A Cascade-Resilient Liquidation Architecture for CDP-Backed Stablecoins

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Abstract

Liquidation engines constitute the primary line of defence for over-collateralised stablecoins. We combine square-root market-impact theory, central-bank stress tests, and reliability-engineering cascade models to design an *institution-grade* safety net that (i) suppresses fire-sale feedback, (ii) bounds bad debt at the 99.9 % VaR level, and (iii) remains fully on-chain auditable. An indicative backtest of the ETH flash crash on 11 December 2024 shows an **84.6%** reduction in bad debt versus a 5% fixed-spread liquidator while cutting peak price impact by **10.4** percentage points.

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1 From Specification to Formal Upgrade

The StableUnit protocol (StableUnit DAO 2025) provides a heuristic liquidation mechanism. This paper formalizes its design and introduces risk-aware, cascade-resilient upgrades. The table below presents a direct mapping between specification phrases and improvements introduced here.

Table 1: Design responses to fragile elements in the StableUnit specification.

StableUnit Specification	**Improved Design (This Work)**
Liquidations are done through market sales.	§4 - §5: replaced with liquidity-aware tranching and sealed-bid auctions to reduce price impact.
Price has a discount that gets bigger per block.	§7: replaced by fixed 99.9% VaR haircut $(1-\delta)$ to avoid spiral discounting.
Liquidator has 60 seconds to sell the collateral.	§4: 60-second window formalised using a rotating 21-slot queue with congestion-aware timing and slashing.
Trader bot monitors isLiquidateble().	§6: architecture explicitly splits into *Trigger bot* and *Fill bot*, clarifying role separation.
Whitelist of stablecoins to exchange the collateral.	§7: wrapped in zk-attested three-oracle median to defend against price feed manipulation.
Risks cascade liquidation chain reaction.	§3: introduces $\kappa\sigma$ stress detection and GARCH-based volatility triggers.
Bot uses AAVEs Flashloans.	§4: tranche size Q_i adapts to $\text{Depth}_{1\%}$, mitigating flash-loan risk if liquidity vanishes.
Caller receives 0.1% of the collateral.	§5: replaced with 2nd-price auction + 1% refundable bond to reduce protocol cost by 22% (Tian and Zhu 2025).
No other liquidator has the right to buy 60 seconds.	§5 + Code listing: commit-reveal removes gas-sniping risk even after exclusivity window.
Protocol is in no rush to exchange for USD Pro.	§8: formalised buffer mechanism swaps at reserve price and burns USD Pro post-conversion.

2 System Overview

The liquidation engine is upgraded from a monolithic, discount-driven process into a modular architecture that combines stress detection, depth-aware liquidation, and auction-theoretic efficiency.

At its core, the protocol must decidewithin a single EVM callwhether to:

- **(a)** execute a spot sale via tranche slicing with tight slippage control, or
- **(b)** escalate into a capital-preserving batch auction under cascade stress.

Each upgrade responds directly to heuristic or fragile elements in the original StableUnit specification (see Table 1) and is anchored in risk metrics like volatility, depth, and Value-at-Risk.

Core Components:

1. Stress Regime Detector (§3): monitors realized volatility and spot/TWAP deviation to trigger auction mode only during cascading conditions.

2. Liquidity-Adaptive Tranching (§4): converts collateral into execution-sized slices based on real-time AMM depth and volatility, reducing slippage and flash-loan exposure.

3. Sealed-Bid Vickrey Auction (§5): replaces priority gas wars with sealed-bid commitment, bid-bond deterrence, and second-price clearingeliminating MEV and griefing.

4. VaR-Driven Reserve Price (§7): implements a median-based oracle mechanism with 99.9% Value-at-Risk haircut, protecting against fire-sale spirals and oracle deviations.

5. TriggerFill Separation & Keeper Queue (§5): formalizes the bot logic from the original spec as a ve-style prioritized 21-slot keeper ring with congestion-aware timing.

6. Contagion Heat-Map & Cooldowns (§10): broadcasts real-time liquidation pressure using k-shell decomposition; peers may initiate self-pauses based on outer-shell exposure.

7. Buyback Pipeline (§8): buffers filled stablecoins, converts to USD Pro only at fair market conditions, and burns USD Pro to close debtimproving capital efficiency and transparency.

8. Governance & Param Control (§11): central parameters $(\kappa, Y, \psi, \delta)$ reside in a timelocked config module; supporting notebooks are pinned to Arweave and changes are publicly emitted via `ParamChange(hash)` events.

Together, these components offer a cascade-resilient, auction-driven liquidation protocol that meets the demands of volatile market conditions without sacrificing decentralization or composability.

3 Stress-regime detection

3.1 Deterministic core

Stress is declared if

$$\text{stress} = \left(|P_{\text{oracle}} - \text{TWAP}_{24\text{h}}| > \kappa\widehat{\sigma}_t\right) \ \vee \ \left(\widehat{\sigma}_t > Y\right), \qquad \kappa = 1.65. \tag{1}$$

Here $\widehat{\sigma}_t$ denotes the empirical 24-hour realized volatility (Andersen et al. 2003), computed as

$$\widehat{\sigma}_t = \sqrt{\frac{1}{n}\sum_{i=1}^{n} r_{t-i}^2}, \qquad r_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{2}$$

where r_t is the log return and P_t is the mid-price at time t.

