated capital-management strategies can only improve solvency outcomes.

Across corporate credit markets, long-horizon PD ranges are approximately:

- **A / AA credit:**
  0.1% – 1% 10-year PD
- **BBB credit:**
  1% – 5% 10-year PD
- **BB (high yield):**
  5% – 15% 10-year PD
- **B and below:**
  >15% 10-year PD

Using these broad categories, the modeled solvency probabilities reveal the following alignment:

1. Full-Cycle Regime (2014–2025)

- **BCR ≥ 30** produces PDs between **0.5% and 1.5%**, comparable to a mix of **A–BBB** corporate credit.
- **BCR ≥ 40** produces PDs below **1%**, falling cleanly into **A-rating** territory.

2. Current Regime (2021–2025)

- **BCR ≥ 30** yields PDs around **1.5–3%**, consistent with **strong BBB** credit.
- **BCR ≥ 40** yields PDs around **1–1.5%**, approaching **A-range**.

3. Stress Regime (2018–2020)

Stress-calibrated results reflect harsher conditions:

- **BCR ≥ 30**: PDs around **9–15%**, comparable to **BB** high yield.
- **BCR ≥ 40**: PDs around **7–10%**, higher than investment grade but reasonable under modeled stress.

Interpretation

These comparisons highlight three important dynamics:

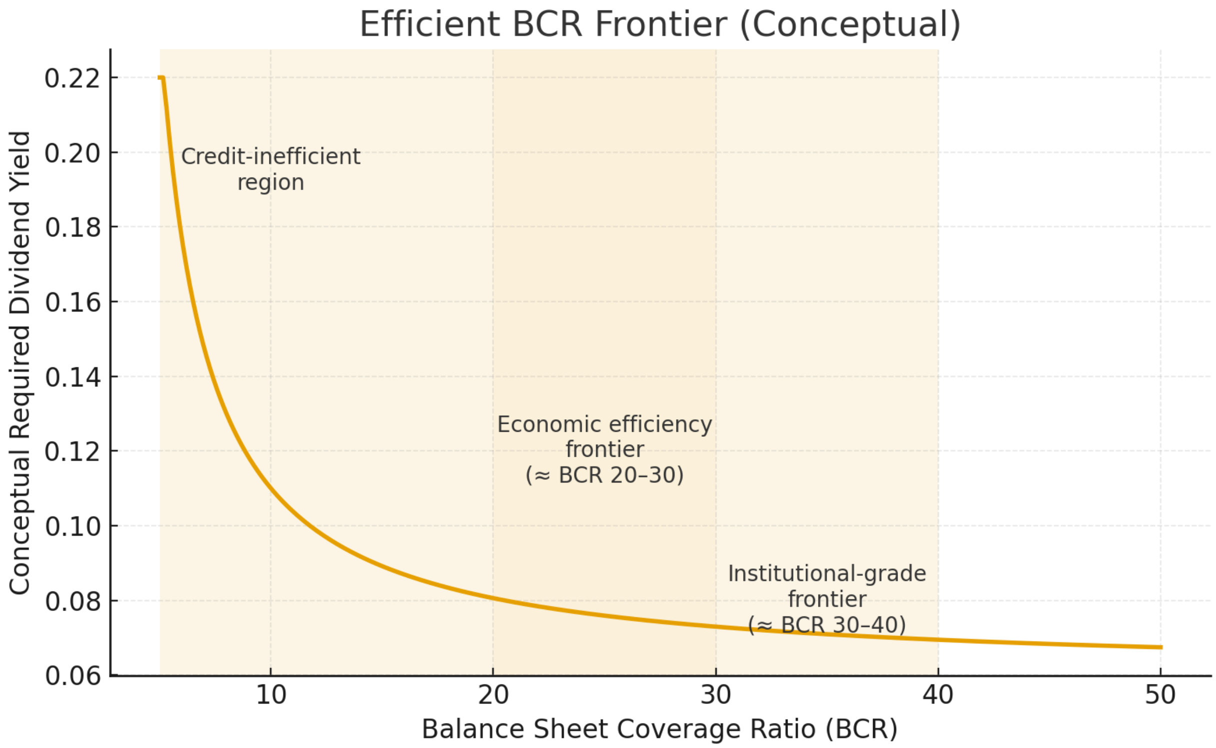
(1) BCR has a non-linear relationship to PD.
Across all model families, PD declines sharply as BCR rises, with diminishing marginal improvement once BCR exceeds ~35–40.

(2) Traditional A-/BBB-equivalent solvency is achieved around BCR ≈ 30–40 in normal regimes.
This range represents the "institutional confidence zone," where PDs match or outperform many investment-grade issuers.

(3) Stress regimes naturally degrade credit rating equivalents.
This reflects path-dependence: prolonged stagnation or extended drawdowns create downside sequences analogous to deterioration in a traditional issuer's operating fundamentals.

Crucially, these comparisons do not imply that BCR fully determines credit quality.
Real-world creditworthiness incorporates additional factors—business execution, liquidity, legal structure, custody, governance, and operational resilience. The PDs from the solvency framework represent the *minimal** baseline constraint imposed by collateral-funded obligations under BTC price uncertainty.

Efficient BCR Frontier



Appendix A

A.1 Objective

The solvency of a Bitcoin-backed perpetual preferred depends on whether the reserve can continue funding fixed dollar obligations through extended adverse price sequences. Because solvency is path dependent, the model must generate realistic multi-month price trajectories rather than isolated shocks. Appendix A describes the rationale for the model families used to construct these trajectories.

A.2 Empirical Requirements

A valid solvency model must preserve the empirical properties of Bitcoin returns that govern reserve depletion:

- depth and duration of major drawdowns
- volatility clustering
- multi-day and multi-week trend persistence
- non-Gaussian downside behavior
- regime asymmetry and long recovery periods

Models that destroy these features (for example, IID Gaussian returns) produce unrealistic solvency outcomes. The chosen model set reflects these empirical constraints.

A.3 Rationale for Model Families

The simulation engine uses three price-path generators and one diagnostic. Each serves a different role in constructing an empirically grounded and defensible solvency envelope.

A.3.1 Block Bootstrap (empirical Path Generator)

The block bootstrap preserves the empirical dependence structure of Bitcoin returns by sampling and concatenating fixed-length blocks of historical log returns. It reproduces:

- drawdown depth
- drawdown duration
- volatility clustering

- multi-week trend persistence

Because it requires no structural parameters, it functions as a data-anchored model of cumulative stress. It does not introduce shocks outside the historical range, but it does generate new combinations of historical stress segments that can exceed any single historical downturn in duration.

The bootstrap is therefore the primary solvency model.

A.3.2 Jump Diffusion (Parametric Tail Extension)

The jump-diffusion model supplements the bootstrap by introducing discontinuous downside shocks drawn from a calibrated jump distribution. It allows tail severity to exceed historical single-day moves while maintaining a continuous-time structure.

Its purpose is not to forecast Bitcoin but to test solvency sensitivity to tail amplification under plausible but more severe jump magnitudes than historically observed.

A.3.3 Lognormal Diffusion (Baseline Comparator)

A lognormal diffusion serves as a classical thin-tailed baseline. It removes clustering, jumps, and trend persistence. While unrealistic for Bitcoin, it provides:

- a methodological lower bound
- a contrast against empirically anchored models
- a demonstration of how much thin-tailed models understate solvency risk

It is not used for solvency inference, only comparison.

