The (In-)Finite Money Glitch

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Abstract. The *"infinite money glitch"* is the strategy where a firm issues convertible debt to purchase crypto assets–primarily Bitcoin–which increases its stock's volatility, in turn boosting hedge fund demand for its convertible bonds and enabling the company to issue even more debt to buy more crypto assets in a self-reinforcing cycle. I build a three-date equilibrium model in which convertible issuance, hedging motives, and an inelastic Bitcoin market jointly determine pricing and deal size. Convertible-arbitrage hedge funds dynamically short and cover the stock as it moves, which transmits Bitcoin shocks into realized equity volatility and raises the value of the conversion option in subsequent issues, supporting further issuance and purchases of Bitcoin. The model shows that, if conversion fails at maturity, forced Bitcoin sales can trigger large drawdowns when sell-side impact is steep, tradable supply is thin, and prior issuance was large. This yields non-monotonic effects: looser intermediation lifts prices near term but increases expected liquidation later, with testable implications for the implied–realized volatility gap, stock-loan tightness, and free-float measures.

Keywords: Infinite money glitch · Microstrategy · convertible arbitrage · Bitcoin price

1 Introduction

The *infinite money glitch* is a new corporate finance strategy wherein firms issue substantial volumes of convertible debt to finance the acquisition of cryptocurrencies, primarily Bitcoin. This strategy relies on a self-reinforcing cycle: The acquisition of Bitcoin increases the firm's asset volatility, which consequently increases its equity volatility. This heightened volatility increases the value of the embedded conversion option in the debt, making the firm's bonds highly attractive to hedge funds engaged in convertible arbitrage. The resulting demand can allow the firm to issue further debt on favorable terms (e.g., low coupons and high conversion premiums) to purchase even more Bitcoin, perpetuating the cycle.

The first and—so far—most successful company to employ this strategy is Strategy (formerly Microstrategy) who managed to issue USD 8.2 billion in debt to purchase over 630,000 Bitcoin as of September 2025, making it the single largest holder of Bitcoin.[1] While this strategy can inflate asset holdings and equity valuations when the price of Bitcoin increases, it introduces significant risks. The accumulation of large, leveraged positions in a volatile zero-cashflow asset, combined with the feedback effects from dynamic hedging, creates potential instability. Currently, there are almost 200 public *crypto reserve* companies following a similar strategy.[2] While the mechanics of the *infinite money glitch* are not too complicated to understand, no paper has formally modeled the mechanism or studied under what conditions the cycle would break or what the implications of that would be for the price of Bitcoin and the value of crypto reserve firms like Strategy.

This paper develops a simple three-date ($t = 0, 1, 2$) equilibrium model to analyze the dynamics of repeated convertible bond issuance and Bitcoin acquisition. The model incorporates the interactions between

[1] Various websites track the amount of Bitcoin held by Strategy and similar companies, including bitcointreasuries.net.

[2] One of them, Nakamoto Holdings Inc., recently saw a 95% drop of its share price from an all-time high of USD 34.7 on 22 May 2025, raising fears about the viability of the business model. However, this drop followed SEC approval that a large group of early investors was allowed to sell their shares in the company, which is different from the kind of risk I model in this paper. See *"Nakamoto (NAKA) stock price drops below BTC value as PIPE equity unlocks"*, Allard Peng, Yahoo! Finance, 16 September 2025 (Source).

a crypto treasury firm (the issuer), a hedge fund, and the Bitcoin market. At $t = 0$ and again at $t = 1$, the firm raises cash by issuing a convertible bond (zero-coupon, with a fixed conversion premium over the stock price) and immediately uses the proceeds to purchase Bitcoin. This increases the firm's Bitcoin holdings and links the firm's asset value to the price of Bitcoin. Buying Bitcoin raises the volatility of the firm's assets and equity. Higher equity volatility increases the value of the conversion option embedded in the firm's debt, which in turn attracts more demand from hedge funds specializing in convertible bond arbitrage. This demand enables the firm to issue even more debt on favorable terms (low yield, high conversion premium), fueling further Bitcoin purchases. Thus, the strategy creates a feedback loop wherein issuance and Bitcoin acquisitions mutually reinforce volatility.

Hedge funds purchasing the convertibles immediately short the stock to hedge their position. Over time, they continuously rebalance their short position as the stock price moves (gamma hedging). This means the hedge fund will sell the stock when its price rises and buy back when it falls. Such dynamic hedging by arbitrageurs amplifies volatility transmission: any jump in Bitcoin's price that lifts the stock induces hedge funds to sell shares (dampening the rise), whereas a drop induces them to buy (dampening the fall). This trading feedback can stabilize small fluctuations but also transmits Bitcoin's inherent volatility into the equity.

The Bitcoin market in the model features *inelastic supply*, meaning large trades can move the price substantially. The firm's Bitcoin purchases thus push the Bitcoin price upward (at issuance dates), modeled via a linear price impact coefficient. Conversely, any large Bitcoin sale by the firm will depress the price. In the model, sales can have a larger impact per coin than purchases, consistent with evidence that market liquidity is worse in downturns. The price impact depends on the market's available liquidity or effective float of Bitcoin: a smaller float (more coins held by passive holders, or lost) makes prices more sensitive to trades.

At each issuance date, the firm chooses the bond size (face value) to maximize proceeds, subject to market constraints. The constraints include (i) hedge fund capital available for this strategy, (ii) a limit on how many shares can be borrowed and shorted (related to the float of the stock available for shorting), and (iii) the stability condition on feedback intensity. If these constraints bind (for example, if hedge funds have insufficient capital or if short-selling is limited), the firm may not be able to issue the desired amount of debt.

The game culminates at $t = 2$, when debt either converts into equity or requires cash repayment. If the stock price at maturity exceeds the conversion price, bondholders optimally convert debt into shares, leaving the firm's Bitcoin treasury intact. If instead the stock price is below the conversion threshold, the firm must repay bond face value in cash. Since the firm's assets are entirely in Bitcoin, a failure to convert forces the firm to liquidate some or all of its Bitcoin holdings to raise cash. Such forced selling of a large Bitcoin position can have a significant adverse effect on the Bitcoin price, especially if market liquidity is poor. This sale in turn reduces the firm's asset value and stock price even further. In extreme cases, this feedback can render the firm insolvent (unable to fully repay its debt). The model explicitly incorporates this end-game feedback loop between Bitcoin liquidation and stock price collapse.

Equilibrium analysis identifies several conditions under which this leveraged crypto strategy can lead to severe instability or collapse in both the Bitcoin market and the firm's stock price. The greatest risk arises at the bond maturity (the final date). If the firm's stock price remains below the bonds' conversion price at maturity, bondholders demand cash repayment instead of converting to equity. The firm then must liquidate Bitcoin to raise cash, as it has no other cashflow-generating assets. In an illiquid market, such a large sell order induces a fire-sale dynamic: the Bitcoin price plummets due to the sale's price impact, which I model via a steep "sell-side" impact coefficient κ_B^-. Because the firm's equity value is tied to its Bitcoin holdings, a drastically reduced Bitcoin price further depresses the stock price, potentially causing even more of the debt to require cash (a self-fulfilling collapse). This spiral can lead to a full-blown collapse of the Bitcoin price and the firm's stock price, and in my model it is associated with the firm's insolvency at maturity.

Counterintuitively, the more "successful" the strategy is in the interim, the more severe the collapse can be at the end. In my model, benign conditions at the intermediate date ($t = 1$), such as plentiful hedge fund capital and easy short-selling (loose constraints on K_1^{HF} and L_1), allow the firm to issue a larger second round of debt and buy more Bitcoin. While this boosts the Bitcoin price and the stock price in the short run (as the firm's purchase pushes up P_1^B and arbitrageurs' hedging supports S_1), it also means the firm now has a larger outstanding face value due at $t = 2$. Thus, if the stock fails to reach the conversion threshold by $t = 2$, the required cash (and corresponding Bitcoin liquidation) is much larger. A bigger forced sale causes a more drastic price drop. In short, high leverage accumulated through repeated bond issuance makes the end-game more fragile.

