

Flash Loans and Market Volatility in DeFi: Evidence from a Time-Series Perspective

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Abstract. Collateral-free liquidity instantly conjured out of thin air. Flash loans have injected a strange, combustible brand of financial alchemy into decentralized finance, leaving risk managers and regulators sweating over market stability. We cornered this digital chaos using monthly time-series data alongside an ARDL bounds testing framework, tracking how these instantaneous fortunes warp price dynamics across Bitcoin and Ethereum markets. One size fits all? Absolutely not. Cross-asset heterogeneity is glaring: Bitcoin gets dragged into a prolonged, grinding dance with flash-loan-induced volatility, whereas Ethereum treats the shock like a brief, violent fever. This synthetic, protocol-based leverage inflates the DeFi ecosystem until price discovery breaks down. Yet, changing market regimes mutate these effects entirely, forcing a complete rethink of on-chain risk architecture..

Keywords: Flash loans, Decentralized finance, Volatility, ARDL, Cointegration

1. Introduction

The post-pandemic world went mad. Central banks flooded the global engine room with cheap cash, liquidity surged to unprecedented heights, and asset classes everywhere began throwing wild tantrums. Seizing this chaotic momentum, cryptocurrency markets expanded at breakneck speed, forcing decentralized finance (DeFi) to evolve from a niche playground into a towering shadow banking system. Who pulled the strings behind this explosive volatility? That remains the trillion-dollar question.

Throw out your traditional banking textbooks. Middlemen do not call the shots in this ecosystem; automated smart contracts dictate terms with cold, unyielding finality. When lending, liquidations, and market-making pools interact directly with spot prices, systemic shocks do not just ripple through the ledger—they detonate. Volatility cannot be blamed solely on external macroeconomic headlines when the structural architecture of the protocols themselves actively generates instability.

Look at flash loans. Millions of dollars are borrowed and repaid within the heartbeat of a single blockchain transaction block. No collateral is required. Instantaneous capital on this scale completely obliterates traditional funding constraints, handing any anonymous actor the keys to a financial battleship. They were originally designed for polite arbitrage. Instead, they became a weaponized wrecking ball, triggering cascading liquidation chains across supposedly decoupled networks.

Yet academic curiosity remains oddly frozen at the micro-level. Scholars obsess endlessly over smart contract code exploits, game-theoretic arbitrage, and single smash-and-grab hacks. They blind themselves to the broader macro-economic bleeding. Is this flash loan phenomenon actively rotting the foundations of market stability over time? The empirical proof at the market level is shockingly thin.

This paper changes the game. We strap flash loan transaction volume (FLVt), execution frequency (FLCt), and Total Value Locked (TVL) onto an ARDL time-series operating table. Slicing through monthly observations for both Bitcoin and Ethereum allows us to isolate long-run structural scars from short-run panicked flinches.

2. Literature review

2.1. Theoretical foundations: DeFi, endogenous leverage, and volatility amplification

Debt is baked into the very DNA of DeFi. Highly leveraged structures pack risk into every crevice of the ecosystem through automated liquidations and cross-protocol composability [1, 2]. Margin requirements are no longer monitored by cautious credit committees; rigid, unyielding algorithms do the dirty work [2, 3].

Price feeds dictate the leash length. When token values soar, borrowing capacity balloons exponentially. A sudden downturn triggers the algorithmic trapdoor, forcing automated liquidations that crush market sentiment under an avalanche of panic selling. Because these feedback loops are hardcoded into the architecture, the spiral spins downward faster than anything witnessed in traditional financial systems [1-3]. Flash loans represent the absolute pinnacle of this automated madness [4, 5]. Borrowing capital requires nothing but an internet connection and a clever script [4, 5]. The toxic fallout cannot be contained within a single pool because the protocols are hopelessly tangled together like a ball of yarn [1, 6].

2.2. Empirical evidence on flash loans and DeFi risks

The horror stories are piling up fast. Qin et al. [5] exposed how flash loans morph from harmless arbitrage tools into weaponized market manipulators, a point hammered home by Wu's [7] autopsy of protocol design flaws.