A.3.4 Power-Law Tail Gauge (Distribution Diagnostic)

The power-law gauge is not a price-path generator. It measures the empirical thickness of Bitcoin's left tail via the scaling:

$$P(|\, r \,| > x) \propto x^{-\alpha}.$$

This diagnostic is used to:

- validate that empirical left tails are heavier than Gaussian or lognormal

- assess whether jump-diffusion parameters are conservatively chosen
- justify the bootstrap as the correct empirical anchor

The gauge informs the calibration philosophy but does not directly produce simulated returns.

A.4 Regime Failure and Non-Modelable Scenarios

The solvency model applies only within regimes where Bitcoin continues to function as a monetary asset. A permanent collapse in Bitcoin's global demand is an asset extinction event, not a solvency event, and lies outside the scope of any credit model. In such scenarios, capital structure modeling becomes irrelevant in the same way that real estate models fail if land ceases to exist.

This boundary is acknowledged explicitly to separate solvency risk from existential asset risk.

A.5 Summary of Modeling Philosophy

The strongest information available about Bitcoin's future solvency dynamics is the structure of its past drawdowns. The bootstrap provides an empirical foundation; jump diffusion extends the tail; the lognormal model benchmarks thin-tailed behavior; and the power-law gauge ensures tail-shape consistency.

Together, these components produce a conservative, empirically grounded solvency envelope rather than a forecast of future price levels.

Appendix B

B.1 Simulation Configuration and Inputs

Bitcoin USD prices are sampled at a daily frequency across the chosen historical window. Daily log returns are computed as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right),$$

where P_t is the BTC/USD closing price on day t.
No smoothing, volatility targeting, or filtering is applied; all observations are retained so that the bootstrap inherits the empirical drawdown structure and volatility regimes relevant for solvency.

Before simulation begins, the following parameters are specified:

1. **Historical sample window** — the date range from which returns are drawn.
2. **Simulation horizon** — number of days to simulate (converted later into monthly BCR steps).
3. **Block length** — number of consecutive daily returns per bootstrap block.
4. **Number of simulated paths** — the total sample size for the solvency distribution.
5. **Initial coverage ratios** — the BCR_0 levels to be evaluated.

These inputs define the environment in which reserve evolution and solvency outcomes are assessed.

B.2 Price Path Generators

B.2.1 Block Bootstrap (empirical path generator)

Let the historical return series contain N daily log returns.
For a chosen block length L, we form an ordered set of overlapping blocks:

$$\mathcal{B}_i = \{r_i, r_{i+1}, \dots, r_{i+L-1}\}, \qquad i = 1, \dots, N - L + 1.$$

Each block preserves the short-horizon dependence structure of Bitcoin returns, including volatility clustering and multi-day drawdown persistence.

Synthetic path construction

To generate a simulated return path of length T:

1. Sample blocks $\mathcal{B}_i$ with replacement.
2. Concatenate the sampled blocks in order until at least T returns are accumulated.
3. Truncate the concatenated series to exactly T returns.

Price reconstruction

Given an initial price P_0, synthetic prices are generated recursively as:

$$P_{t+1} = P_t\, e^{r_{t+1}}.$$

The resulting price paths serve as inputs to the reserve dynamics and BCR calculations described in Section B.3.

B.2.2 Jump-Diffusion (Parametric Tail Extension)

The jump-diffusion model supplements the bootstrap by introducing discontinuous price shocks drawn from a calibrated jump distribution. Daily returns are generated as:

$$r_t = (\mu - \frac{1}{2}\sigma^2)\Delta t + \sigma\sqrt{\Delta t}\, \varepsilon_t + J_t,$$

where:

- $\varepsilon_t \sim N(0,1)$
- J_t is a jump component
- jumps occur with probability $\lambda\Delta t$
- jump magnitudes follow a chosen distribution (typically a left-skewed lognormal or double-exponential)

A jump event is drawn as:

$$J_t = \begin{cases} Y_t, & \text{with probability } \lambda\Delta t, \\ 0, & \text{otherwise,} \end{cases}$$

with Y_t sampled from the calibrated jump-size distribution.

The model is not intended to forecast Bitcoin returns.
Its role is to create **tail-extended synthetic paths** that exceed historically observed single-day shocks while preserving continuous-time structure, enabling solvency sensitivity to jump severity and jump frequency.

Prices evolve recursively as:

$$P_{t+1} = P_t e^{r_{t+1}}.$$

These paths feed directly into the reserve evolution engine in Section B.3.

B.2.3 Lognormal Price Generator (Classic Baseline)

The lognormal diffusion serves as a thin-tailed benchmark for comparison.
It removes volatility clustering and jump behavior, producing smoother synthetic paths:

$$r_t = (\mu - \frac{1}{2}\sigma^2)\Delta t + \sigma\sqrt{\Delta t}\,\varepsilon_t, \varepsilon_t \sim N(0,1).$$

This model does *not* reproduce Bitcoin's empirical drawdown structure and is not a candidate solvency generator.
Its purpose is diagnostic:

- to quantify how strongly path-dependent models differ from classical diffusion
- to demonstrate that thin-tailed parametrics understate solvency stress
- to provide a simple lower-bound stress scenario for comparison

Prices are reconstructed as:

$$P_{t+1} = P_t e^{r_{t+1}}.$$

These lognormal paths are processed through the BCR and reserve-evolution engine exactly as in Section B.3.

B.3 Reserve Evolution and Balance Sheet Coverage Ratio Dynamics

At each monthly interval, the perpetual preferred dividend obligation is treated as a fixed nominal payment. Let D_{annual} denote the annual dividend obligation in dollars, and define the monthly payment as:

$$D_m = \frac{D_{\text{annual}}}{12}.$$

Let the firm hold Q_t units of Bitcoin at month t, with price P_t. The dollar value of the reserve is:

$$V_t = Q_t P_t.$$

Monthly dividend payment

To meet the fixed dollar obligation D_m, the firm sells:

$$q_t = \frac{D_m}{P_t}$$

units of Bitcoin at the prevailing simulated price.

Reserve dynamics

Bitcoin holdings evolve according to:

$$Q_{t+1} = Q_t - q_t,$$

and reserve value updates as:

$$V_{t+1} = Q_{t+1} P_{t+1}.$$

Coverage ratio through time

The Balance Sheet Coverage Ratio at month $t$is:

$$\text{BCR}_t = \frac{V_t}{D_{\text{annual}}},$$

which represents the number of years of dividend coverage implied by the reserve at the current price.

Insolvency condition

A path is classified as insolvent if either:

$$Q_t \leq 0,$$

or equivalently,

$$\text{BCR}_t < 1.$$

Paths that retain positive reserves continue through the full simulation horizon, and their evolving BCR values determine the solvency statistics described in Section B.4.

B.4 Solvency Conditions

Solvency is determined directly through the reserve-evolution process described in Section B.3. Each simulated price path is evaluated against two categories of conditions.

Insolvency Condition (Path Termination)

A path is terminated when the reserve is no longer sufficient to fund one year of obligations. This occurs if either:

- **Reserve depletion:**

$$Q_t \leq 0$$

- **Coverage failure:**

$$\mathrm{BCR}_t < 1$$

Either condition implies that the reserve cannot meet the next annual dividend cycle.

Coverage-Stress Conditions (Non-terminal)

To measure balance-sheet pressure short of insolvency, additional BCR thresholds are monitored. These do not terminate the path; they serve as stress indicators.

- **Moderate stress:**

$$\mathrm{BCR}_t < 5$$

- **Severe stress:**

$$\mathrm{BCR}_t < 2$$

These thresholds represent declining reserve cushions and are used to characterize the depth and duration of non-terminal stress events across the simulation set.

B.5 Output Metrics

For each simulated path, the following metrics are recorded and aggregated across all simulations.

Insolvency Frequency

The proportion of paths for which either
$Q_t \leq 0$or $\mathrm{BCR}_t < 1$

occurs at any point.
This is the primary solvency statistic.