The model shows that a collapse is especially severe when the Bitcoin market has low liquidity or a small effective float. When few coins are available for trade (many coins are hoarded or "lost"), a given dollar sale exerts a larger price impact. I quantify this with a smaller B^f (float) and a higher κ_B^-. In such scenarios, even a moderate required liquidation can trigger a large drop in Bitcoin's price. The price impact asymmetry (higher κ_B^-) means that downside moves (forced sales) are far more damaging than the upside impact of purchases. My crisis simulations confirm that the deepest Bitcoin price drawdowns occur when large prior debt issuance meets an illiquid market microstructure.

I distinguish two types of adverse outcomes: (i) a gradual decline during the life of the bond, and (ii) a sharp cras at maturity. A steep drop in the interim ($t = 0$ to $t = 1$) is most likely triggered by an exogenous negative shock to Bitcoin fundamentals or sentiment (modeled as a negative drift $\mu_B < 0$). In my simulations, the worst mid-course outcomes for S_1 and P_1^B are indeed driven by scenarios of sharply negative Bitcoin returns between issuance dates. In contrast, the most extreme end-of-game crashes (S_2, P_2^B plunging) are typically driven not by interim news, but by the endogenous leverage-liquidity spiral described above. In those cases, Bitcoin's price collapse is not fully apparent until the conversion failure forces a liquidation at $t = 2$, at which point the feedback loop takes over.

The availability of hedge fund capital and stock loan supply has non-monotonic effects on outcomes. If hedge funds' capacity to absorb convertibles (capital K^{HF}) or to short shares (borrowable shares L) is severely limited, the strategy might stall early—the firm simply cannot issue much debt at $t = 1$, which actually caps its leverage and limits potential damage. Somewhat paradoxically, the worst collapses occur when these constraints are *sufficiently loose to enable large issuance, but not so loose as to guarantee conversion success*. In that regime, the firm takes on a lot of debt (thanks to eager arbitrageur demand) but ultimately cannot support the debt if Bitcoin underperforms. My model quantifies this: in crisis calibrations with moderate K_1^{HF} and L_1, I find scenarios where a large $t = 1$ issuance is followed by a collapse at $t = 2$. If K_1^{HF} and L_1 were even higher (or if hedge funds were infinitely deep-pocketed), they would either absorb even more stock in hedging or facilitate equity raises that might avert default. Thus, partial arbitrage capacity can sometimes exacerbate tail risks, consistent with theories of limited arbitrage and market fragility.

In all equilibria I consider, the hedging feedback parameter Ψ_t (the fraction of a stock price move offset by arbitrageurs' reactive trading) stays below 1. This stability condition is crucial: $\Psi_t < 1$ means that while arbitrage trading amplifies volatility, it does not become an infinite feedback loop in itself. If Ψ were to approach 1, the model would effectively produce infinite volatility (a locally insatiable "positive feedback" loop). My equilibrium selection explicitly rules out such cases. Nonetheless, values of Ψ_t closer to 1 imply higher volatility amplification $A_t = 1/(1 - \Psi_t)$. I find that in stress scenarios the feedback intensity Ψ rises (as volatility spikes and arbitrageurs' gamma exposure grows), further contributing to the equity volatility observed. This mechanism echoes the volatility spiral effects documented in prior work on dynamic hedging and crashes.

Prior studies have shown that hedge funds specializing in convertible bond arbitrage act as important suppliers of capital to issuing firms. [3] document that the availability of arbitrage capital can facilitate larger convertible bond issuances and affect the terms of those issues. Relatedly, [4] find that convertible bond arbitrage can create liquidity externalities for the underlying stock, as the short-selling and hedging by arbitrageurs tend to improve stock liquidity. My model incorporates these insights by explicitly modeling hedge fund demand for convertibles and the short-selling of the stock. However, this paper highlight a different angle: while previous work emphasizes liquidity provision by arbitrageurs (e.g., narrowing spreads, improving liquidity when they enter the trade), I show that their presence can also set the stage for liquidity *dry-ups* in extreme scenarios. In particular, if arbitrageurs withdraw or face constraints at a critical moment (e.g., at $t = 2$ in my model), the unwind of their positions can exacerbate a crash—a possibility foreshadowed by the convertible arbitrage unwinding episodes documented by practitioners in 2005 and studied in [10].

Second, I also draw on [1], who model liquidity spirals in which market liquidity and funding liquidity reinforce each other. In my setting, the feedback between the firm's funding liquidity for the crypto investment and market liquidity (Bitcoin market depth) can likewise create a spiral: When the firm needs liquidity the most (to repay debt), the market provides the least, yielding a sharp price drop. The asymmetry between buying and selling impact in my simple model is consistent with empirical findings that market liquidity is worse in downturns, as documented by [6] for equity markets.

Finally, this paper contributes to the emerging discussion on corporate finance of cryptocurrency and speculative balance sheet management. The idea of a firm levering up to invest in a zero-cashflow, speculative asset like Bitcoin can be viewed through the lens of classic agency theory. In particular, it provides yet another illustration of risk-shifting motives [8]: Equity holders benefit from volatility increases (the upside of Bitcoin), while debt holders bear more downside risk, especially when the debt is convertible and initially mispriced due to assumed volatility. Unlike traditional risk-shifting where the gamble's payoff might be idiosyncratic, here the risk is systemic to the crypto market and is amplified by feedback trading. While simple, my model sheds light on the conditions under which such strategies might create systemic risks in cryptocurrency markets.

The remainder of the paper is organized as follows. Section 2 presents the model setup, including the agents, timeline, and key equations governing Bitcoin price impact and equity dynamics. Section D defines equilibrium and describes the numerical solution approach. Section 3 analyzes the baseline equilibrium and highlights the feedback effects at work.

2 Model

There are three dates $t \in \{0, 1, 2\}$ and three agents: a unit mass of risk-averse retail investors, a crypto treasury firm, and a hedge fund. A zero-yield safe asset is available at all dates, and I set the risk-free rate $r = 0$. Let S_t be the dollar price of one share at date t, $P_{B,t}$ the Bitcoin price (USD), and H_t the firm's BTC holdings (coins). The firm has N_0 shares outstanding at $t = 0$ and the number of shares updates only at $t = 2$ upon conversion of two convertible zero-coupon bonds issued at $t = 0, 1$ with face F_t at per-\$-face price $P_{CB,t}$, raising gross proceeds:

$$B_t \; = \; P_{CB,t} \, F_t. \tag{1}$$

The conversion price is a fixed premium over the date-τ stock,

$$K_\tau \; = \; (1 + \pi_\tau) \, S_\tau, \qquad c_\tau \; \equiv \; \frac{1}{K_\tau} \; = \; \frac{1}{(1 + \pi_\tau) \, S_\tau}, \tag{2}$$

where c_t is the per-\$-face conversion ratio. Full conversion of the tranche issued at t delivers $c_t \, F_t$ shares at $t = 2$. For simplicity, set $\pi_1 = \pi_0 \equiv \pi$.[3] Let $V_{s,\tau}$ denote the per-\$-face value at date s of the convertible issued at date τ. At issuance $P_{CB,t} = V_{t,t}$.

The firm uses all proceeds to buy Bitcoin at each issuance date:

$$\Delta H_t \; = \; \frac{B_t}{P_{B,t}}, \qquad H_{t+1} \; = \; H_t + \Delta H_t, \qquad t \in \{0, 1\}. \tag{3}$$

With two tranches potentially outstanding by $t = 1$, the net asset value at date t is:

$$\text{NAV}_t \; = \; H_t \, P_{B,t} \; - \; \sum_{\tau=0}^{t} V_{t,\tau} \, F_\tau. \tag{4}$$

[3] A typical value for π in the case of Strategy is 0.3–0.4 (see, for example, here for their June 2024 offering).

