

SwingGuard: Risk-Conditioned Multi-Agent Swing Trading with Dual-Timescale Governance

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Abstract

Cryptocurrency swing trading spans mismatched timescales: positions remain active while market and event risk can change within minutes. However, many predictive and large language model (LLM)-based trading systems assess risk after strategy generation or run both functions at the same cadence, leaving proposals unconditioned by current risk and exposure weakly governed between revisions. We propose SwingGuard, a dual-timescale, long-only multi-agent framework for risk-conditioned strategy generation. At the strategy timescale, specialized analysts synthesize point-in-time technical, sentiment, on-chain, and macroeconomic evidence through bullish–bearish deliberation. The resulting evidence and current risk context are then combined by a Portfolio Architect to form a target position. At the governance timescale, a five-minute Risk Controller performs conditional diagnosis, maintains persistent risk states with staged recovery, audits the proposal, and constrains execution until the next strategy revision. This design allows risk to shape the feasible strategy before proposal finalization while continuing to govern the active position afterward. Evaluations on Bitcoin (BTC) and Ether (ETH) show that SwingGuard preserves positive returns after transaction costs while maintaining shallow drawdowns and strong risk-adjusted performance on both assets. The exposure-capped joint portfolio achieves a Sharpe ratio of 2.98, compared with 2.79 for an otherwise identical Post-hoc Risk variant. Structured traces further link risk evidence and state transitions to strategy constraints and executed position changes, providing an auditable framework for asynchronous cryptocurrency swing trading. Overall, the results indicate that conditioning strategy formation on current risk, together with persistent high-frequency governance, improves risk-adjusted performance without sacrificing auditability.

Introduction

Cryptocurrency swing trading creates an asynchronous control problem: a strategy formed from a completed daily research window remains active while prices, liquidity, on-chain activity, and event risk can change within minutes. A medium-horizon thesis may therefore remain directionally valid after its planned exposure becomes unsafe. Trading systems must coordinate what position to seek with how much of that position remains executable and when exposure may be restored (Liu and Tsyvinski 2021; Liu, Tsyvinski, and Wu

2022; Makarov and Schoar 2020; Corbet et al. 2019; Fang et al. 2025; Omrane et al. 2025).

Forecasting and reinforcement-learning methods primarily learn price or return patterns and map predictive signals to trading decisions or portfolio positions (Jiang and Liang 2017; Lahmiri and Bekiros 2019; Tharun et al. 2023; Cakici et al. 2024; Liu et al. 2023b; Jing and Kang 2024). These representative methods mainly optimize prediction or strategy decisions without explicitly modeling the independent fast risk-governance layer studied here. Sequence forecasters model long-horizon and general temporal structure (Zhou et al. 2021; Wu et al. 2021; Nie et al. 2023; Wu et al. 2023a). Large language models (LLMs) support increasingly structured forms of reasoning and financial-domain adaptation (Wei et al. 2022; Xiong et al. 2025; Xiong, Payani, and Fekri 2026; Liu et al. 2023a; Xie et al. 2023), while LLM-based multi-agent trading systems use complementary mechanisms including specialized analysis, agent coordination, deliberation, and memory (Luo et al. 2025; Yu et al. 2024; Xiao et al. 2024). Yet proposal-only risk review neither shapes the preceding deliberation nor governs the position at a faster cadence.

The central distinction is intervention timing. For strategy information X_t , policy π , and risk context R_t , a post-hoc operator $g(\pi(X_t), R_t)$ modifies a completed proposal, whereas $\pi(X_t, R_t)$ lets risk alter direction, exposure, and parameters during deliberation. We ask whether this conditioning improves the return–risk trade-off over an otherwise identical post-hoc design while preserving an auditable path to execution.

We propose **SwingGuard**, a dual-timescale multi-agent architecture for risk-conditioned cryptocurrency swing trading. Technical, sentiment, and fundamentals analyzers inform bullish–bearish deliberation, after which a Portfolio Architect forms a long-only target. A coupled five-minute risk chain diagnoses threats, maintains a persistent state with staged recovery, and constrains execution. Its current risk context enters the Portfolio Architect before proposal finalization; a deterministic audit subsequently enforces the controller boundaries. The strategy and governance layers operate at distinct timescales: strategy reasoning occurs over the completed research window, while risk governance updates every five minutes.