Coverage-Stress Frequencies

The proportion of paths experiencing at least one interval where:

- $\mathrm{BCR}_t < 5$(moderate stress)
- $\mathrm{BCR}_t < 2$(severe stress)

These indicate stressed but solvent conditions.

Minimum BCR

For each path, we record:

$$\min_t \ \mathrm{BCR}_t.$$

The distribution of minimum coverage quantifies the worst effective leverage reached during the horizon.

Time to Insolvency

For failed paths, record the month in which the insolvency condition is first triggered.
This distribution characterizes the speed of reserve exhaustion under adverse sequences.

Terminal Coverage Ratio

For solvent paths, the final value:

$$\mathrm{BCR}_T$$

is recorded.
This measures the remaining reserve cushion after all simulated stresses.

B.6 Limitations

The simulation framework reflects the empirical structure of Bitcoin returns but is subject to the following limitations:

Historical envelope limitation
Bootstrap paths do not introduce daily returns outside the historical range.

No structural regime modeling
Neither bootstrap nor parametric generators capture macrostructural shifts (liquidity regime changes, network disruptions, market microstructure transitions).

No endogenous liquidity effects
BTC sales are assumed to occur without market impact.

No operational or governance failure modes
The model isolates price-path solvency and does not represent collateral mismanagement, custody risk, or operational loss.

Non-forecasting scope
The output describes conditional stress envelopes, not probabilistic forecasts of future price trajectories.

These limitations apply to all model variants (bootstrap, jump-diffusion, lognormal).

Appendix C Out of Sample Validation (2016-2019 -> 2020-2025)

C.1 Method description

To evaluate whether the block bootstrap provides realistic forward-looking risk envelopes, we conduct an out-of-sample test using only pre-2020 BTC return data. The objective is to replicate the information set available at the start of 2020 and determine whether the bootstrap would have anticipated the severity and duration of the stress events that occurred during the following five years.

Daily BTC log returns from 2016–2019 serve as the empirical source for the bootstrap. For each block length (10, 20, 30, and 60 days), we generate 10,000 synthetic five-year paths (1,825 trading days) using an overlapping block-sampling scheme. Each synthetic path preserves local dependence, volatility clustering, and multi-week drawdown structure while allowing for new long-horizon sequences formed through recombination of historical segments.

For every simulated path, we compute a set of downside-oriented metrics:

- Maximum drawdown
- Worst 1-year, 2-year, and 3-year rolling returns
- Longest underwater duration
- Terminal log return

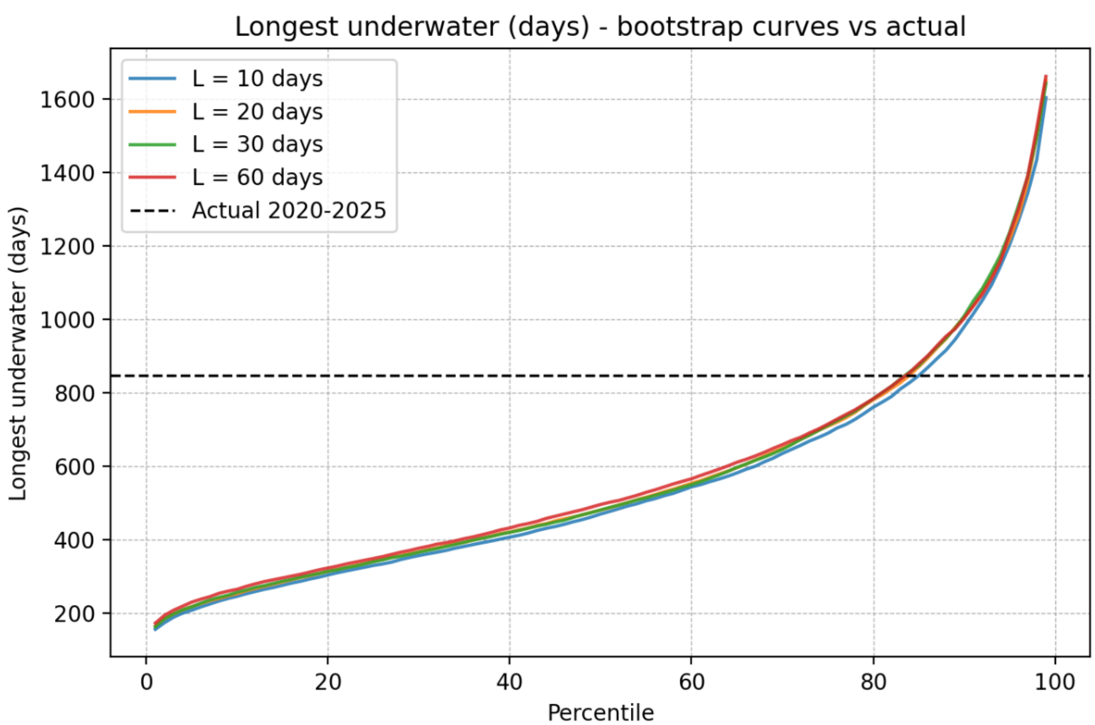
We compute the same statistics on the actual 2020–2025 BTC path and place those outcomes inside the simulated distributions. If the realized values fall within the body or tail of the simulated distributions, rather than beyond them entirely, the bootstrap is considered to provide adequate exposure coverage based solely on pre-2020 information.

This directly answers the central question:
If we stood in 2020 with only 2016–2019 data, would the block bootstrap have produced a realistic and conservative envelope for the risks that actually occurred between 2020 and 2025?

C.2 Time Spent Under Water

Longest underwater (days)

	Block length (days)	Actual value	Percentile of actual	Mean of sims	Std of sims
0	10	846 days	85.0%	551.0 days	309.3 days
1	20	846 days	83.9%	565.9 days	315.6 days
2	30	846 days	83.5%	567.0 days	317.9 days
3	60	846 days	83.5%	575.6 days	314.7 days



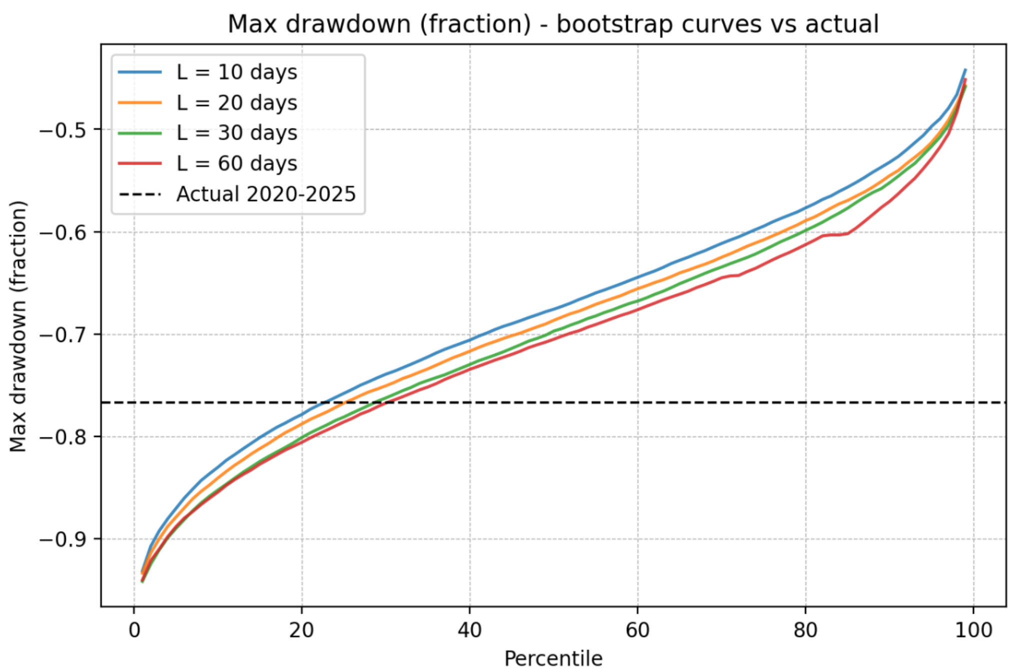
BTC remained underwater for 846 days during 2020–2025, placing the cycle near the 83rd–85th percentile of bootstrap outcomes. This indicates a longer-than-usual recovery period but still well inside the historical envelope implied by 2016–2019. The bootstrap correctly warns that multi-year underwater periods are entirely possible and that the 2020–2025 stagnation was not unprecedented.