At each $t \in \{0,1\}$ the firm chooses B_t (equivalently F_t) to maximize proceeds subject to market-clearing and feasibility constraints. The one-period dollar change in the Bitcoin price follows:

$$\Delta P_{B,t+1} \equiv P_{B,t+1} - P_{B,t} \; = \; P_{B,t}\,\mu_B \; + \; \kappa_B \,\frac{B_t}{B_t^f} \; + \; \varepsilon_{t+1}, \qquad \mathbb{E}[\varepsilon_{t+1} \,|\, \mathcal{F}_t] = 0, \quad \mathrm{Var}(\varepsilon_{t+1} \mid \mathcal{F}_t) = \sigma^2_{B,t}, \quad (5)$$

where μ_B is an exogenous drift (constant), κ_B is an inelasticity coefficient, and B_t^f is the effective BTC float (coins) over $[t, t+1]$. A simple regression:

$$P_{B,t+1} - P_{B,t} \; = \; \Lambda_t \, Q_{B,t} \; + \; \text{controls} \; + \; \varepsilon_t, \qquad Q_{B,t} \equiv \Delta H_t = \frac{B_t}{P_{B,t}}, \quad (6)$$

identifies the float as $B_t^f = \kappa_B \, P_{B,t}/\Lambda_t$. As a simple heuristic, one may set $B_t^f = \phi_h \, S_{B,t}^{\text{free}}$ with exogenously fixed participation rate $\phi_h \in (0,1]$ and $S_{B,t}^{\text{free}}$ equal to circulating supply minus estimated immobile coins.[4]

Let $\Delta_{t,\tau}^{\text{CB}}$ and $\Gamma_{t,\tau}^{\text{CB}}$ denote, respectively, the delta and gamma per \$/face at date t of the convertible issued at τ. Immediately after the tranche issued at τ is purchased at date τ, the hedge fund shorts:

$$Q_\tau^{\text{short}} \; = \; \Delta_{\tau,\tau}^{\text{CB}} \, F_\tau. \quad (7)$$

At the start of period t the aggregate short equals $\sum_{\tau \le t} \Delta_{t,\tau}^{\text{CB}} \, F_\tau$. Over each trading period,

$$\Delta Q_{t+1} \; = \; \left(\sum_{\tau \le t} \Gamma_{t,\tau}^{\text{CB}} \, F_\tau \right) \big(S_{t+1} - S_t\big), \qquad t \in \{0,1\}, \quad (8)$$

so the hedge fund sells into rises and buys into dips. With zero coupon and no carry, the expected delta-hedged P&L over $[t, t+1]$ is

$$\mathbb{E}\big[\Pi_{t,t+1}^H \,\big|\, \mathcal{F}_t\big] \; \approx \; \frac{1}{2} \left(\sum_{\tau \le t} \Gamma_{t,\tau}^{\text{CB}} \, F_\tau \right) \big(\sigma^2_{S,t} - \sigma^{2,\text{imp}}_{S,t}\big), \qquad \sigma^2_{S,t} \equiv \mathrm{Var}(S_{t+1} - S_t \mid \mathcal{F}_t)\,, \quad (9)$$

where $\sigma^{2,\text{imp}}_{S,t}$ is the dollar variance used in CB pricing at t. In a frictionless competitive market, $\sigma^2_{S,t} = \sigma^{2,\text{imp}}_{S,t}$ when some $\Gamma_{t,\tau}^{\text{CB}} \neq 0$.[5]

At issuance date $t \in \{0,1\}$ the convertible clears only if the following constraints hold:

$$B_t \le K_t^{\text{HF}} \quad \text{(capital)}, \qquad \Delta_{t,t}^{\text{CB}} \, F_t \le L_t \quad \text{(borrowable shares)}, \qquad 0 \le \psi_t < 1 \quad \text{(stability)}, \quad (10)$$

where K_t^{HF} is available hedge fund capital (exogenously given), L_t the number of borrowable shares, and

$$\psi_t \; \equiv \; \lambda \left(\sum_{\tau \le t} \Gamma_{t,\tau}^{\text{CB}} \, F_\tau \right). \quad (11)$$

[4] Including, for example, Satoshi Nakamoto's coins that have never been moved. In 2020, about 20% of all coins have been "lost" already (see Chainalysis). I take this as a reasonable estimate. Other industry estimates put the amount of free floating Bitcoin at roughly 14 Million as of August 2025 (see BTC.SplyFF from CoinMetrics).

[5] In practice, industry reports indicate that the implied volatility of Strategy's convertible bonds was below the actual volatility, which explains why the trade is so attractive for hedge funds. See, for example, *"Hedge funds bet big on MicroStrategy"*, HedgeWeek 6 December 2024. FT Alphaville writes that Strategy's 252-day historic volatility was at 106 per cent in December 2024, while its USD 3 billion convertible note of November 2024 was marketed at 60 per cent implied volatility. See "MicroStrategy's secret sauce is volatility, not bitcoin," Dec. 6, 2024, FT Alphaville.

At $t = 2$ firm assets equal $H_2 \, P_{B,2}$ with $H_2 = H_0 + \mathit{\Delta} H_0 + \mathit{\Delta} H_1$. Each tranche $\tau \in \{0, 1\}$ converts if $S_2 \geq K_\tau$ and otherwise requires cash face F_τ. The firm is insolvent if:

$$H_2 \, P_{B,2} \; < \; \sum_{\tau \in \{0,1\}} F_\tau \, \mathbf{1}\{S_2 < K_\tau\}. \tag{12}$$

At $t = 1$ the new issue proceeds B_1 are zero if any constraint in (10) fails or if hedged economics would imply negative expected P&L. The baseline case is successful bond issuance at $t = 0$ and $t = 1$. However, it is also possible that the firm is unable to place the convertible bond at $t = 1$, for example when constraints bind or asset-side conditions (e.g., a BTC drawdown or an excessively high conversion premium) depress hedge fund demand.

For valuation of the convertible bond, let $V_{s,\tau}$ denote the per-\$-face value, computed at date s, of the tranche issued at date $\tau \in \{0, 1\}$. At issuance, the observed per-face price equals its model value: $P_{CB,t} = V_{t,t}$. The associated per-\$-face Greeks of the tranche issued at τ and evaluated at date $t \geq \tau$ are $\mathit{\Delta}^{\mathrm{CB}}_{t,\tau}$ and $\mathit{\Gamma}^{\mathrm{CB}}_{t,\tau}$.

Given the hedging-feedback intensity Ψ_t, define the pass-through amplifier as $A_t \;\equiv\; 1/(1 - \psi_t)$. Equity dollar changes then obey:

$$\big(1 - \psi_t\big)\big(S_{t+1} - S_t\big) \;=\; \beta \left(P_{B,t+1} - P_{B,t}\right) \;+\; \eta_{t+1}, \qquad \mathbb{E}[\eta_{t+1} \,|\, \mathcal{F}_t] = 0, \;\; \mathrm{Var}(()\, \eta_{t+1} \,|\, \mathcal{F}_t) = \sigma^2_\eta, \tag{13}$$

so the equity dollar-variance over $[t, t{+}1]$ is:

$$\sigma^2_{S,t} \;=\; A_t^2 \left(\beta^2 \, \sigma^2_{B,t} + \sigma^2_\eta\right). \tag{14}$$

At $t = 0$ only retail investors are long. Net supply clears as:

$$x^R_0 - Q^{\text{short}}_0 \;=\; N_0, \qquad Q^{\text{short}}_0 \;=\; \mathit{\Delta}^{\mathrm{CB}}_{0,0} \, F_0, \qquad \Rightarrow \qquad x^R_0 \;=\; N_0 + \mathit{\Delta}^{\mathrm{CB}}_{0,0} \, F_0. \tag{15}$$