We evaluate Bitcoin (BTC) and Ether (ETH) from Au-

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gust 2024 through January 2025 against passive, rule-based, machine-learning, and single-agent references using cost-adjusted performance and trace-level evidence.

The main contributions of this paper are summarized as follows:

- **Risk-conditioned strategy generation:** the current System Risk Context constrains the feasible strategy before the Portfolio Architect finalizes a proposal.
- **Dual-timescale risk governance:** daily structural reasoning is coordinated with five-minute detection, persistent state transitions, staged recovery, and execution constraints.
- **Auditable risk-to-execution linkage:** structured records connect risk evidence and state transitions to strategy constraints and executed positions.

Related Work

Cryptocurrency forecasting and reinforcement learning estimate returns or map signals to positions (Zhang, Cai, and Wen 2024; John, Binnewies, and Stantic 2024; Jiang and Liang 2017; Liu et al. 2023b; Jing and Kang 2024), while technical, news, and momentum evidence remains regime sensitive (Hudson and Urquhart 2021; Anamika and Subramaniam 2022; Asness, Moskowitz, and Pedersen 2013; Cakici et al. 2024). Volatility-managed and regime-switching methods instead treat exposure and persistent market state as control objects (Moreira and Muir 2017; Harvey et al. 2018; Hamilton 1989). SwingGuard builds on this distinction between a directional thesis and executable exposure.

Financial LLMs combine domain resources (Li et al. 2023; Liu et al. 2023a; Xie et al. 2023) with trading-oriented reflection and specialized reasoning (Koa et al. 2024; Li et al. 2024; Wang et al. 2024; Ding et al. 2024). Multi-agent frameworks add structured roles (Wu et al. 2023b; Hong et al. 2024), debate (Du et al. 2023; Liang et al. 2024), and scalable collaboration (Qian et al. 2025). Beyond role specialization, recent work on general LLM reasoning increasingly introduces explicit structure and control into long-horizon inference. Structure-aware planning organizes intermediate reasoning around structured state transitions and verification (Xiong et al. 2025), multi-level reasoning decomposes long trajectories into high-level planning and low-level execution (Xiong, Payani, and Fekri 2026), and adaptive information control regulates the extent and granularity of evidence acquisition in search-augmented reasoning (Xiong et al. 2026). These approaches motivate structured reasoning and controlled information flow, but address general reasoning or retrieval rather than financial risk governance. Financial systems apply role-based and deliberative mechanisms to research and trading (Yu et al. 2024; Xiao et al. 2024), while recent cryptocurrency applications employ multi-agent reasoning in portfolio allocation and adversarial trading environments (Luo et al. 2025, 2026). SwingGuard instead addresses the asynchronous case: faster risk updates condition strategy generation and govern the active swing position. Beyond post-hoc attribution and the broader interpretable-ML literature (Lundberg and Lee 2017; Rudin 2019; Yeo et al.

2023), it links evidence, risk states, constraints, and realized positions through an auditable strategy–risk interface.

Methodology

We first formulate the asynchronous decision problem, then describe the strategy and risk chains and their mapping to executed exposure.

Problem Formulation

Let d index a completed daily strategy-generation window and τ a subsequent five-minute governance instant. The strategy input $X_d = (M_d, N_d, F_d)$ contains technical market, news and event sentiment, and on-chain and macroeconomic evidence observable by the close of d . Let $Z_{d,\tau}$ be the latest completed five-minute observation. From it, the controller assigns $S_{d,\tau}$ to NORMAL, ALERT, SURVIVAL, or RECOVERY and exposes the *System Risk Context*

$$R_{d,\tau} = (S_{d,\tau}, q_{d,\tau}, \bar{w}_{d,\tau}, \xi_{d,\tau}, \ell_d), \quad (1)$$

where q is the composite risk score, $\bar{w}$ the position cap, ξ supporting short-horizon evidence, and ℓ the long-horizon market regime.