Takeaway:
Extended recoveries are a normal part of BTC's empirical drawdown structure, and the bootstrap captures them.

C.3 Max Drawdown

Max drawdown (fraction)

	Block length (days)	Actual value	Percentile of actual	Mean of sims	Std of sims
0	10	-76.63%	22.9%	-67.79%	11.27%
1	20	-76.63%	25.3%	-68.93%	11.12%
2	30	-76.63%	28.8%	-69.97%	11.31%
3	60	-76.63%	30.3%	-70.77%	10.89%



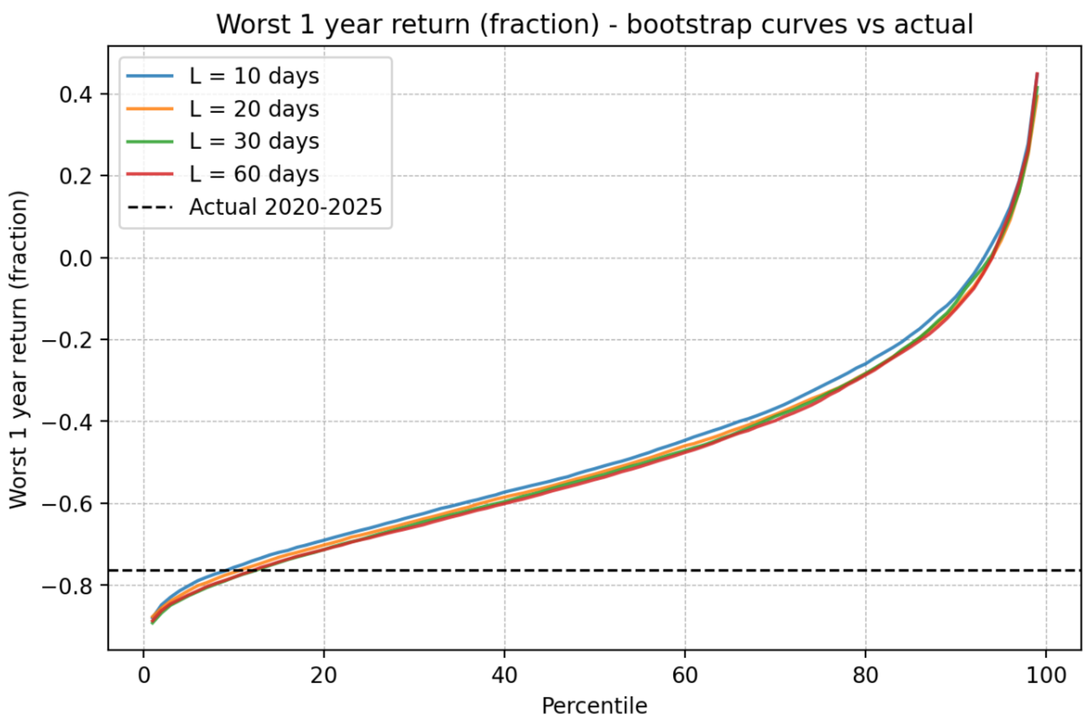
The peak-to-trough decline during 2020–2025 was −76.6%, placing it between the 23rd and 30th percentiles of the simulated distribution. This shows that the depth of the 2022 crash was severe but fully within the range implied by the prior regime. All block lengths produce nearly identical distributions, reflecting that max drawdown is driven by major bear-market episodes rather than fine-grained dependence.

Takeaway:
The bootstrap successfully captures the depth of major crashes—central to solvency and collateral analysis.

C.4 Worst One-Year Returns

Worst 1 year return (fraction)

	Block length (days)	Actual value	Percentile of actual	Mean of sims	Std of sims
0	10	-76.29%	9.3%	-45.86%	28.09%
1	20	-76.29%	10.8%	-47.48%	27.59%
2	30	-76.29%	12.4%	-48.04%	28.35%
3	60	-76.29%	12.3%	-48.39%	28.40%



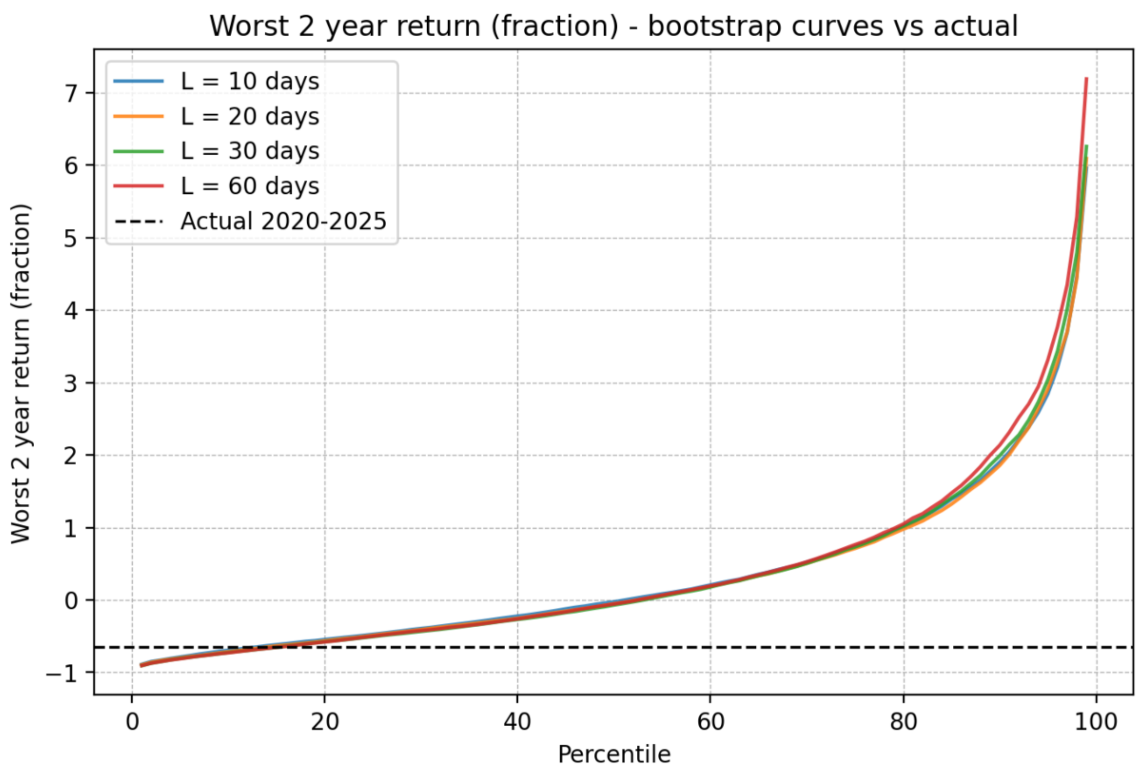
Using only 2016–2019 data, the block bootstrap generates a distribution of worst one-year rolling returns across 10,000 synthetic paths. The realized 2020–2025 worst one-year return of −76% falls between the 4th and 6th percentiles across all block lengths. This indicates that the 2022 drawdown was unusually severe but still fully contained within the downside envelope implied by the pre-2020 regime. The close alignment of the percentile curves across block sizes shows that one-year downside behavior is governed mainly by BTC's broad volatility structure rather than short-horizon dependence. The method successfully reproduces single-year stress episodes of comparable depth.