With CARA–Normal preferences, this yields:

$$x^R_0 \;=\; \frac{\mathbb{E}[S_1 - S_0 \,|\, \mathcal{F}_0]}{\alpha \, \sigma^2_{S,0}} \qquad \Rightarrow \qquad \mathbb{E}[S_1 - S_0 \,|\, \mathcal{F}_0] \;=\; \alpha \, \sigma^2_{S,0} \left(N_0 + \mathit{\Delta}^{\mathrm{CB}}_{0,0} \, F_0\right). \tag{16}$$

Consistency with (13) gives the equivalent pass-through expression

$$\mathbb{E}[S_1 - S_0 \,|\, \mathcal{F}_0] \;=\; A_0 \, \beta \, \mathbb{E}[P_{B,1} - P_{B,0} \,|\, \mathcal{F}_0] \;=\; A_0 \, \beta \left(P_{B,0} \, \mu_B \;+\; \kappa_B \, \frac{B_0}{B^f_0}\right). \tag{17}$$

The opening price S_0 can be observed and calibrated to e.g. Strategy's stock price at the time of their largest convertible bond issuance, which was \$3 billion with a 55% conversion premium over the \$ 433 stock price averaged on 19 November 2024.[6]

Lately, MicroStrategy has not been able to place convertible bonds with zero coupon. To allow for a fixed coupon on the $t = 0$ convertible bond, assume that at $t = 1$ the tranche pays q_0 dollars per \$/face. Define the dollar coupon obligation:

$$C_0 \;\equiv\; q_0 \, F_0.$$

At $t = 1$ I adopt an ex-coupon convention for the $t = 0$ tranche: The value entering (4) is the ex-coupon value $V_{1,0}$ (i.e., $V_{1,0}$ equals cum-coupon value minus q_0). No other term in (4) changes. Servicing the coupon reduces the dollars directed to Bitcoin at $t = 1$. Define the net dollars allocated to BTC:

$$\widetilde{B}_t \;\equiv\; B_t - \mathbf{1}\{t = 1\} \, C_0,$$

and replace B_t by $\widetilde{B}_t$ in (3). Equivalently,

$$\mathit{\Delta} H_0 = \frac{B_0}{P_{B,0}}, \qquad \mathit{\Delta} H_1 = \frac{B_1 - C_0}{P_{B,1}}, \qquad H_{t+1} = H_t + \mathit{\Delta} H_t.$$

[6] Details on the issuance can be found here.

When $B_1 < C_0$, $\Delta H_1 < 0$ (a net sale). For $t = 1$ only, replace B_1 by $\widetilde{B}_1$ in (5) (and hence in (6) via $Q_{B,1} = \Delta H_1$). All other dates are unchanged.

The $t = 0$ tranche is valued with its coupon schedule; $P_{CB,0} = V_{0,0}$, and at $t = 1$ the model uses $V_{1,0}$ ex coupon. Greeks $\Delta_{t,0}^{\mathrm{CB}}$ and $\Gamma_{t,0}^{\mathrm{CB}}$ are computed under these terms. No other pricing block changes. To obtain the equilibrium in this setting, augment the parameter set by q_0 and interpret all $t = 1$ occurrences of B_1 as $\widetilde{B}_1$ and $V_{1,0}$ as ex-coupon. The acceptance, feasibility, stability, and variance relations remain as stated; (9) is unchanged in form under $r = 0$ because the coupon carry over $[0, 1]$ offsets the ex-coupon drop at $t = 1$.

The model is solved via backward induction. A formal equilibrium definition can be found in the Online Appendix.

3 Results

3.1 Baseline and crisis calibration

Table 4 lists all model parameters and their *baseline calibration* values. We pin the stock anchor to MicroStrategy's November 2024 issuance window and set $S_0 = \$433.7997$ and $\pi_0 = \pi_1 = 0.55$, matching the VWAP used for the deal and the stated conversion premium in the firm's 3 billion 0% coupon convertible due 2029.[7] The Bitcoin anchor $P_{B,0} = \$92{,}362.09$ is chosen to be consistent with the late-November 2024 range. We set $N_0 = 1.6968 \times 10^7$ to reflect the roughly 17 million Class A shares outstanding around that period (consistent with SEC filings), and $q = 0$ to align with the zero-coupon terms of the 2024 issuance. The baseline credit hazard $\lambda_c = 0.02$ is a reduced-form choice consistent with a low annual default intensity for a large, seasoned issuer with access to repeated convertible bond markets.[8] This parameter has a limited impact and matters only through survival discounting in the bond-plus-warrant approximation.

For the effective BTC float I use $B_t^f = 1.43 \times 10^7$ coins, consistent with industry "free-float" methodologies that exclude provably lost, long-dormant, and closely held balances. Coin Metrics defines and publishes a Free Float Supply series (SplyFF) precisely for this purpose: The value chosen lies well within the range implied by Coin Metrics' methodology and contemporaneous commentary.[9] The flow-to-price coefficients are set to $\kappa_B^+ = 5$ and $\kappa_B^- = 10$ to match order-of-magnitude impact elasticities reported in the market-impact literature: when normalized by free float, dollar parent orders in liquid assets typically move prices by well below one percent per billion dollars of notional, with larger (more concave) effects for sales than buys.[10] With $B^f \approx 14.3$M coins, $\kappa_B^{\pm}$ in this range imply $< 1\%$ price moves for \$1B dollar flows at late-2024 prices, consistent with deep-liquidity conditions.

We set $\sigma_{B,0}^2 = \sigma_{B,1}^2 = 7.5 \times 10^6$ USD^2 so that $\sqrt{\sigma_{B,t}^2} \approx \$2.7$k (i.e., $\sim$3% daily volatility at \$90–95k BTC), in line with typical realized levels over 2023-2024. The equity block uses $\beta = 4.5 \times 10^{-2}$ (pre-amplifier dollar beta) and idiosyncratic variance $\sigma_\eta^2 = 10^4$ USD^2 (about \$100 daily idiosyncratic standard deviation), which together reproduce the well-documented high sensitivity and volatility of MicroStrategy equity to BTC moves. The linear price-impact coefficient on equity, $\lambda = 2 \times 10^{-6}$ USD/share, is calibrated so that the feedback intensity $\Psi_t = \lambda\, \Gamma_t^{\mathrm{agg}}$ remains safely below unity in the issuance region, consistent with no-arbitrage constraints on dynamic hedging. Financing frictions are anchored to observable market capacity and lendable inventory. The t=0 hedge-fund capital cap of $K_0^{HF} = 3$B USD mirrors the actual deal size placed in November

[7] See "MicroStrategy Completes \$3.0 Billion Offering of Convertible Senior Notes Due 2029 at 0% Coupon and 55% Conversion Premium," press release (Nov. 21, 2024). The release reports the VWAP of \$433.7997 used to determine the conversion price and the 55% premium. Source.

[8] This choice is consistent with long-run corporate default evidence in which investment-grade one-year default rates are well below 1%, while speculative-grade issuers average only a few percent per year depending on the cycle. See the comprehensive annual studies by S&P Global Ratings and Moody's Investors Service. This is a canonical way of modeling credit risk. See, for example, [7, 5].

[9] Coin Metrics, *Network Data: Supply*, definition of Free Float supply. Docs. See also CoinDesk coverage of Coin Metrics' free-float approach (June 30, 2020) here.

[10] See, for example, [2] for a baseline estimate of impact elasticities and [6] as motivation of the asymmetric impact of liquidations. I linearize around small flows with asymmetric slopes to capture higher sell-side impact.

2024, while $K_1^{HF} = 1.5$B USD provides a conservative half-sized capacity at the subsequent issuance. The share-borrow caps are set to be non-binding at t=0 ($L_0 = 10^8$) and plausibly tight at t=1 ($L_1 = 5 \times 10^6$ shares), the latter corresponding to a sizable but realistic fraction of the free float. Finally, I allow a small one-off coupon $q_0 = 0.02$ to reflect that some of the convertible bonds issued by Microstrategy had positive coupon payments (see Table 5).