Let D_d denote analysis and deliberation, and U_d the carried position and strategy feedback. The Portfolio Architect produces a raw long-only target $\hat{w}_d$ and executable parameters Θ_d :

$$\begin{aligned} (\hat{w}_d^{\text{full}}, \Theta_d^{\text{full}}) &= \pi(D_d, R_{d,0}, U_d), \\ (\hat{w}_d^{\text{post}}, \Theta_d^{\text{post}}) &= \pi(D_d, U_d). \end{aligned} \quad (2)$$

Let $p(d, \tau)$ denote the preceding execution instant and $w_{p(d,\tau)}^{\text{exec}}$ its realized position. Both variants then use the same deterministic audit-and-arbitration mapping:

$$w_{d,\tau} = g(\hat{w}_d, \Theta_d, R_{d,\tau}, w_{p(d,\tau)}^{\text{exec}}), \quad 0 \leq w_{d,\tau} \leq \bar{w}_{d,\tau}. \quad (3)$$

Here g abbreviates the two-stage deterministic application of audit h followed by arbitration a , detailed below. Thus the ablation changes when risk enters reasoning, not the downstream safety mechanism. Targets formed from completed observations apply only to the next return interval.

The distinction can be stated as a difference in feasible strategy spaces. Let Θ_d collect entry, exit, stop, validity-horizon, and sizing parameters, let $\Gamma_d = (\hat{w}_d, \Theta_d)$ denote the complete proposal, and let $\mathcal{F}(R_{d,0})$ denote the set admitted by the current risk state. Risk-conditioned generation and post-hoc control can be represented as

$$\begin{aligned} \Gamma_d^{\text{full}} &= \pi(D_d, U_d; \mathcal{F}(R_{d,0})), \\ \Gamma_d^{\text{post}} &= \mathcal{P}_{\mathcal{F}(R_{d,0})}[\pi(D_d, U_d; \mathcal{F}_0)], \end{aligned} \quad (4)$$

where $\mathcal{F}_0$ is the risk-agnostic strategy space under the fixed long-only rules and $\mathcal{P}$ is the downstream audit projection. These operators are not generally equivalent: projection can enforce safety bounds, but cannot reconstruct the rationale and coupled parameters that would have been formed inside the risk-conditioned feasible set.

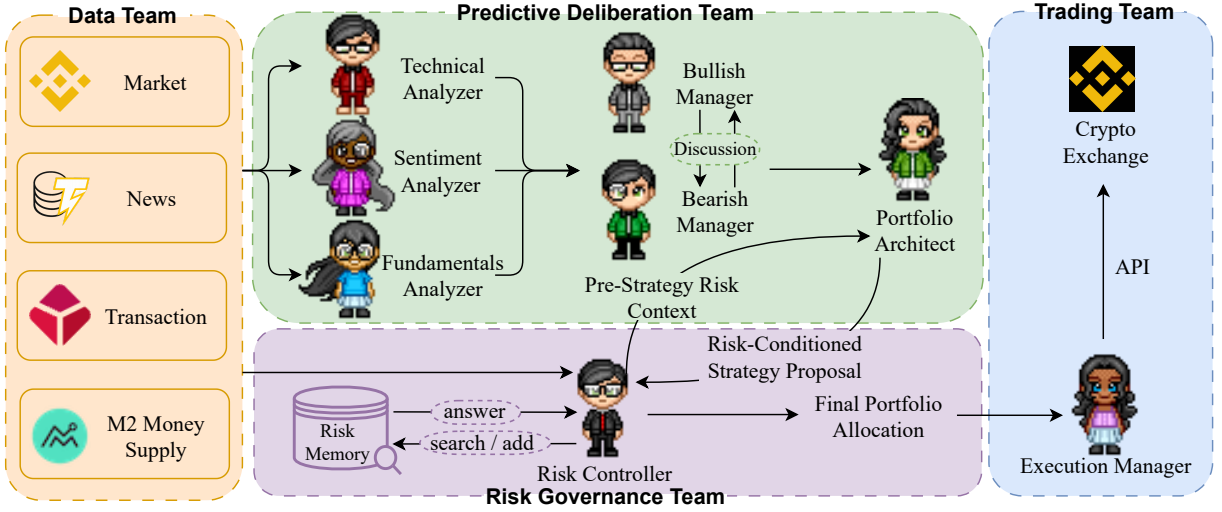


Figure 1: Overall SwingGuard architecture. The Data Team provides market, news, and on-chain transaction evidence to the analytical agents and adds the latest observable U.S. M2 broad-money context before deliberation. The Risk Controller supplies pre-generation risk context to the Portfolio Architect, audits the proposed target position, and continues five-minute governance before the validated target reaches the Execution Manager.