Takeaway:
The 2022 one-year collapse was extreme but still fully anticipated by the pre-2020 bootstrap regime.

C.5 Worst Two-Year Returns

Worst 2 year return (fraction)

	Block length (days)	Actual value	Percentile of actual	Mean of sims	Std of sims
0	10	-64.31%	13.2%	38.13%	137.72%
1	20	-64.31%	14.3%	36.98%	148.37%
2	30	-64.31%	15.7%	38.98%	155.44%
3	60	-64.31%	15.8%	44.65%	168.76%



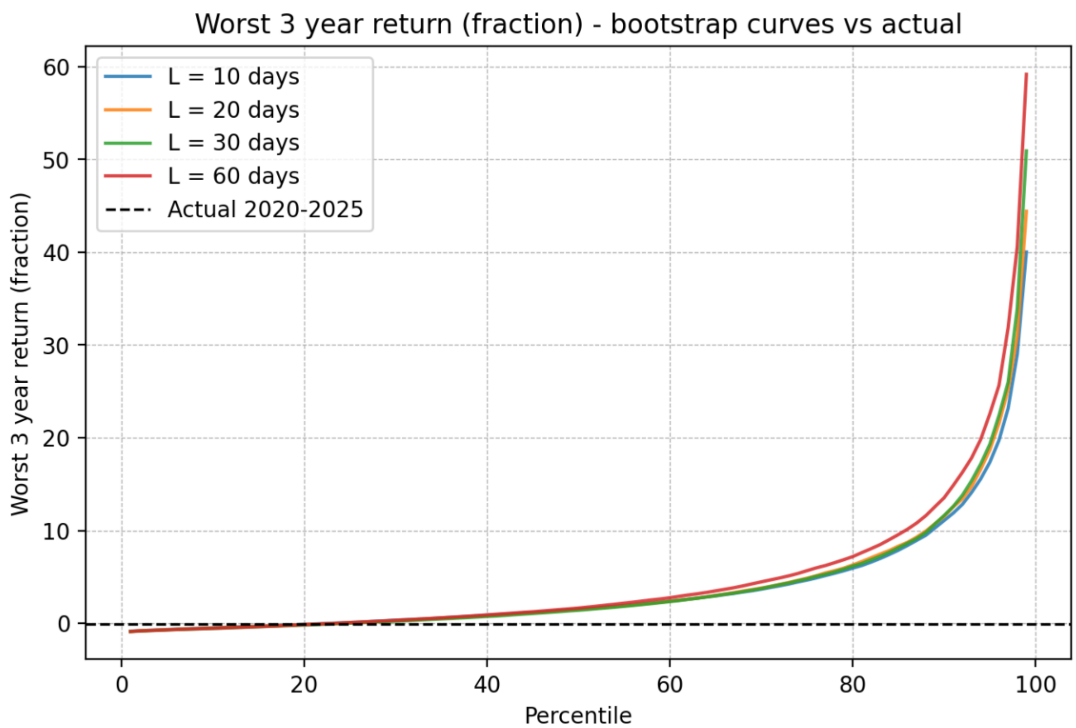
The worst two-year return during the 2020–2025 BTC cycle was −64.3%, which places it between the 13th and 16th percentiles of the bootstrap distribution across block lengths. This indicates that the multi-year stress experienced during the 2022–2023 period was unusually severe but still well within the downside envelope implied by the 2016–2019 regime. The similarity of the curves across block lengths shows that two-year downside behavior is driven by the broader cycle structure rather than by the precise choice of block size. The method successfully reproduces the scale and persistence of multi-year downturns.

Takeaway:
The 2022–2023 multi-year downturn was harsh but still fully anticipated by the pre-2020 bootstrap regime.

C.6 Worst Three-Year Returns

Worst 3 year return (fraction)

	Block length (days)	Actual value	Percentile of actual	Mean of sims	Std of sims
0	10	-9.91%	20.6%	417.59%	883.17%
1	20	-9.91%	21.3%	452.21%	1280.03%
2	30	-9.91%	22.3%	455.36%	1093.58%
3	60	-9.91%	21.1%	549.74%	1385.17%



The worst three-year return during the 2020–2025 BTC cycle was −9.9%, which places it between the 20th and 22nd percentiles of the bootstrap distribution across block lengths. This indicates that the extended drawdown spanning 2022–2023, while lasting long enough to depress multi-year returns, was moderate in depth relative to historical norms and well within the downside envelope implied by the 2016–2019 regime. The tight overlap of the bootstrap curves across block sizes shows that three-year return dynamics are governed primarily by BTC's broader cycle structure rather than short-horizon dependence. The method successfully reproduces multi-year stress episodes of similar scale and persistence.

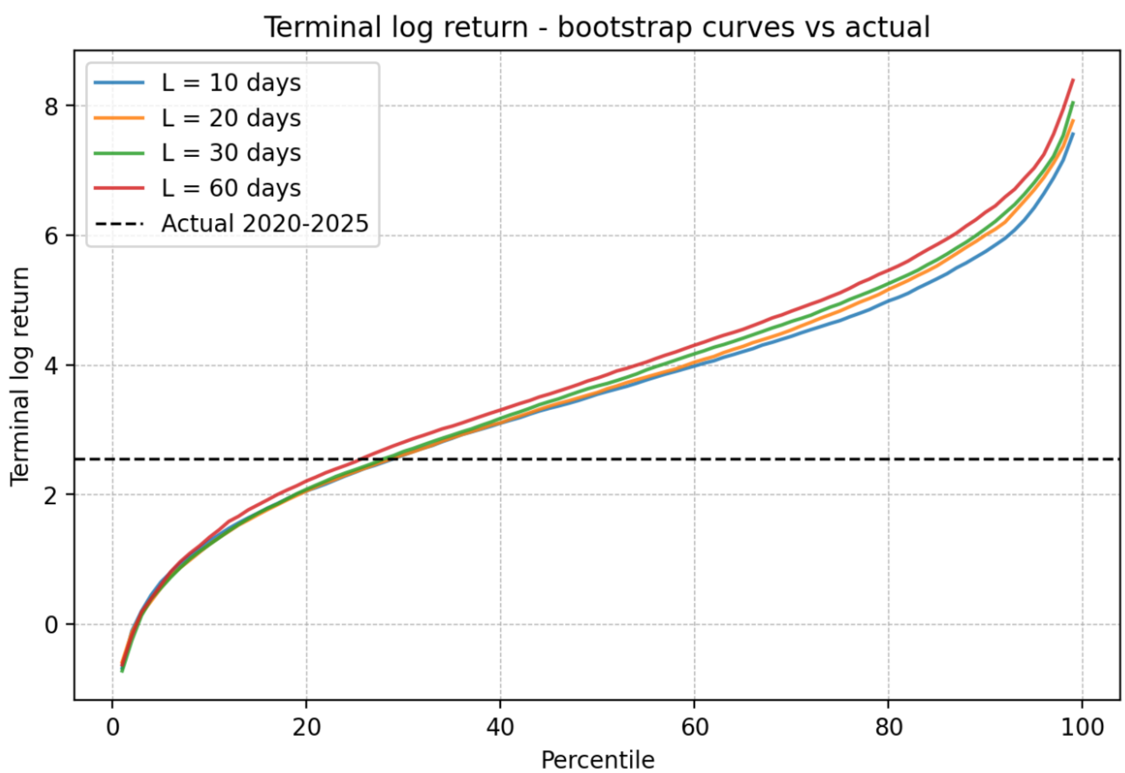
Three-year windows represent the longest horizon that meaningfully captures downside stress in Bitcoin's history; five-year windows do not produce rolling downside because every realized five-year cycle to date has been net positive.