To study stressed conditions in a *crisis calibration*, I also consider tighter liquidity, adverse flow impact, and reduced balance-sheet intermediation capacity. First, I set a negative BTC drift at $t = 0$ ($\mu_B = -0.01$) as a proxy for worsening regulatory environment or overall sentiment regarding Bitcoin. Next, I steepen the sell-side inelasticity to $\kappa_B^- = 50$ (and sweep it over $\{1, 5, 10, 15, 20, 30, 50, 75, 100, 150, 200\}$) to account for psychological effects, and compress the effective BTC float at t=1 to $B_1^f = 8.0 \times 10^6$ coins (while holding $B_0^f = 1.43 \times 10^7$ fixed and sweeping B_1^f up to 1.8×10^7). Financing frictions tighten via a lower and uncertain second-period intermediation capacity: I anchor $K_1^{HF} = 2.0 \times 10^9$ USD (vs. $K_0^{HF} = 3.0 \times 10^9$) and sweep a wide range from market-closure 0 to 3.0×10^9. Borrowable inventory at t=1 is reduced to $L_1 = 1.0 \times 10^6$ shares and swept on a log-like grid over $\{10^3, \dots, 10^7\}$. The buy-side impact and other date-0 anchors remain fixed ($\kappa_B^+ = 5$, N_0, S_0, P_0^B as in Table 4).

To reflect heightened volatility and tighter funding, I allow the t=1 BTC dollar variance to move materially while keeping $\sigma_{B,0}^2 = 7.5 \times 10^6$ USD^2 fixed: $\sigma_{B,1}^2$ is swept from 1.0×10^6 to 2.0×10^7 USD^2. I also sweep the equity idiosyncratic variance σ_η^2 over $\{10^3, \dots, 5 \times 10^4\}$ USD^2. On the liability side, I impose a substantially higher coupon on the t=0 tranche (crisis anchor $q_0 = 0.10$), reflecting worsening credit conditions for Microstrategy, and examine $q_0 \in [0, 0.05]$ to isolate sensitivity to servicing costs at t=1 under ex-coupon pricing. All other terms—including π_0 and the date-0 hedging/market-depth parameters—are maintained at their baseline values to ensure that differences trace directly to the crisis channels above.

The results of the equilibrium analysis using the baseline calibration is shown in Figures 1 and 2. Across all one–parameter sweeps, the initial anchor prices P_0^B and S_0 are constant by construction, while P_1^B, P_2^B and S_1, S_2 change with parameter choices. First, the BTC path shifts almost linearly with the drift μ_B via (5), and the equity path co-moves through (13), which links equity dollar changes to BTC dollar changes with pass-through $A_t = (1 - \Psi_t)^{-1}$ and loading β since combining (5) and (13) yields:

$$S_{t+1} - S_t \;=\; A_t\big(\beta\big[(P_{t+1}^B - P_t^B)\big] + \eta_{t+1}\big) \;=\; A_t\Big(\beta\big[P_t^B \mu_B + \kappa_B\, B_t/B_t^f + \varepsilon_{t+1}\big] + \eta_{t+1}\Big)\,.$$

Second, a larger issuance at $t = 1$ feeds directly into the BTC flow term $\kappa_B\, B_1/B_1^f$ in (5), lifting P_1^B and, thus S_1. This near-term boost can, however, be followed by a reversal at $t = 2$: A larger B_1 implies a larger outstanding face and higher potential cash due at settlement. When post-propagation equity fails to clear the conversion strikes, the required cash can trigger a larger dollar sale L of BTC at $t = 2$, which lowers P_2^B through the same flow-to-price channel (with the sell-side coefficient κ_B^-) and transmits to S_2 via (13). In short, parameters that raise acceptance and sizing at $t = 1$ (e.g., higher K_1^{HF} or looser borrowing constraint L_1) tend to raise P_1^B and S_1, but—by increasing cash obligations—can also amplify liquidation risk and reduce P_2^B and S_2 in scenarios where conversion does not occur.

Overall, second-period Bitcoin and stock price are most sensitive to: (i) the sell-side impact coefficient κ_B^-, which governs the price response to liquidation at $t = 2$ and therefore has a first-order effect on P_2^B with immediate pass-through to S_2; (ii) the BTC drift μ_B, which shifts the entire BTC path and, consequently, the equity path; and (iii) market depth at $t = 1$ through the effective float B_1^f, which scales per-dollar impact. Increases in $\sigma_{B,1}^2$ and σ_η^2 primarily affect Ψ_t, and acceptance through the variance/amplifier relation (13)–(14); their effect on mean levels is secondary but they can meaningfully change issuance feasibility and thus the likelihood and size of liquidation at $t = 2$. Capacity and borrow limits (K_1^{HF}, L_1) influence P_2^B, S_2 through the two-step mechanism noted above: relaxing them tends to increase B_1 and raise P_1^B, S_1, yet can also raise cash due at settlement and thereby magnify the expected liquidation L, lowering P_2^B, S_2 conditional on non-conversion. By contrast, moderate changes in π_1 and q_0 mainly operate through pricing and net dollars deployed, with comparatively smaller effects on average terminal levels in the ranges considered.

Under the crisis calibration, the one–parameter sweeps exhibit the same directional mechanisms as in the baseline but with two qualitative differences that recur across parameters. First, acceptance at t=1 is fragile:

Since the feasibility constraint (10) binds more often (via the borrow cap L_1 and higher induced variance), many settings produce $B_1 = 0$. When issuance does go through, the net dollar flows into BTC are smaller because $\widetilde{B}_1 = B_1 - q_0 F_0$ deducts the larger coupon. For modest B_1 this net can even turn negative, so that the t=1 flow term in (5) becomes a sale rather than a purchase, lowering P_1^B and S_1. Second, the reversal mechanism into t=2 is stronger and arises over a wider range of parameters. The combination of a larger κ_B^- and a smaller B_1^f makes the liquidation mapping at settlement steeper, so that a given cash requirement translates into a larger within-period BTC price impact at t=2, with immediate pass-through to S_2 by (13). As a result, parameters that expand t=1 sizing in the baseline (e.g., higher K_1^{HF} or looser L_1) now generate more pronounced non-monotonicities: they still raise P_1^B and S_1 when acceptance occurs, but—by increasing faces and cash due conditional on non-conversion—they more frequently imply larger liquidation and lower average P_2^B and S_2.

Quantitatively, sensitivities of P_2^B and S_2 to κ_B^-, B_1^f, K_1^{HF}, and L_1 are magnified relative to the baseline, whereas the drift μ_B shifts the entire path downward. Raising $\sigma_{B,1}^2$ or σ_η^2 has limited effect on mean levels but more often tightens the feasibility margin by increasing $\sigma_{S,1}^2$, thereby reducing issuance frequency at t=1. Changes in π_1 and q_0 mainly act through pricing and net dollars deployed; in the crisis calibration, a higher q_0 systematically lowers $\widetilde{B}_1$ and, therefore, dampens the t=1 boost to P_1^B and S_1.

3.2 Crises across the parameter space

Tables 1 and 2 report tail averages for the BTC and equity paths across a large grid of parameter configurations by conditioning on the bottom (and top) quantiles of P_1^B, P_2^B and S_1, S_2. Two robust patterns emerge. First, severe one-period declines at t=1 are primarily associated with negative drift: In rows conditioned on the bottom 5% of P_1^B (resp. S_1), the mean μ_B is near its lower bound (about -5% per period), while other parameters are close to their unconditional averages. This is consistent with (5), which makes the t=0$\to$1 BTC change proportional to $P_0^B \mu_B$ plus the t=0 issuance flow. The equity co-movement then follows mechanically from (13).