Dual-Timescale SwingGuard Framework

Figure 1 shows two coupled loops. The deterministic Data Team aligns point-in-time sources for the daily analytical loop, which combines multimodal evidence and bullish–bearish debate into $\hat{w}_d$. The five-minute loop supplies $R_{d,0}$ before generation, audits the proposal, and updates the executable cap until the next daily cycle without rerunning the strategy LLMs. The deterministic Execution Manager converts approved position changes into exchange actions. This manager–specialist organization follows established role-based agent coordination, while the explicit controller boundary restricts open-ended conversation with a deterministic execution interface (Wu et al. 2023b; Hong et al. 2024; Qian et al. 2025).

Daily Multi-Agent Strategy Generation

The Technical Analyzer, Sentiment Analyzer, and Fundamentals Analyzer transform X_d into technical-market, news-event-sentiment, and on-chain-macroeconomic reports,

$$A_d = (\phi_M(M_d), \phi_N(N_d), \phi_F(F_d)). \quad (5)$$

The Bullish and Bearish Managers receive the same reports and construct opposing long-only interpretations: the former argues for exposure, while the latter argues for reduction or cash rather than short selling. This deliberation exposes competing reasoning paths before synthesis (Du et al. 2023; Liang et al. 2024). Their trace is

$$B_d = \beta(A_d, U_d), \quad D_d = (A_d, B_d). \quad (6)$$

The Portfolio Architect internally uses a Research Manager to synthesize D_d and a Trader to convert that plan into a target and executable parameters Θ_d (entry, stop, take-profit, validity, and size). Full SwingGuard supplies $R_{d,0}$ to both internal stages, so the risk state can alter the direction, feasible

size, and parameters considered before finalization. Post-hoc Risk omits this input while holding reports, debate, strategy memory, and downstream control fixed.

Five-Minute Hierarchical Risk Diagnosis

As summarized in Figure 2, for every completed five-minute bar, Stage 1 screens market, on-chain, and news anomalies with deterministic rules. Stage 2 evaluates multi-source accumulation, recent density, and source diversity over a six-hour buffer. Only an accumulated trigger $\gamma_{d,\tau}$ or designated severe event $b_{d,\tau}$ invokes Stage 3:

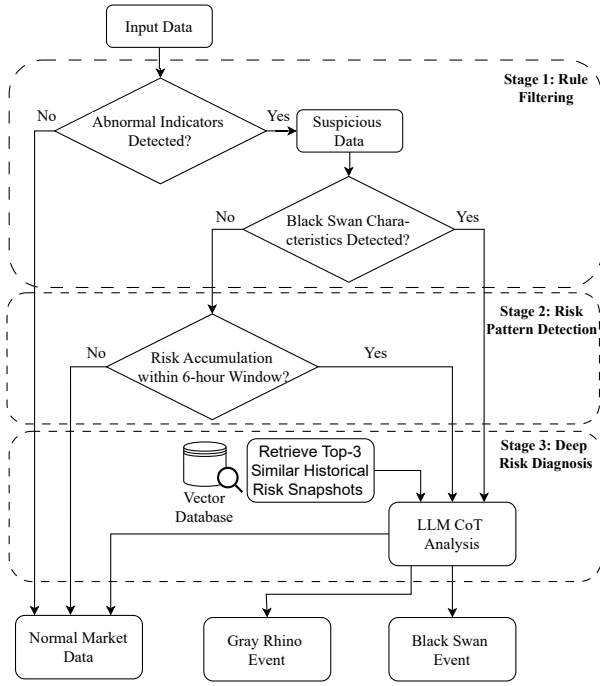
$$\mathcal{D}_{d,\tau} = \begin{cases} \mathcal{L}(Z_{d,\tau}, \mathcal{C}_{d,\tau}, \mathcal{K}_{d,\tau}), & \gamma_{d,\tau} \vee b_{d,\tau}, \\ \emptyset, & \text{otherwise,} \end{cases} \quad (7)$$

where $\mathcal{C}_{d,\tau}$ is recent context and $\mathcal{K}_{d,\tau}$ historical context. The LLM classifies the current condition as normal, gray-rhino risk, or black-swan risk, with confidence and supporting evidence; a deterministic fallback handles invalid outputs. Conditional invocation concentrates LLM reasoning on persistent or severe events.