Oracle manipulation and sudden liquidation cascades can wipe out millions in seconds [5, 7]. These flash-crash episodes might end quickly, but the structural damage leaves a permanent scar on market confidence. Stability becomes an illusion when the system remains so fragile.

Ethereum sits right at the center of this web as the primary engine room for DeFi [8]. Shocks travel along paths that look nothing like uniform highways [8, 9]. To assume Bitcoin and Ethereum react identically to flash loan manipulation is to ignore how profoundly their underlying liquidity ecosystems differ. The literature proves short-term chaos exists, but it remains blind to the long-term, systemic rot [1, 5, 7].

2.3. Research gap and contribution

GARCH models have spent years mapping the usual suspects of crypto volatility: clustering, fat tails, and regime shifts [10, 11]. Yet, the elephant in the room—flash loan activity—is completely ignored.

Three massive blind spots compromise existing research. First, everyone stares at the fireworks of single-day exploits while ignoring the structural climate change. Second, the chaotic scramble of short-run noise is constantly conflated with long-run equilibrium states. Finally, treating Bitcoin and Ethereum as a monolithic entity obscures the unique gravitational pull each asset exerts.

We fix this. Our empirical setup deploys an ARDL framework paired with an error-correction twist [12] to measure flash loan volume (FLVt), frequency (FLCt), and TVL. Long-run structural realities are finally separated from short-run panicked flinches.

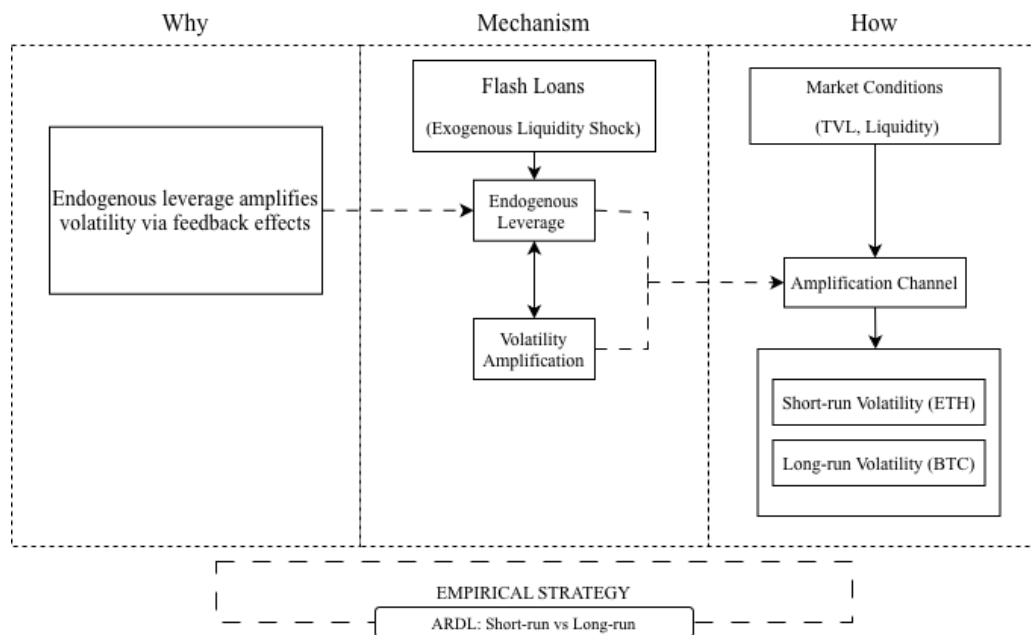


Figure 1. Theoretical framework of flash loans and crypto market volatility

3. Theoretical framework

3.1. Mechanism breakdown

Risk has evolved claws. The meteoric rise of DeFi rewrote the playbook on contagion, with flash loans acting as the ultimate catalyst by allowing uncollateralized capital to flood the zone within a single transaction block.