Second, the most pronounced t=2 drawdowns occur mostly for configurations that (i) steepen sell-side impact, (ii) thin BTC market depth at t=1, and (iii) permit larger issuance at t=1. In the rows conditioned on the bottom 5%–1% of P_2^B, the sell-side impact coefficient κ_B^- is markedly above its unconditional mean (roughly $170-180$ vs. ~ 100), the effective float B_1^f is low (about 10 million coins vs. ~ 13 million), the hedge-fund capacity and borrow cap (K_1^{HF}, L_1) are elevated (e.g., $K_1^{HF} \simeq 1.52 \times 10^9$ USD and $L_1 \simeq 2.5 \times 10^6$ shares), and coupons are small (e.g., q_0 near 1–2%). These combinations raise acceptance and sizing at t=1, increasing outstanding faces and the cash requirement at settlement. When conversion fails, the implied liquidation L depresses P_2^B through the sell-side term $(\kappa_B^-/B_1^f)\, L$, which transmits one-for-one into lower S_2. The equity tails (Table 2) follow the same logic: very low S_2 realizations occur where κ_B^- is high, B_1^f is low, and K_1^{HF}, L_1 are loose, with $\mu_B < 0$ further shifting the distribution down. By contrast, configurations in the top 5% of P_2^B and S_2 display the mirror image: Smaller κ_B^- (e.g., $\sim$64), larger B_1^f (e.g., $\sim$15.8 million), tighter K_1^{HF} and L_1, and higher coupons—attenuating issuance size and, hence, liquidation exposure at t=2.

Taken together, the tables map the parameter regions that generate the biggest t=1 and t=2 price declines. Large one-period drops (P_1^B, S_1) are concentrated where μ_B is strongly negative, which is not surprising. The largest terminal losses (P_2^B, S_2) cluster where liquidation risk is mechanically amplified: High sell-side impact κ_B^-, low effective float B_1^f, and relaxed issuance constraints (K_1^{HF}, L_1) jointly raise the expected t=1 face and the cash due at settlement, increasing L and lowering P_2^B with immediate pass-through to S_2. Lower coupons q_0 (when varied) reinforce this channel by increasing net dollars allocated to BTC at t=1 (higher $\widetilde{B}_1$), further enlarging faces and potential liquidation. In short, the deepest t=2 drawdowns arise in regions combining *adverse microstructure* (high κ_B^-, low B_1^f) with *ample* t=1 *issuance capacity* (high K_1^{HF}, high L_1), whereas the worst t=1 outcomes are dominated by $\mu_B < 0$.

4 Conclusion

This paper develops a tractable three-date equilibrium in which repeated convertible issuance to acquire Bitcoin interacts with dynamic hedging and inelastic market depth. The framework endogenizes the equity variance used to price convertibles via a hedging–feedback channel, links issuance flows to Bitcoin through linear impact scaled by the effective float, and closes the system with market clearing constraints on hedge fund capital and stock lending. Calibrations anchored to observed issuance episodes show that the strategy can increase both the price of Bitcoin and the stock price at the interim date by boosting option value and issuance capacity. The principal risk materializes on the final date: When the stock fails to clear conversion strikes, forced liquidations transmit through a steep sell-side impact and thin Bitcoin float, depressing the final-date price of Bitcoin and, via passthrough, the firm's stock price. The sharpest terminal drawdowns occur precisely when adverse market conditions meet ample prior issuance, so that larger outstanding faces magnify the cash need and the endogenous sale.

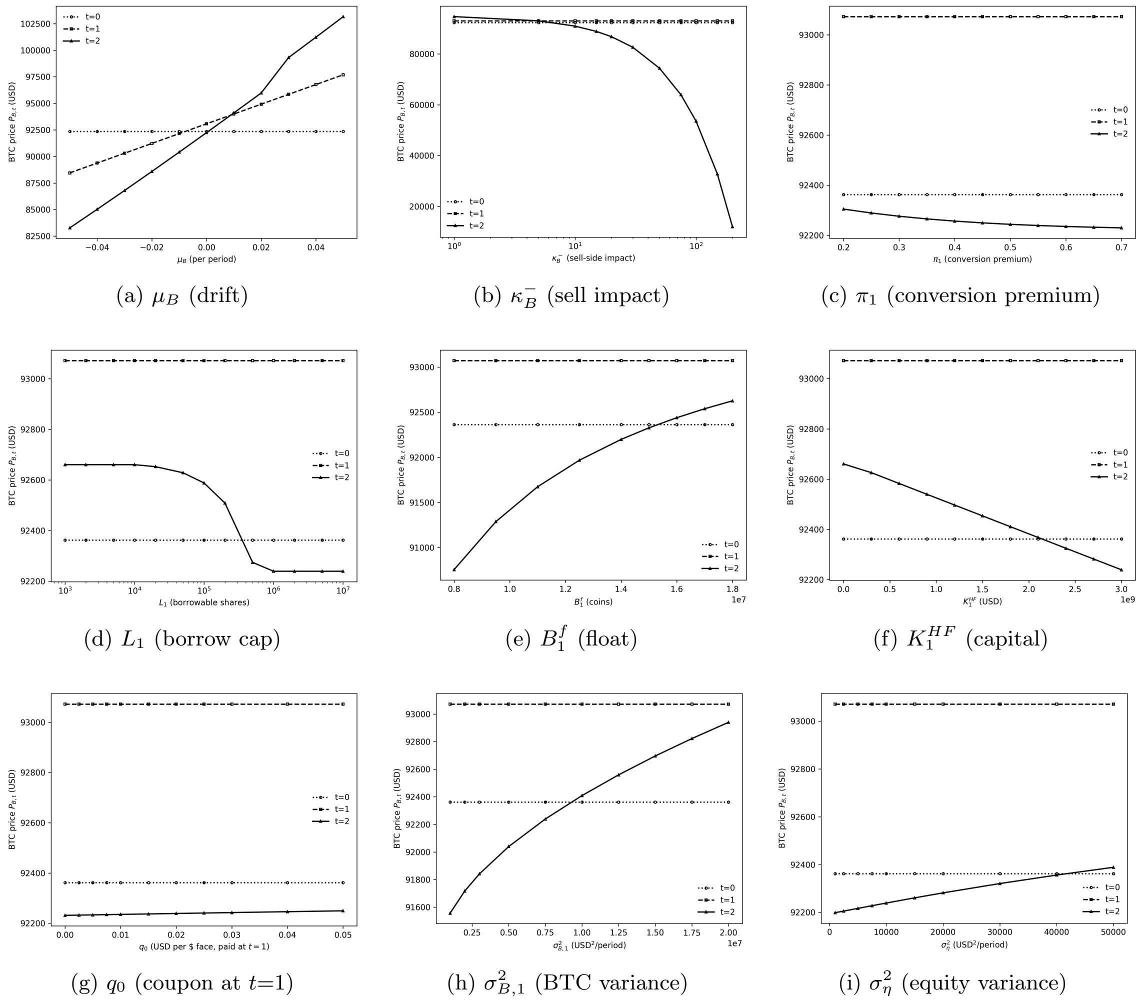
These findings have testable and practical implications. Empirically, the model predicts: (i) stronger interim uplifts in the price of Bitcoin and the firm's stock price when issuance is unconstrained; (ii) concentration of terminal crashes around conversion/maturity windows when the available Bitcoin float is low and hedge fund balance-sheet capacity was previously ample; and (iii) a widening wedge between realized and implied volatility as a sufficient statistic for hedgeable demand and feedback intensity. From a risk management perspective, stress tests that jointly shock float, sell-side impact, and issuance size are more informative than exercises focused on any single margin. The analysis is stylized–linear impact, a representative arbitrageur, reduced-form credit, and discrete dates–but it isolates the key mechanism: an issuance-cum-hedging loop that is benign while conversions succeed and potentially destabilizing when conversions fail.