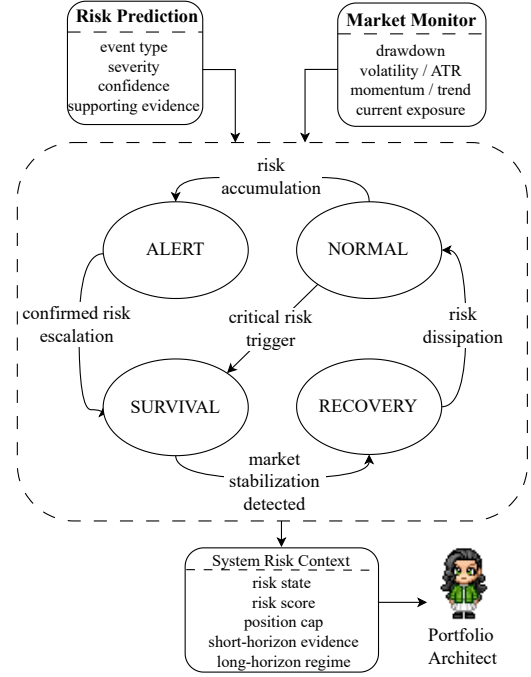
For historical context, each archived snapshot e_i stores symbol s_i , metadata time t_i^{meta} , diagnostic fields, and a vector v_i . A fixed, normalized 14-dimensional vector summarizes market, transaction, and news conditions. For traded symbol s_d , the current vector $v_{d,\tau}$ retrieves only earlier same-symbol snapshots:

$$\mathcal{K}_{d,\tau} = \left\{ e_i : i \in \underset{i: s_i = s_d, t_i^{\text{meta}} < t_{d,\tau}}{\text{Top3}} \cos(v_{d,\tau}, v_i) \right\}. \quad (8)$$

Here, Top3 returns the indices of the three highest cosine similarities. The retrieved snapshots provide precursors, causes, drawdown, and recovery profiles for diagnosis. This design draws on retrieval augmentation and episodic-memory mechanisms (Lewis et al. 2020; Shinn et al. 2023),



(a) Three-Stage Risk Detection and Diagnosis.



(b) Persistent Risk-State Transition and Strategy Conditioning.

Figure 2: Hierarchical risk diagnosis and control framework. Panel (a) uses rule screening and six-hour persistence to trigger retrieval-augmented diagnosis. Panel (b) combines confirmed evidence and market conditions into persistent state transitions, producing the System Risk Context for strategy generation. “LLM CoT” records Stage 3’s bounded diagnostic rationale.

while keeping the historical archive distinct from the online persistence state: the former supplies similar-event evidence for diagnosis, whereas the latter tracks whether current risk is accumulating, dissipating, or recovering.

Persistent Risk State and Recovery

The *Risk Prediction* interface normalizes event type, severity, confidence, and supporting evidence, while the *Market Monitor* supplies drawdown, volatility/average true range (ATR), momentum/trend, and current exposure. Their fusion produces $q_{d,\tau}$. Given predecessor $p(d, \tau)$, the state evolves with active events $\mathcal{E}$, hold counters $\mathbf{u}$, and recovery evidence ρ :

$$S_{d,\tau} = T(S_{p(d,\tau)}, q_{d,\tau}, \mathcal{E}_{d,\tau}, \mathbf{u}_{d,\tau}, \rho_{d,\tau}). \quad (9)$$

Hysteresis and minimum holds prevent a quiet bar from immediately erasing risk. Recovery requires jointly satisfied hold, price, volatility, quiet, and market-repair predicates:

$$\rho_{d,\tau} = \mathbb{I}[c^{\text{hold}} \wedge c^{\text{price}} \wedge c^{\text{vol}} \wedge c^{\text{quiet}} \wedge c^{\text{repair}}]. \quad (10)$$

NORMAL permits the standard cap; ALERT compresses exposure; SURVIVAL forces zero; and RECOVERY restores exposure in stages. Renewed risk can re-escalate any recovery. The resulting control is

$$(\tilde{w}_{d,\tau}, a_{d,\tau}^{\text{risk}}) = \psi(S_{d,\tau}, s_{d,\tau}^{\text{rec}}, \mathcal{E}_{d,\tau}, E_{d,\tau}^{\text{int}}). \quad (11)$$

Here s^{rec} is the staged-recovery level, E^{int} is the active set of intervention constraints, and a^{risk} is the resulting controller

action. At $\tau = 0$, the controller first consumes the latest completed bar, updates the state, and serializes Eq. (1) before building either strategy prompt. This ordering implements pre-strategy conditioning without seeing the subsequent return.