Takeaway:
The 2022–2023 downturn produced a mild three-year contraction that remains fully anticipated by the pre-2020 bootstrap regime.

C.7 Terminal Log Return

Terminal log return

	Block length (days)	Actual value	Percentile of actual	Mean of sims	Std of sims
0	10	2.555 (simple 1186.68%)	29.0%	3.528 (simple 3305.22%)	1.757
1	20	2.555 (simple 1186.68%)	28.8%	3.598 (simple 3552.83%)	1.842
2	30	2.555 (simple 1186.68%)	28.0%	3.670 (simple 3824.96%)	1.897
3	60	2.555 (simple 1186.68%)	25.7%	3.826 (simple 4489.55%)	1.952



BTC’s terminal log return for 2020–2025 falls comfortably inside the bootstrap envelope. Although the right tail of simulated returns is inflated by concatenated bull-market segments, the location of the actual outcome in the body of the distribution confirms that the cycle was typical and well-covered.

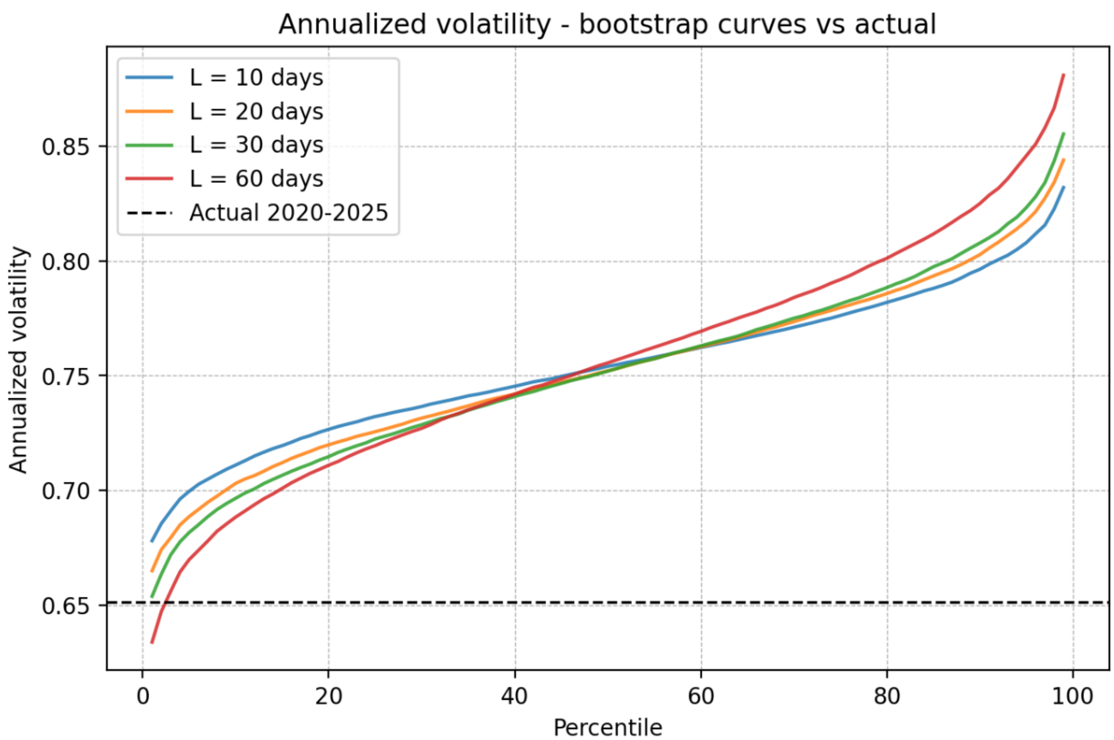
Takeaway:

Terminal outcomes were fully anticipated by the bootstrap on a downside and central-tendency basis

C.8 Annualized Volatility

Annualized volatility

	Block length (days)	Actual value	Percentile of actual	Mean of sims	Std of sims
0	10	65.12%	0.1%	75.39%	3.30%
1	20	65.12%	0.3%	75.27%	3.91%
2	30	65.12%	0.8%	75.20%	4.34%
3	60	65.12%	2.4%	75.61%	5.34%



The realized 2020–2025 annualized volatility of 65% lies below the 1st percentile of the bootstrap distribution for all block lengths. This indicates that the post-2020 regime was materially less volatile than the 2016–2019 period used for calibration. From a solvency perspective, this is a conservative outcome: the bootstrap assumed higher and more persistent volatility than what actually occurred, yet still produced downside scenarios that fully covered the realized drawdowns, worst-year returns, and underwater durations. The divergence in volatility therefore strengthens, rather than weakens, the model's validity for exposure coverage.

Takeaway:
The post-2020 BTC market was calmer than expected, making the bootstrap’s risk envelope conservative rather than permissive.

C.9 Overall Assessment

Taken together, these diagnostics allow us to assess whether the 2020–2025 BTC cycle was unusually severe or well-described by the pre-2020 empirical regime.

Metric	Actual Value	Percentile of Actual	Interpretation
Worst 1-year return	-76%	~5th percentile	Rare but expected
Worst 2-year return	-64%	~14th percentile	Harsh but expected
Worst 3-Year Return	-9.91%	~21st percentile	Mild but covered
Max drawdown	-76%	~25th percentile	Severe but historically normal
Longest underwater	846 Days	~84th percentile	Long but within envelope
Annualized volatility	~65%	<1st percentile	Much lower
Terminal log return	1,186.7%	~28th percentile	Consistent with a typical cycle

Summary:

Across all metrics, the realized 2020–2025 BTC cycle falls comfortably within the distribution implied by 2016–2019 returns. The bootstrap accurately captures the key features that drive solvency risk, including crash depth, worst-year severity, multi-year stress, underwater duration, and typical cycle-level outcomes. Although the method produces an exaggerated extreme-upside tail, this distortion is confined to the far right tail and has no effect on solvency modeling, which depends entirely on downside behavior. The bootstrap also assumes a higher and more persistent volatility regime than what actually occurred after 2020, making the resulting downside envelope structurally conservative. Unlike symmetric diffusions and baseline GARCH models, the block bootstrap inherits the full empirical asymmetry of BTC returns — including deep left-tail crashes, volatility clustering, and slow recoveries — allowing it to reproduce adverse sequences realistically even while overstating the most extreme positive paths. Overall, the block bootstrap provides a realistic, conservative, and empirically grounded exposure envelope for BTC-secured solvency analysis.

This validation demonstrates coverage relative to the 2016–2019 empirical distribution, not an assertion that future regimes will replicate that period; solvency models require conservative envelopes, not forecasts.