References

1. Brunnermeier, M.K., Pedersen, L.H.: Market liquidity and funding liquidity. The Review of Financial Studies **22**(6), 2201–2238 (2009)
2. Campbell, J.Y., Ramadorai, T., Schwartz, A.: Caught on tape: Institutional order flow and stock returns. Journal of Financial Economics **92**(1), 66–91 (2009)
3. Choi, D., Getmansky, M., Henderson, B., Tookes, H.: Convertible bond arbitrageurs as suppliers of capital. The Review of Financial Studies **23**(6), 2492–2522 (2010)
4. Choi, D., Getmansky, M., Tookes, H.: Convertible bond arbitrage, liquidity externalities, and stock prices. Journal of Financial Economics **91**(2), 227–251 (2009)
5. Duffie, D., Singleton, K.J.: Modeling term structures of defaultable bonds. The Review of Financial Studies **12**(4), 687–720 (1999)
6. Hameed, A., Kang, W., Viswanathan, S.: Stock market declines and liquidity. The Journal of Finance **65**(1), 257–293 (2010)
7. Jarrow, R.A., Turnbull, S.M.: Pricing derivatives on financial securities subject to credit risk. The Journal of Finance **50**(1), 53–85 (1995)
8. Jensen, M.C., Meckling, W.H.: Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics **3**(4), 305–360 (1976)
9. MicroStrategy Incorporated: Press releases. Company website (2025), https://www.microstrategy.com/en/company/press, accessed 2025-09-09
10. Mitchell, M., Pedersen, L.H., Pulvino, T.: Slow moving capital. American Economic Review **97**(2), 215–220 (2007)

A Figures

Fig. 1: **BTC price levels** $P_{B,t}$ across parameter sweeps for baseline parameters. Line styles: t=0 dotted, t=1 dashed, t=2 solid. Panels (row-wise): μ_B, κ_B^-, π_1; L_1, B_1^f, K_1^{HF}; q_0, $\sigma_{B,1}^2$, σ_η^2.



(a) μ_B (drift)

(b) κ_B^- (sell impact)

(c) π_1 (conversion premium)

(d) L_1 (borrow cap)

(e) B_1^f (float)

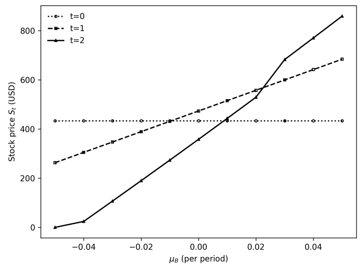
(f) K_1^{HF} (capital)

(g) q_0 (coupon at t=1)

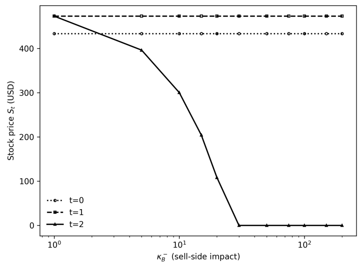
(h) $\sigma_{B,1}^2$ (BTC variance)

(i) σ_η^2 (equity variance)

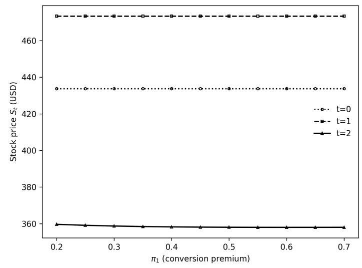
Fig. 2: **Stock price levels** S_t across parameter sweeps for baseline parameters. Line styles: t=0 dotted, t=1 dashed, t=2 solid. Panels (row-wise): μ_B, κ_B^-, π_1; L_1, B_1^f, K_1^{HF}; q_0, $\sigma^2_{B,1}$, σ^2_η.



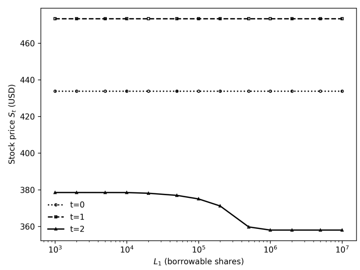
(a) μ_B (drift)



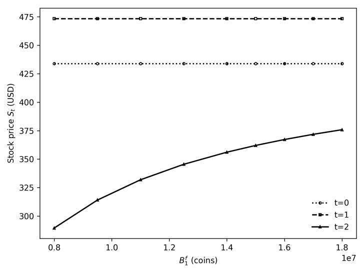
(b) κ_B^- (sell impact)



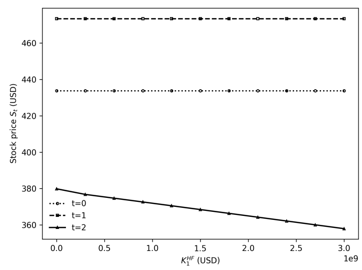
(c) π_1 (conversion premium)



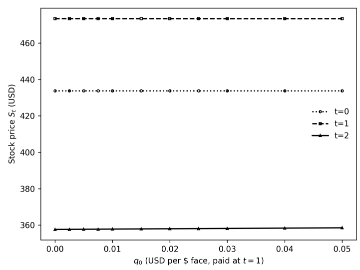
(d) L_1 (borrow cap)



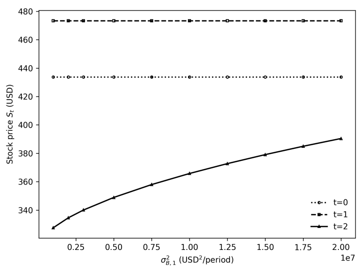
(e) B_1^f (float)



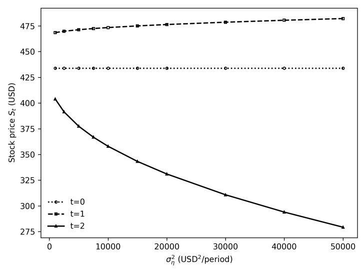
(f) K_1^{HF} (capital)



(g) q_0 (coupon at t=1)

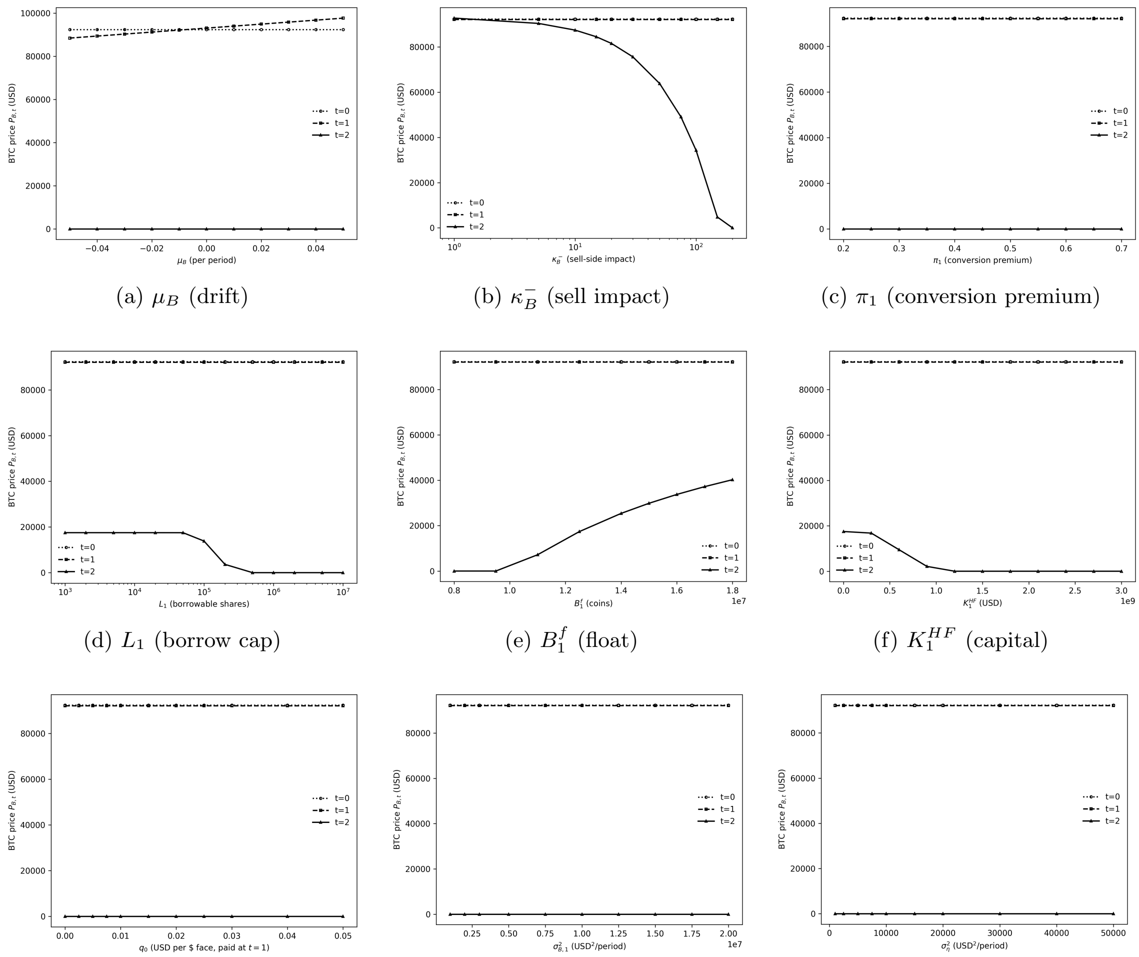


(h) $\sigma^2_{B,1}$ (BTC variance)