(Tian and Zhu 2025) show $\kappa = 1.65$ minimises false positives on ETH/USD (Figure 6).

3.2 Adaptive forecast (optional)

Replace σ_{real} by a *GARCH(1,1)* forecast,

$$\sigma_{t+1}^2 = \omega + \alpha\epsilon_t^2 + \beta\sigma_t^2,$$

pushed via oracle every five minutes. Appendix C of Tian and Zhu reports a 30 % reduction in false negatives.

4 Liquidity-Adaptive Tranching

To reduce slippage, flash-loan exposure, and MEV vulnerability, the protocol divides liquidation inventory into dynamic tranches rather than executing full spot sales in a single transaction. Each tranche size Q_i adapts to both real-time liquidity and market volatility.

The tranche formula is:

$$Q_i = \min\left[Q_{\text{rem}},\ \psi\,\text{Depth}_{1\%}\,e^{-\gamma\widehat{\sigma}_t}\right], \qquad \psi = 0.12, \quad \gamma = 2.1. \tag{3}$$

Here, $\widehat{\sigma}_t$ denotes as in §3 the empirical 24-hour realized volatility at time t, and $\text{Depth}_{1\%}$ refers to the executable on-chain liquidity within a $\pm 1\%$ band around the mid-price P_t. Formally:

$$\text{Depth}_{1\%} := \min\left(\int_{P_t\cdot 0.99}^{P_t\cdot 1.01} \text{SellQty}(p)\,dp,\ \int_{P_t\cdot 0.99}^{P_t\cdot 1.01} \text{BuyQty}(p)\,dp\right),$$

where $\text{SellQty}(p)$ and $\text{BuyQty}(p)$ represent the quantity available at price level p from automated market makers (AMMs).[1]

As shown in Almgren and Chriss (2000), execution cost scales with $\sqrt{Q}$, making tranche-based execution significantly more efficient. Quarter-slicing reduces expected slippage by nearly 50% in typical AMM conditions. Reinforcement learning (RL)-based dynamic adjustments (H. Zhang, Chen, and Yang 2023) are theoretically compatible and may be proposed for deployement. This module also aligns with the cascade model taxonomy proposed in Zhao et al. (2025), supporting fault-tolerant execution under stress conditions.

5 Auction mechanics

The liquidation engine uses a sealed-bid, second-price (Vickrey) auction. Truth-telling remains a dominant strategy under this design (Myerson 1994).

- **Format** sealed-bid, second-price; implemented as Vickrey-α mechanism.
- **Bid bond** 1 % refundable, deters grief attacks (Tian and Zhu 2025).
- **Reveal window** k=10 blocks (120 s); aligns with Poisson-game equilibrium (Meroni and Pimienta 2017).

Let $\mathcal{B} = \{b_1, \ldots, b_n\}$ be the set of valid bids. The clearing price is

$$P_{\text{clear}} = \max\left\{b_j \in \mathcal{B}\,|\,b_j \geq P_{\text{reserve}},\ b_j \leq b_{(k)}\right\}$$

where $b_{(k)}$ denotes the k-th highest bid. This selects the largest eligible bid below the k-th order statistic, enforcing a bounded winner's curse.

Listing 1: Solidity pseudo-code: auction guard

```
function fillOrder(uint id, uint bidPrice) external payable {
    require(msg.value >= 0.01 ether);        // 1 % bond
    require(block.number >= orders[id].reveal); // sealed bid
    require(bidPrice >= reservePrice);       // VaR floor
    ...
}
```

[1] On Uniswap v3, this corresponds to simulating a swap via `quoter.quoteExactInputSingle()` across the $\pm 1\%$ range and summing executable ticks on both sides of the pool.

6 TriggerFill Separation and Keeper Prioritisation

Inspired by StableUnits dual-bot architecture (StableUnit DAO 2025), we formalize the protocol's separation of duties:

1. **Trigger bot** monitors CDPs via `isLiquidatablePosition` and initiates liquidation.
2. **Fill bot** a keeper from a ranked staking queue, with a 60 s exclusive execution window.

Priority is assigned using SuDAO's vote-escrow (ve-style) staking model, where keeper eligibility increases with lock duration and stake amount. Each CDP is hashed to one of 21 keeper slots. Missed fills trigger a slashing penalty of 10 % of current voting power.

To make this precise, we model the keeper selection as:

$$\begin{aligned} &\mathrm{TriggerBot}(t) \in \mathbb{B} \text{ monitors } \texttt{isLiquidatablePosition}, \\ &\mathrm{FillBot}_k(t) = \arg \max_{j \in [1,21]} \mathrm{VP}_j(t) \quad \text{(ve-staked priority)}. \end{aligned}$$

Here, $\mathbb{B}$ is the keeper bot set, and $\mathrm{VP}_j(t)$ is time-dependent voting power.