Risk-Conditioned Strategy Generation, Audit, and Execution

After proposal generation, a hard-boundary auditor h validates long-only direction, size, stop, validity horizon, and controller limits; an arbiter a applies the current state action:

$$(\tilde{w}_{d,\tau}, V_{d,\tau}) = h(\tilde{w}_d, \Theta_d, R_{d,\tau}), \quad (12)$$

$$w_{d,\tau} = a(\tilde{w}_{d,\tau}, R_{d,\tau}, w_{p(d,\tau)}^{\text{exec}}). \quad (13)$$

The audit verdict $V_{d,\tau}$ records any validation or clipping decision. Until the next five-minute open, the preceding executed position remains active; at that open, $w_{d,\tau}^{\text{exec}} = w_{d,\tau}$ and $a_{d,\tau}^{\text{exec}}$ records the corresponding position change. Both Full and Post-hoc Risk retain this audit; only Eq. (2) differs. Between daily updates, $R_{d,\tau}$ may reduce, liquidate, or stage re-entry without regenerating the strategy. The Execution Manager maps the change from the preceding executed position to OPEN, ADD, HOLD, REDUCE, or CLOSE and records

$$\mathcal{Q}_{d,\tau} = (R_{d,\tau}, \Theta_d, \tilde{w}_d, V_{d,\tau}, \tilde{w}_{d,\tau}, w_{d,\tau}, a_{d,\tau}^{\text{exec}}, w_{d,\tau}^{\text{exec}}). \quad (14)$$

This trace separates the LLM proposal, validated target, state-driven constraint, and realized position, linking risk evidence

to execution.

Experimental Setup

We evaluate cost-adjusted value, cross-asset consistency, and risk-to-execution auditability. External baselines measure comparative performance; controlled variants test architectural effects.

Data and protocol. We evaluate long-only BTC and ETH from August 1, 2024 through January 31, 2025. Each asset provides 52,992 five-minute observations; earlier data support indicator warm-up and Random Forest training. Decisions use only completed bars, preceding-seven-day news, observable on-chain records, and the latest released U.S. M2 broad-money observation (series code WM2NS); ex-post regimes serve analysis only. Single-asset tests start with unit wealth and zero exposure. The joint portfolio synchronizes executed BTC and ETH positions without another LLM decision. For $w_t^B, w_t^E \in [0, 1]$,

$$(\omega_t^B, \omega_t^E) = \begin{cases} (w_t^B, w_t^E), & w_t^B + w_t^E \leq 1, \\ \frac{(w_t^B, w_t^E)}{w_t^B + w_t^E}, & w_t^B + w_t^E > 1. \end{cases} \quad (15)$$

Gross joint return is $\omega_t^B r_{t+1}^B + \omega_t^E r_{t+1}^E$; costs are charged on both weight changes after scaling.

Models and baselines. The controlled SwingGuard variants share the GPT-4o backbone, zero-temperature decoding, a 2,048-token response limit, identical prompts for retained components, and all other non-ablated settings; variants retaining the debate module use one round. Baselines include buy-and-hold and a 20-day moving average (MA); a 4-hour Donchian-ATR rule motivated by prior cryptocurrency technical-trading evidence (Hudson and Urquhart 2021) and the average true range (ATR) (Wilder 1978); a 4-hour ATR trend-exposure rule using momentum signals (Assess, Moskowitz, and Pedersen 2013); a pre-evaluation 4-hour Random Forest strategy (Breiman 2001; Gu, Kelly, and Xiu 2020); a daily volatility-managed rule that scales exposure toward 35% annualized volatility estimated over 20 days (Moreira and Muir 2017; Harvey et al. 2018); an observable regime-switching rule combining a 120-day trend with 20-day volatility relative to its trailing 120-day median (Hamilton 1989); and a Daily Single-Agent LLM. The latter uses the same model, decoding settings, token limit, point-in-time modalities, and daily cadence, but a single tool-free prompt that directly outputs a long-only target exposure in $[0, 1]$, held until the next revision.