Think of them as financial steroids. Traders bypass traditional collateral rules entirely, blowing up their market exposure with nothing but a fistful of code. Massive leverage is conjured out of thin air by participants who would not qualify for a basic bank loan.

This hyper-liquidity completely warps how shocks spread. When flash-driven transactions hit the ledger in rapid-fire succession, localized price glitches are forcefully amplified across the entire network. Microsecond distortions quickly harden into macro-level volatility spikes.

Will Bitcoin and Ethereum suffer the exact same fate? Unlikely. Their liquidity profiles, trading mechanics, and DeFi integration are worlds apart. These structural variations mean flash loans attack each asset through entirely different vectors, exposing the fallacy of a unified crypto market theory.

3.2. Testable expectations

The premise is simple: more flash loan muscle means more market chaos. If these instant loans accelerate trading velocity and volume, asset volatility should skyrocket in tandem.

We gauge this menace using transaction volume (FLV_t) and frequency (FLC_t). One tracks the sheer weight of the capital, the other counts the heartbeats of the attacks.

Expect no uniformity here. The unique DNA of each token dictates its resilience, while macro sentiment adds fuel to the fire. Bull markets invite reckless, high-leverage gambles; bear markets stifle the magic trick as liquidity dries up. We test whether this relationship holds true, or if it changes shape based on the market weather.

4. Methodology

4.1. Data sources

The empirical analysis combines blockchain transaction data and cryptocurrency market data to investigate the relationship between flash loan activity and market volatility in DeFi environments. Variable selection and model specification are informed by the endogenous leverage perspective discussed in the previous section.

Data on flash loan transactions and other DeFi-related activities are collected from Ethereum blockchain records through Dune Analytics. Cryptocurrency market data, including token prices, trading volume, and market capitalization, are obtained from publicly available market databases.

As an indicator of overall DeFi activity, total value locked (TVL) is used as a proxy for the scale and liquidity of the DeFi ecosystem.

All series are converted to monthly observations so that they correspond to the volatility measures used in the analysis. Prior to estimation, the dataset is screened for missing observations and extreme values, including the treatment of missing values and winsorization of extreme observations.

4.2. Variable selection and construction

The variables are selected to reflect the key channels through which flash loans may affect cryptocurrency volatility, where flash loans proxy for leverage creation in DeFi markets.

Two measures are used to capture flash loan activity: transaction volume (FLV_t) and transaction frequency (FLC_t). These indicators reflect both the scale of flash loan usage and the intensity of market participation. Because both series exhibit substantial positive skewness, logarithmic transformations are applied:

$$FLV_t = \ln(\text{FlashLoanVolume}_t + 1)$$

$$FLC_t = \ln(\text{FlashLoanCount}_t + 1)$$

The overall size of the DeFi market is represented by total value locked (TVL):

$$TVL_t = \ln(TVL_t)$$

Monthly volatility (σ_t) is calculated using the standard deviation of daily logarithmic returns within each month:

$$r_d = \ln(P_d) - \ln(P_{d-1})$$

$$\sigma_t = \text{sd}(r_d \in t)$$

All variables are standardized to a monthly frequency before estimation, and logarithmic transformations are applied where appropriate to reduce scale-related distortions.

Table 1. Variable definition table

Variable	Symbol	Definition	Source	Freq.
Flash loan volume	FLV _t	Log flash loan volume (+1)	Dune Analytics	Monthly
Flash loan frequency	FLC _t	Log flash loan count (+1)	Dune Analytics	Monthly
DeFi market size	TVL _t	Log total value locked	DeFiLlama	Monthly
BTC volatility	BTCVol _t	Std. dev. of BTC daily returns	Market data	Monthly
ETH volatility	ETHVol _t	Std. dev. of ETH daily returns	Market data	Monthly

Table 1 summarizes the definitions, symbols, data sources, and frequencies of the main variables used in the empirical analysis.