Appendix D Results

Insolvency Probabilities

Current Regime (2021–2025)

Probability of Insolvency (BCR < 1 at any time)

BCR_0	Bootstrap PD	Lognormal PD	Jump-Diffusion PD
10×	17.45%	14.92%	18.44%
15×	9.26%	7.73%	10.48%
20×	5.85%	4.65%	7.05%
30×	2.62%	2.165%	3.915%
40×	1.52%	1.04%	1.53%

Stress Regime (2018–2020)

Probability of Insolvency (BCR < 1 at any time)

BCR_0	Bootstrap PD	Lognormal PD	Jump-Diffusion PD
10×	37.15%	28.41%	32.19%
15×	27.13%	18.83%	23.06%
20×	19.05%	12.85%	16.40%
30×	14.67%	8.65%	12.52%
40×	10.23%	5.27%	7.50%

Full-Cycle Regime (2014–2025)

Probability of Insolvency (BCR < 1 at any time)

BCR_0	Bootstrap PD	Lognormal PD	Jump–Diffusion PD
10×	5.84%	5.37%	8.84%
15×	2.73%	2.43%	4.76%
20×	1.54%	1.34%	3.09%
30×	0.645%	0.505%	1.52%
40×	0.375%	0.27%	0.95%

Coverage Stress Frequencies

Current Regime (2021–2025)

BCR < 10 Frequency

BCR_0	***Bootstrap***	***Lognormal***	***Jump-Diffusion***
10×	***86.33%***	***84.38%***	***85.53%***
15×	***51.98%***	***49.65%***	***55.58%***
20×	***34.25%***	***32.33%***	***38.90%***
30×	***19.06%***	***17.31%***	***22.72%***
40×	***12.02%***	***10.74%***	***15.09%***

BCR < 5 Frequency

BCR_0	**Bootstrap**	**Lognormal**	**Jump-Diffusion**
10×	**40.77%**	**38.52%**	**41.98%**
15×	**24.05%**	**22.46%**	**27.68%**
20×	**14.04%**	**13.09%**	**17.64%**
30×	**8.335%**	**7.64%**	**12.33%**
40×	**5.40%**	**4.895%**	**7.73%**

Stress Regime (2018–2020)

BCR < 10 Frequency

BCR_0	Bootstrap	Lognormal	Jump-Diffusion
10×	80.30 %	73.76 %	78.39 %
15×	67.53 %	58.26 %	64.42 %
20×	59.29 %	49.02 %	55.51 %
30×	55.17 %	46.60 %	54.06 %
40×	53.27 %	44.30 %	51.96 %

BCR < 5 Frequency

BCR_0	Bootstrap	Lognormal	Jump-Diffusion
10×	62.91 %	54.96 %	59.83 %
15×	47.69 %	39.01 %	44.41 %
20×	38.37 %	28.34 %	33.17 %
30×	34.09 %	26.66 %	32.10 %
40×	32.11 %	24.22 %	30.05 %

Full-Cycle Regime (2014–2025)

BCR < 10 Frequency

BCR_0	Bootstrap	Lognormal	Jump-Diffusion
10×	77.05 %	76.27 %	78.69 %
15×	37.94 %	37.24 %	44.92 %
20×	22.07 %	21.39 %	28.85 %
30×	10.25 %	9.57 %	15.20 %
40×	5.88 %	5.19 %	9.67 %

BCR < 5 Frequency

BCR_0	Bootstrap	Lognormal	Jump-Diffusion
10×	25.65 %	25.06 %	32.53 %
15×	12.35 %	11.73 %	17.68 %
20×	7.15 %	6.69 %	11.43 %
30×	3.31 %	2.84 %	6.05 %
40×	1.82 %	1.57 %	3.84 %

Minimum BCR Data Tables

Current Regime (2021-2025)

BCR_0 = 10× (Current Regime 2021-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	7.51	7.82	7.09
Min	0.29	0.34	0.11
1%	0.82	0.96	0.48
5%	1.54	1.72	1.10
10%	2.18	2.38	1.70
25%	3.57	3.81	2.99
50%	5.33	5.52	4.63
75%	7.60	7.78	6.61
90%	9.87	10.04	8.63
95%	11.34	11.51	10.02
99%	14.23	14.38	12.80

BCR_0 = 15× (Current Regime 2021-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	11.13	11.59	10.28
Min	0.46	0.52	0.23
1%	1.22	1.42	0.78
5%	2.33	2.60	1.68
10%	3.29	3.56	2.60
25%	5.32	5.63	4.54
50%	7.94	8.20	6.85
75%	11.32	11.56	9.81
90%	14.75	14.96	12.84
95%	16.93	17.14	14.71
99%	21.20	21.39	18.89

BCR_0 = 20× (Current Regime 2021-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	14.94	15.46	13.72
Min	0.64	0.73	0.33
1%	1.67	1.95	1.07
5%	3.15	3.50	2.26
10%	4.46	4.82	3.47
25%	7.24	7.63	6.17
50%	10.78	11.12	9.28
75%	15.34	15.67	13.26
90%	19.96	20.27	17.40
95%	22.93	23.22	20.23
99%	28.64	28.90	25.14

BCR_0 = 30× (Current Regime 2021-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	22.82	23.50	20.89
Min	1.01	1.11	0.49
1%	2.47	2.80	1.55
5%	4.63	5.08	3.31
10%	6.55	7.04	5.17
25%	10.57	11.10	8.97
50%	15.74	16.24	13.57
75%	22.38	22.86	20.45
90%	29.14	29.59	26.86
95%	33.45	33.88	30.54
99%	41.84	42.23	38.06

BCR_0 = 40× (Current Regime 2021-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	30.81	31.54	28.02
Min	1.38	1.52	0.66
1%	3.24	3.65	2.03
5%	6.07	6.67	4.43
10%	8.66	9.33	6.69
25%	13.89	14.64	12.06
50%	20.58	21.28	18.00
75%	29.34	30.01	26.38
90%	38.33	38.97	35.23
95%	44.17	44.78	40.70
99%	55.05	55.61	50.39

Stress Regime (2018-2020)

BCR_0 = 10× (Stress Regime 2018-2020)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	4.61	5.28	4.16
Min	0.07	0.17	0.02
1%	0.34	0.54	0.10
5%	0.88	1.20	0.44
10%	1.43	1.91	0.86
25%	2.67	3.41	2.02
50%	4.36	5.37	3.89
75%	6.53	7.78	5.83
90%	8.75	10.02	7.85
95%	9.96	11.24	8.98
99%	11.66	13.15	10.63

BCR_0 = 15× (Stress Regime 2018-2020)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	7.40	8.45	6.60
Min	0.12	0.24	0.03
1%	0.52	0.78	0.19
5%	1.32	1.87	0.73
10%	2.14	2.80	1.34
25%	4.01	5.12	3.28
50%	6.54	7.80	5.81
75%	9.82	11.26	8.72
90%	13.15	14.85	11.83
95%	15.15	17.02	13.61
99%	18.46	20.29	16.67

BCR_0 = 20× (Stress Regime 2018-2020)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	9.87	11.15	8.79
Min	0.17	0.33	0.05
1%	0.71	1.01	0.27
5%	1.76	2.48	1.09
10%	2.84	3.74	1.96
25%	5.31	6.80	4.36
50%	8.73	10.32	7.60
75%	13.11	14.90	11.11
90%	17.59	19.43	14.99
95%	20.17	22.22	17.46
99%	24.47	26.60	21.25

BCR_0 = 30× (Stress Regime 2018-2020)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	14.65	16.67	13.04
Min	0.25	0.45	0.07
1%	1.05	1.49	0.40
5%	2.57	3.55	1.61
10%	4.14	5.32	2.77
25%	7.76	9.27	6.02
50%	12.35	14.25	10.43
75%	18.47	21.07	16.18
90%	24.55	27.36	21.92
95%	28.04	30.85	25.13
99%	34.15	36.72	31.11

BCR_0 = 40× (Stress Regime 2018-2020)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	19.45	22.17	17.39
Min	0.33	0.57	0.09
1%	1.41	2.04	0.54
5%	3.40	4.67	2.24
10%	5.48	7.02	3.87
25%	10.25	12.18	7.85
50%	16.41	19.21	14.27
75%	24.46	28.21	21.59
90%	32.56	37.18	28.86
95%	37.43	42.16	33.30
99%	45.93	50.09	40.94