Controlled comparisons. Table 1 supports two adjacent risk comparisons and two supporting component removals. Full versus Post-hoc Risk changes only whether $R_{d,0}$ enters strategy generation while retaining the same subsequent audit and controller. Post-hoc Risk versus No Risk Controller then changes only the downstream audit and five-minute governance while keeping pre-generation conditioning absent; the strategy-native stop remains active. The final two variants remove the three analyst reports as one group or remove bullish-bearish deliberation. Point-in-time source windows

and unaffected upstream outputs are held fixed, while affected downstream decisions are regenerated.

Mode	Pre	Post	Analysts	Debate
Full SwingGuard	Yes	Yes	Yes	Yes
Post-hoc Risk	No	Yes	Yes	Yes
No Risk Controller	No	No	Yes	Yes
No Analyst Team	Yes	Yes	No	Yes
No Bull/Bear Debate	Yes	Yes	Yes	No

Table 1: Controlled SwingGuard configurations. Pre and Post denote risk conditioning before strategy generation and risk governance afterward.

Execution and metrics. Signals execute at the next five-minute open. Every method uses the same prices, long-only constraint, 10-basis-point commission, and 5-basis-point slippage, for a 15-basis-point one-way cost; turnover is charged whenever executed exposure changes. Primary comparisons use cumulative net return, annualized Sharpe (Sharpe 1994), and maximum drawdown. We additionally compute annualized volatility, Sortino (Sortino and Price 1994), Calmar, turnover, and average exposure from the five-minute marked-to-market series, using a 365-day cryptocurrency calendar and zero risk-free rate. Monthly net returns measure temporal concentration, while single-asset and exposure-capped portfolio results measure cross-asset consistency.

Look-ahead bias control. All decision inputs obey a point-in-time availability boundary. For a decision timestamp t , technical features use only bars closed by t ; the news window ends at t ; on-chain observations must already be observable; and WM2NS contributes only the latest observation whose release date has occurred by t . The Random Forest is trained exclusively on data before August 1, 2024 and is frozen throughout evaluation. SwingGuard and every baseline form signals from the same historical boundary, and any resulting position change is executed no earlier than the next five-minute open. Finally, ex-post regime labels and future local troughs are used only for retrospective analysis and figure annotation; neither enters agent prompts, baseline features, portfolio construction, nor ablation regeneration.

Experimental Results

Cross-Asset Economic Performance

Table 2 compares cost-adjusted BTC and ETH performance. SwingGuard is the only reported method that produces double-digit positive returns on both assets while maintaining Sharpe ratios above 2 and maximum drawdown (MDD) below 6%. It also has the highest Sharpe and smallest drawdown point estimates, together with the lowest reported annualized volatility, in both single-asset comparisons.

Volatility management preserves much of the BTC opportunity (42.13% return and 1.93 Sharpe) but transfers weakly to ETH. Observable regime switching improves ETH return to 9.23% and Sharpe to 0.68, yet retains 22.48% drawdown.

Method	BTC				ETH			
	Sharpe $\uparrow$	Return (%) $\uparrow$	MDD (%) $\uparrow$	Vol. (%) $\downarrow$	Sharpe $\uparrow$	Return (%) $\uparrow$	MDD (%) $\uparrow$	Vol. (%) $\downarrow$
Buy-and-hold	1.94	58.25	-24.70	54.45	0.40	1.96	-33.06	68.97
MA (20d)	1.91	41.69	-15.32	40.52	-0.52	-14.53	-31.10	42.34
Donchian-ATR 4h	1.95	36.94	-12.22	35.22	0.28	1.78	-23.64	38.58
ATR trend exposure 4h	1.34	17.29	-10.91	26.25	0.07	-0.67	-16.74	25.06
Random Forest 4h	0.50	6.00	-21.98	36.75	-0.54	-12.94	-28.76	37.91
Volatility managed	1.93	42.13	-19.70	40.23	0.22	0.60	-22.31	38.19
Observable regime switching	1.52	27.54	-18.50	36.00	0.68	9.23	-22.48	34.75
Daily Single-Agent LLM	0.56	7.02	-12.41	36.79	0.23	1.17	-16.45	35.64
Full SwingGuard	2.70	19.91	-3.74	13.67	2.36	15.35	-5.78	12.32

Table 2: Cost-adjusted performance from August 2024 to January 2025. MDD is reported as a negative return; Vol. denotes annualized volatility. Arrows show the preferred direction. Blue, orange, green, and gray-blue identify the top three results per column for Sharpe, return, MDD, and volatility, respectively; the best result is boldfaced.