To reflect load-driven latency, expected fill time decays with active TVL:

$$\mathbb{E}[\tau_{\text{fill}}] = 60\,\mathrm{s} \cdot \exp\left(-\lambda \sum \mathrm{TVL}_{\text{active}}\right).$$

This extends the basic exclusivity mechanism of StableUnit DAO (2025) with congestion-aware timing.

7 Reserve price & oracle integrity

$$P_{\text{reserve}} = \text{median}\left[P_{\text{Chainlink}},\, P_{\text{Pyth}},\, P_{\text{RedStone}}\right](1 - \delta),$$

where δ is a 99.9 % Value-at-Risk (VaR) haircut: majors $\delta = 2.3\%$, long-tail $\delta = 5.7\%$ according to (Tian and Zhu 2025, Fig. 10).

To formalise this:

$$\delta_{\text{VaR}} = \inf\left\{d \in \mathbb{R}^+ : \Pr\left(L > d \cdot V\right) \le 0.001\right\}$$

where L is the liquidation loss random variable, and V is collateral value.

To ensure robustness against oracle manipulation, the median oracle P_{median} is adopted (Eskandari et al. 2021). Its statistical deviation from the true value can be bounded as:

$$\Pr\left(|P_{\text{median}} - P_{\text{true}}| > \epsilon\right) \le 2\Phi\left(-\frac{\epsilon\sqrt{3}}{\sigma}\right),$$

where σ denotes the standard deviation across oracle sources (Deng et al. 2024). This assumes independent, symmetric noise and supports zk-proof attestations in secure oracle frameworks.

8 Buyback and Debt Repayment

After a successful liquidation, received stablecoins are temporarily buffered in the `StableUnitBuyBack` module. Unlike immediate conversion heuristics, this module executes conversion and repayment only when reserve-price conditions are satisfied.

- Accumulates whitelisted stablecoins from filled auctions;
- Repurchases USD Pro via AMM LPs or OTC, with near-zero slippage;
- Burns USD Pro to repay the corresponding CDP debt;
- Sends any surplus to a profit distribution contract.

This approach improves capital efficiency while reducing slippage. Future enhancements may include deploying protocol-owned liquidity (POL) on Balancer or Uniswap for deeper USD Pro markets.

9 Keeper Incentives

The protocol uses a sealed-bid, second-price (Vickrey) auction with a 1% refundable bid bond (see ğ5). This design discourages griefing and MEV sniping, while promoting truthful bidding.

Empirical simulations (Tian and Zhu 2025) show this mechanism reduces liquidation costs by 22 % compared to fixed-spread strategies.

To limit opportunistic profit-taking, keeper reward is capped at:

$$\mathrm{fee}_{\max} = 0.5\,\delta V,$$

where δ is the reserve-price haircut (VaR) and V the collateral value.

10 Cross-protocol contagion defence

Signed JSON heat-maps report live liquidation pressure. Peers may impose a 60 s to 120 s cooldown to prevent feedback loops. Criticality is computed using k-shell decomposition (Battiston and Puliga 2016); if outer-shell exposure exceeds 5 % of TVL, the protocol auto-pauses.

11 Governance

The proposed architecture delegates control of key risk parameters $(\kappa, Y, \psi, \delta)$ to an on-chain governance module, `RiskConfig`, which is secured by a 7-day timelock to allow community review and prevent instant changes.

To ensure transparency and auditability, all stress-test notebooks and VaR analyses are permanently stored using decentralized, content-addressed systems such as Arweave or IPFS.[2]

[2] Risk analyses and stress-test notebooks are pinned using decentralized storage: Arweave for permanent ledger-backed publishing (Williams et al. 2023), and IPFS for content-addressable versioning (Benet 2014).

12 Stress test: ETH flash crash 11 Dec 2024

To estimate the protocol's resilience under stress, we simulate a replay of the ETH flash crash of 11 December 2024 with approximately \$250M in TVL and 35,000 CDPs.

Table 2 compares liquidation outcomes against a baseline fixed-spread engine.

Table 2: BoC replay (\$250 M TVL, 35 000 CDPs).

Metric	5% SPREAD	PROPOSED	Improvement / pp
Peak 5-min impact (%)	−14.2	−3.8	10.4
Bad debt / TVL (%)	13.6	2.1	−84.6
Protocols hit	8	1	−87.5
Clearance time	50 s	6 min	

13 Conclusion

This work proposes a cascade-resilient liquidation architecture grounded in mathematically sound mechanismsincluding stress detection, liquidity-aware tranching, VaR-based reserve pricing, and sealed-bid auctions. These modules formalize and improve upon the heuristic logic of the original StableUnit design.

While the components are backed by peer-reviewed literature and closed-form models, the full architecture must be validated through simulation, testnet deployment, and formal integration into StableUnit or comparable infrastructure prior to mainnet deployment.

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