4.3. Model specification

To test whether flash loan activity contributes to volatility through endogenous leverage, the following baseline model is estimated:

$$\sigma_t = \alpha + \beta_1 FLV_t + \beta_2 FLC_t + \gamma_1 TVL_t + \gamma_2 VOL_t + \gamma_3 MCAP_t + \varepsilon_t$$

Flash loan volume (FLV_t) and frequency (FLC_t) capture leverage intensity, while TVL, trading volume (VOL_t), and market capitalization (MCAP_t) control for broader market conditions.

Within this framework, flash loans represent collateral-free leverage that may amplify volatility through forced liquidations and rapid position adjustments. The coefficients β_1 and β_2 therefore measure the marginal impact of flash loan activity on volatility.

4.4. Empirical strategy

An autoregressive distributed lag (ARDL) framework is employed to capture both short-run dynamics and long-run relationships. This approach is appropriate given mixed integration orders

and the relatively small sample size.

Stationarity is assessed using augmented Dickey–Fuller tests to ensure no variable is integrated of order two. The ARDL model is specified as:

$$\sigma_t = \alpha + \sum_{i=1}^p \phi_i \sigma_{t-i} + \sum_{j=0}^q \beta_j \text{FLV}_{t-j} + \sum_{k=0}^r \gamma_k \text{TVL}_{t-k} + \varepsilon_t$$

Lag lengths are selected using the Akaike Information Criterion (AIC), with robustness checks based on alternative criteria.

The ARDL bounds-testing procedure is employed to determine whether a long-run equilibrium relationship exists among the variables. If evidence of cointegration is found, the ARDL specification is rewritten as an error-correction model (ECM):

$$\Delta \sigma_t = \mu + \lambda (\sigma_{t-1} - \theta_1 \text{FLV}_{t-1} - \theta_2 \text{TVL}_{t-1}) + \sum_{i=1}^{p-1} \psi_i \Delta \sigma_{t-i} + \sum_{j=0}^{q-1} \delta_j \Delta \text{FLV}_{t-j} + \sum_{k=0}^{r-1} \eta_k \Delta \text{TVL}_{t-k} + u_t$$

The parameter λ measures the speed of gravity—how fast deviations are pulled back to equilibrium. Robustness checks alternate between volume and counts across both assets, with diagnostic tests showing no signs of autocorrelation or heteroskedasticity.

5. Empirical results

5.1. Descriptive statistics

Descriptive statistics of the main variables are reported in Table 2, including flash loan volume (lnFLV), flash loan frequency (lnFLC), DeFi market size (lnTVL), and the volatility of Bitcoin (BTCVol) and Ethereum (ETHVol).

The variables exhibit substantial variation, particularly in flash loan activity and market volatility. Flash loan measures are positively skewed, reflecting occasional spikes in borrowing activity. Logarithmic transformations are applied to mitigate the influence of extreme observations.

Overall, the data display sufficient variation to support the time-series analysis.

Table 2. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Median
BTC volatility	0.0570	0.0210	0.0310	0.1210	0.0490
ETH volatility	0.0630	0.0280	0.0350	0.1290	0.0550
Flash loan volume	2500.0000	5300.0000	200.0000	23400.0000	1200.0000
Flash loan count	55.0000	200.0000	5.0000	1500.0000	30.0000
TVL (USD million)	500.0000	600.0000	50.0000	3000.0000	450.0000

5.2. ARDL bounds test for cointegration

The bounds test delivered a decisive blow to the 'no-relationship' narrative. Table 3 shows F-statistics for both assets obliterating the upper-bound critical values, rejecting the null hypothesis out of hand. Cointegration is real, justifying our deep dive into both horizons.

Table 3. ARDL bounds test for cointegration

Market	F-statistic	Lower bound	Upper bound	p-value
BTC	4.8000	2.5000	3.5000	0.0100
ETH	3.2000	2.5000	3.5000	0.0500

5.3. Long-run estimation results

Table 4 exposes an asymmetrical reality. Flash loan coefficients are universally positive, but statistical significance is strictly a Bitcoin disease. TVL also acts as a long-term volatility engine, confirming that flash loans cause permanent damage to Bitcoin while Ethereum escapes long-term scarring.