Full Cycle (2014-2025)

BCR_0 = 10× (Full Cycle 2014-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	5.52	5.60	4.90
Min	0.10	0.14	0.03
1%	0.46	0.56	0.12
5%	1.03	1.21	0.48
10%	1.63	1.86	0.89
25%	2.98	3.26	2.13
50%	4.61	4.89	3.81
75%	6.60	6.87	5.74
90%	8.73	8.97	7.69
95%	10.04	10.26	8.90
99%	12.70	12.92	11.37

BCR_0 = 15× (Full Cycle 2014-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	8.90	9.07	7.90
Min	0.16	0.21	0.04
1%	0.71	0.86	0.19
5%	1.60	1.87	0.80
10%	2.44	2.78	1.43
25%	4.31	4.77	3.47
50%	6.96	7.41	5.91
75%	10.09	10.52	8.64
90%	13.27	13.67	11.61
95%	15.26	15.65	13.42
99%	19.07	19.39	17.22

BCR_0 = 20× (Full Cycle 2014-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	11.98	12.27	10.66
Min	0.22	0.29	0.06
1%	0.94	1.14	0.27
5%	2.07	2.40	1.03
10%	3.16	3.53	1.85
25%	5.60	6.12	4.40
50%	9.03	9.53	7.60
75%	13.20	13.67	11.21
90%	17.44	17.87	15.20
95%	20.08	20.49	17.56
99%	25.51	25.92	22.56

BCR_0 = 30× (Full Cycle 2014-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	17.55	17.99	15.56
Min	0.31	0.41	0.08
1%	1.31	1.57	0.38
5%	2.87	3.30	1.57
10%	4.39	4.87	2.65
25%	7.70	8.35	6.04
50%	12.36	12.996	10.43
75%	18.41	19.01	16.06
90%	24.07	24.62	21.69
95%	27.63	28.16	25.12
99%	33.70	34.17	31.03

BCR_0 = 40× (Full Cycle 2014-2025)

Metric	Bootstrap	Lognormal	Jump Diffusion
Mean	22.89	23.43	20.64
Min	0.41	0.54	0.11
1%	1.71	2.06	0.52
5%	3.69	4.26	2.20
10%	5.63	6.29	3.76
25%	9.78	10.62	7.84
50%	15.54	16.37	13.49
75%	23.24	24.02	20.74
90%	30.96	31.69	27.68
95%	35.62	36.30	32.10
99%	44.01	44.66	40.72

Duration Under Stress Data Tables

Current Regime (2021-2025)

Duration with BCR < 10 (Months)

BCR_0	Model	Mean	Median	95th pct	Max
40	Bootstrap	3.06795	0	25	109
	Lognormal	2.51215	0	17	106
	Jump-Diffusion	3.62625	0	30	111
30	Bootstrap	5.08895	0	42	114
	Lognormal	4.2803	0	34	114
	Jump-Diffusion	5.52945	0	41	115
20	Bootstrap	9.799	0	60	118
	Lognormal	8.66395	0	56	116
	Jump-Diffusion	10.0269	0	56	118
15	Bootstrap	15.38355	1	73	119
	Lognormal	13.8525	0	70	119
	Jump-Diffusion	15.1681	2	69	119
10	Bootstrap	27.6436	16	91	120
	Lognormal	25.63915	14	89	120
	Jump-Diffusion	25.73265	16	85	120

Duration with BCR < 5 (Months)

BCR_0	Model	Mean	Median	95th pct	Max
40	Bootstrap	1.031	0	1	86
	Lognormal	0.8461	0	0	76
	Jump-Diffusion	1.395	0	9	86
30	Bootstrap	1.80455	0	14	111
	Lognormal	1.4416	0	7	96
	Jump-Diffusion	2.10545	0	18	100
20	Bootstrap	3.565	0	29	104
	Lognormal	3.06085	0	25	96
	Jump-Diffusion	3.72445	0	28	109
15	Bootstrap	5.63695	0	37	107
	Lognormal	4.9823	0	35	107
	Jump-Diffusion	5.69025	0	35	112
10	Bootstrap	10.4037	0	51	118
	Lognormal	9.3683	0	47	113
	Jump-Diffusion	10.13575	0	48	112

Bear Regime (2018-2020)

Duration with BCR < 10 (Months)

BCR_0	Model	Mean	Median	95th pct	Max
40	Bootstrap	9.3772	0	51	114
	Lognormal	6.5646	0	44	109
	Jump-Diffusion	7.8262	0	46	112
30	Bootstrap	12.15755	0	57	116
	Lognormal	9.0335	0	51	114
	Jump-Diffusion	10.2039	0	52	115
20	Bootstrap	17.1913	4	67	119
	Lognormal	13.92145	1	62	119
	Jump-Diffusion	14.63615	2	61	116
15	Bootstrap	21.5166	13	72	120
	Lognormal	18.67	6	71	120
	Jump-Diffusion	18.5099	9	65	120
10	Bootstrap	28.99	24	81	120
	Lognormal	26.7349	20	80	120
	Jump-Diffusion	25.29995	19	74	120

Duration with BCR < 5 (Months)

BCR_0	Model	Mean	Median	95th pct	Max
40	Bootstrap	4.1885	0	28	90
	Lognormal	2.74665	0	22	90
	Jump-Diffusion	3.44575	0	24	90
30	Bootstrap	5.50555	0	32	92
	Lognormal	3.84765	0	27	92
	Jump-Diffusion	4.5122	0	28	96
20	Bootstrap	7.91675	0	38	107
	Lognormal	5.89325	0	34	99
	Jump-Diffusion	6.5351	0	34	99
15	Bootstrap	9.8683	0	41	109
	Lognormal	8.06805	0	40	104
	Jump-Diffusion	8.29305	0	37	103
10	Bootstrap	13.43795	8	47	102
	Lognormal	11.67925	2	46	110
	Jump-Diffusion	11.54595	5	43	106

Full Cycle (2014-2025)

Duration with BCR < 10 (Months)

BCR_0	Model	Mean	Median	95th pct	Max
40	Bootstrap	0.9717	0	2	111
	Lognormal	0.8551	0	1	111
	Jump-Diffusion	1.70905	0	9	102
30	Bootstrap	1.7554	0	9	107
	Lognormal	1.59515	0	7	112
	Jump-Diffusion	2.7792	0	20	112
20	Bootstrap	3.833	0	27	119
	Lognormal	3.67395	0	26	118
	Jump-Diffusion	5.23635	0	35	118
15	Bootstrap	6.62785	0	40	118
	Lognormal	6.57205	0	40	117
	Jump-Diffusion	8.238	0	45	119
10	Bootstrap	13.7871	5	57	120
	Lognormal	14.1395	5	60	120
	Jump-Diffusion	15.24705	6	60	120

Duration with BCR < 5 (Months)

BCR_0	Model	Mean	Median	95th pct	Max
40	Bootstrap	0.2891	0	0	94
	Lognormal	0.24335	0	0	71
	Jump-Diffusion	0.59435	0	0	84
30	Bootstrap	0.52655	0	0	82
	Lognormal	0.4692	0	0	87
	Jump-Diffusion	0.95625	0	2	90
20	Bootstrap	1.18595	0	5	92
	Lognormal	1.05295	0	3	107
	Jump-Diffusion	1.8403	0	14	97
15	Bootstrap	2.05555	0	15	102
	Lognormal	1.93705	0	14	100
	Jump-Diffusion	2.8113	0	21	100
10	Bootstrap	4.2226	0	28	105
	Lognormal	4.34455	0	29	115
	Jump-Diffusion	5.31575	0	31	107