(i) σ^2_η (equity variance)

Fig. 3: **BTC price levels** $P_{B,t}$ across parameter sweeps for *crisis* parameters. Line styles: t=0 dotted, t=1 dashed, t=2 solid. Panels (row-wise): μ_B, κ_B^-, π_1; L_1, B_1^f, K_1^{HF}; q_0, $\sigma^2_{B,1}$, σ^2_η.



(a) μ_B (drift)

(b) κ_B^- (sell impact)

(c) π_1 (conversion premium)

(d) L_1 (borrow cap)

(e) B_1^f (float)

(f) K_1^{HF} (capital)

(g) q_0 (coupon at t=1)

(h) $\sigma^2_{B,1}$ (BTC variance)

(i) σ^2_η (equity variance)

B Tables

Table 1: Parameters grouped by their impact on the BTC price. μ_B is the per-period drift of the BTC price. κ_B^- is the sell-side BTC flow-to-price impact coefficient (applies when net BTC flow is negative, $B_t < 0$). B_1^f is the effective BTC float in coins over $[1, 2]$. $\sigma^2_{B,1}$ is the BTC dollar variance over $[1, 2]$. π_1 is the conversion premium at $t = 1$. q_0 is the coupon (USD per \$ face) paid at $t = 1$ on the tranche issued at $t = 0$. K_1^{HF} is the available hedge-fund capital at $t = 1$. L_1 is defined as the borrowable-share cap for the $t = 1$ tranche. The p-values (under the values in brackets) use Welch's two-sample test with a Normal approximation and compute tails via erfc. Comparison is always with sample average. Sample size $N = 10,000,000$.

	Lower Range	Upper Range	Average	PB_1 Bot. 5%	PB_2 Bot. 5%	PB_2 Bot. 1%	PB_2 Top 5%
$P_{B,1}$			$93,071.26$	$88,684.92$	$92,451.02$	$92,717.54$	$97,089.77$
$P_{B,2}$			$67,038.38$	$58,646.33$	$17,876.74$	$2,097.14$	$101,838.92$
S_1			473.32	273.62	445.09	457.22	656.31
S_2			91.83	0.55	0.00	0.00	798.06
μ_B	-0.05	0.05	0.00	-0.05	-0.01	0.00	0.04
				(0.000)	(0.000)	(0.000)	(0.000)
κ_B^-	1.00	200.00	100.53	100.55	173.49	179.70	64.25
				(0.841)	(0.000)	(0.000)	(0.000)
B_1^f	8.00×10^6	1.80×10^7	1.30×10^7	1.30×10^7	9.95×10^6	9.23×10^6	1.33×10^7
				(0.845)	(0.000)	(0.000)	(0.000)
$\sigma^2_{B,1}$	1.00×10^6	2.00×10^7	8.00×10^6	8.00×10^6	7.54×10^6	7.35×10^6	8.99×10^6
				(0.358)	(0.000)	(0.000)	(0.000)
π_1	0.20	0.70	0.50	0.50	0.53	0.55	0.43
				(0.896)	(0.000)	(0.000)	(0.000)
q_0	0.00	0.2	0.10	0.10	0.09	0.09	0.08
				(0.292)	(0.000)	(0.000)	(0.000)
K_1^{HF}	0.00	3.00×10^9	1.50×10^9	1.50×10^9	1.97×10^9	2.34×10^9	1.41×10^9
				(0.442)	(0.000)	(0.000)	(0.000)
L_1	1.0×10^3	1.00×10^7	1.09×10^6	1.08×10^6	2.23×10^6	2.90×10^6	$934,551.80$
				(0.184)	(0.000)	(0.000)	(0.000)

Table 2: Parameters grouped by their impact on firm stock price. μ_B is the per-period drift of the BTC price. κ_B^- is the sell-side BTC flow-to-price impact coefficient (applies when net BTC flow is negative, $B_t < 0$). B_1^f is the effective BTC float in coins over $[1, 2]$. $\sigma^2_{B,1}$ is the BTC dollar variance over $[1, 2]$. π_1 is the conversion premium at $t = 1$. q_0 is the coupon (USD per \$ face) paid at $t = 1$ on the tranche issued at $t = 0$. K_1^{HF} is the available hedge-fund capital at $t = 1$. L_1 is defined as the borrowable-share cap for the $t = 1$ tranche. The p-values (under the values in brackets) use Welch's two-sample test with a Normal approximation and compute tails via erfc. Comparison is always with sample average.

	Lower Range	Upper Range	Average	S_1 Bot. 5%	S_2 Bot. 5%	S_2 Bot. 1%	S_2 Top 5%
$P_{B,1}$			$93,071.26$	$88,684.93$	$92,587.27$	$92,587.27$	$97,088.72$
$P_{B,2}$			$67,038.38$	$58,647.33$	$59,748.05$	$59,748.05$	$101,838.90$
S_1			473.32	273.62	451.29	451.29	656.27
S_2			91.83	0.55	0.00	0.00	798.06
μ_B	-0.05	0.05	0.00	-0.05	-0.01	-0.01	0.04
				(0.000)	(0.000)	(0.000)	(0.000)
κ_B^-	1.00	200.00	100.53	100.54	116.90	116.90	64.23
				(0.899)	(0.000)	(0.000)	(0.000)
B_1^f	8.00×10^6	1.80×10^7	1.30×10^7	1.30×10^7	1.29×10^7	1.29×10^7	1.33×10^7
				(0.934)	(0.000)	(0.000)	(0.000)
$\sigma^2_{B,1}$	1.00×10^6	2.00×10^7	8.00×10^6	8.00×10^6	7.91×10^6	7.91×10^6	8.99×10^6
				(0.406)	(0.000)	(0.000)	(0.000)
π_1	0.20	0.70	0.50	0.50	0.50	0.50	0.43
				(0.979)	(0.000)	(0.000)	(0.000)
q_0	0.00	0.05	0.10	0.10	0.10	0.10	0.08
				(0.000)	(0.000)	(0.000)	(0.000)
K_1^{HF}	0.00	3.00×10^9	1.50×10^9	1.50×10^9	1.52×10^9	1.52×10^9	1.42×10^9
				(0.439)	(0.000)	(0.000)	(0.000)
L_1	$1,000.00$	1.00×10^7	1.09×10^6	1.08×10^6	1.13×10^6	1.13×10^6	$935,889.29$
				(0.205)	(0.000)	(0.000)	(0.000)

Table 3: Distribution summaries for PB_1, PB_2, S_1, and S_2 across sampled parameter draws.

	All	Top 10%	Top 25%	Bottom 25%	Bottom 10%
P_1^B	200,926.90	210,019.46	208,513.80	193,287.95	191,803.03
P_2^B	1,000,386.00	1,363,173.95	1,273,636.98	791,756.07	765,795.32
S_1	8,588.29	9,298.79	9,181.04	7,991.80	7,875.97
S_2	44,488.95	60,818.08	56,780.93	35,092.91	33,910.81