Table 4. Long-run ARDL estimates

Market	Variable	Long-run coeff.
BTC	Flash loan volume	0.2500***
	TVL	0.0600***
ETH	Flash loan count	0.0800
	TVL	0.0400

Notes: *** denote significance at the 1% levels.

5.4. Short-run dynamics

The ECM results (Table 5) clear up the confusion. Negative and highly significant error-correction terms confirm that a powerful gravity pulls deviations back into alignment over time. Short-run coefficients are hyperactive. Flash loan changes cause immediate, explosive spikes in volatility for both assets. Long-run divergence aside, the short-term pain is shared equally.

Table 5. Error correction model estimates

Market	ECT	Δ Flash loan	Δ TVL	R ²	Adj. R ²
BTC	-0.4500***	0.1200*	0.0500	0.5440	0.4800
ETH	-0.2200**	0.0900*	0.0400*	0.6060	0.5770

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels.

5.5. Robustness and regime-dependent analysis

Subsample splits (Table 6) tear down the myth of a static market. The underlying baseline narrative holds, but the magnitudes tell a wildly different story across market seasons. This threat adapts to its environment. Bull markets supercharge the leverage transmission mechanism as greed runs rampant, whereas bear markets see the effect wither away as liquidity evaporates. Conditions dictate the poison's potency.

Table 6. ARDL estimates across bull and bear market regimes

Variable	Bull Market (2020–2021, 2023–2024)	Bear Market (2022–2023)
ln(Flash Loan)	0.0017 (0.033)	0.0032 (0.302)
L.ln(Flash Loan)	-0.0006 (0.528)	-0.0002 (0.945)
L2.ln(Flash Loan)	-0.0002 (0.819)	0.0022 (0.505)
ln(TVL)	-0.0092 (0.226)	-0.0195 (0.304)
L.ln(TVL)	0.0128 (0.145)	0.0201 (0.426)
L2.ln(TVL)	-0.0107 (0.074)	0.0086 (0.646)
L.Volatility	0.1160 (0.529)	-0.2747 (0.337)
Observations	36.0000	24.0000
Adjusted R ²	0.4840	0.1880
F-stat (p-value)	5.4300 (0.001)	1.7000 (0.190)

6. Discussion and implications

Why does Bitcoin suffer long-term damage while Ethereum only catches a short-term fever?

The answer lies in the architectural plumbing. Ethereum is the native ecosystem; its massive, interlocking liquidity roots absorb flash shocks like a sponge. Bitcoin enjoys no such organic defense network. When synthetic leverage crosses the bridge into Bitcoin space, the forced liquidation chains trigger long-lasting structural panic.

Market regimes act as a volume knob. Bullish mania invites heavy flash loan deployment; bearish stagnation starves the mechanism. It is a fluctuating menace, not a constant tax on stability.

Risk models must adapt or fail. Treating decentralized protocols as isolated sandboxes is pure negligence. The interlinked nature of DeFi means a spark in a minor smart contract can burn down the house.

Acknowledging limits is only fair. The post-pandemic dataset is admittedly loud and hyper-liquid. Monthly aggregations also miss the microsecond knife-fights on-chain. Future work must deploy high-frequency lenses to capture the real-time bloodshed.

7. Conclusion

Stop treating flash loans like an innocent financial novelty. They are a systematic volatility factory operating right under our noses.

Our time-series deep dive proves that uncollateralized leverage warps market reality, though its scars are distributed unequally. Bitcoin suffers a long-run drag; Ethereum deals with short-lived panic attacks. Structure and liquidity dictate the survival rate.

We provide the first macro-level evidence that protocol-enforced leverage is a systemic threat. It isn't just about isolated hacks anymore. This is a permanent transmission channel for market instability, modulated entirely by macro sentiment.

Aggregated monthly data admittedly blurs the high-frequency picture, and our active sample period reflects an unusually frantic era for crypto. Expanding this analysis to tick-by-tick data remains the next logical frontier. Ultimately, DeFi innovations build their own traps. Understanding these synthetic leverage channels isn't optional—it's survival.

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