SwingGuard remains profitable on both assets, exceeds passive ETH return by 13.39 percentage points, and reduces ETH drawdown by 82.5%. Its higher Sharpe and lower drawdown on both assets are not reproduced by either simple exposure scaling or an observable trend-volatility filter. Its BTC and ETH annualized volatilities, 13.67% and 12.32%, are approximately half the next-lowest reported values of 26.25% and 25.06%, respectively.

The Daily Single-Agent LLM aligns the daily cadence and continuous long-only position space, providing a direct single-agent reference. It is profitable on both assets but transfers weakly to ETH, whereas SwingGuard preserves double-digit ETH return and improves BTC Sharpe and drawdown. The remaining system-level distinction is SwingGuard’s specialized roles, deliberation, and five-minute risk governance.

Capital Efficiency and Temporal Concentration

SwingGuard attains this risk-adjusted performance with limited capital deployment: average exposure is 19.42% for BTC, 12.56% for ETH, and 31.74% after the joint cap. The synchronized, cost-adjusted portfolio returns 37.16% with 2.98 Sharpe and 6.44% drawdown, versus 30.11%, 1.19, and 28.47% for equal-weight buy-and-hold. Because the joint result uses capped positions rather than summed returns, its comparison with buy-and-hold reflects active timing, cash allocation, proportional exposure scaling, and associated trading costs under a shared capital budget. BTC, ETH, and joint turnover are 14.54, 11.50, and 25.80. Repricing the same executed positions at 5, 30, and 50 basis points one-way cost leaves joint returns of 40.75%, 31.95%, and 25.31% and Sharpe ratios of 3.21, 2.62, and 2.15, respectively.

With 31.74% average exposure, the capped portfolio exceeds equal-weight buy-and-hold return by 7.05 percentage points, raises Sharpe from 1.19 to 2.98, and reduces drawdown magnitude by 77.4%, linking selective deployment to capital efficiency and downside control.

Downside-sensitive metrics reinforce the shallow-drawdown result. BTC and ETH obtain Sortino ratios of 3.89 and 3.36 and Calmar ratios of 11.60 and 5.66; the capped portfolio reaches 4.26 and 13.54, respectively. Sortino ratios above the corresponding Sharpe ratios indicate that downside variation is smaller than total return variation. Separately, low

average exposure shows that this risk-adjusted performance is achieved through selective capital deployment rather than continuous market participation.

BTC, ETH, and the portfolio are profitable in five of six months. November provides the largest common opportunity, while divergent December and January exposures offset losses across assets. Returns are therefore concentrated but not confined to a single month: the largest single-asset monthly loss is 0.94%, and the portfolio’s sole monthly loss is 0.02%. SwingGuard captures the principal opportunity while preserving gains as the assets later weaken or diverge.

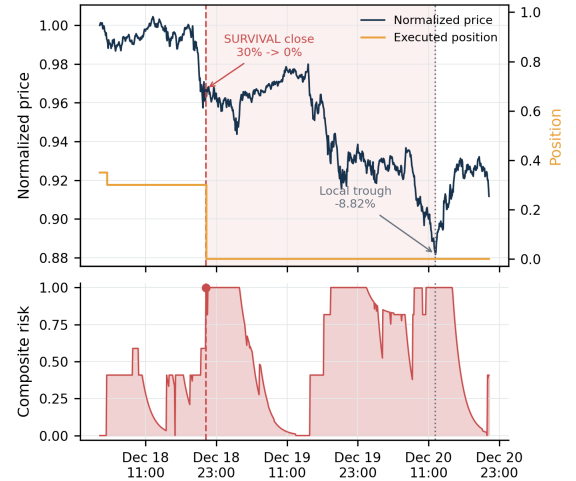


Figure 3: BTC risk-to-execution trace around the December 18 SURVIVAL intervention. The controller closed a 30% position before an 8.82% decline to the subsequent local trough.

Risk-to-Execution Auditability

Figure 3 traces a representative intervention while the system held an active BTC position. At 21:15 on December 18, the controller entered the SURVIVAL response and closed the 30% exposure. BTC subsequently declined 8.82% to the local trough on December 20 while executed exposure remained zero. The trace links detected risk, state transition, controller

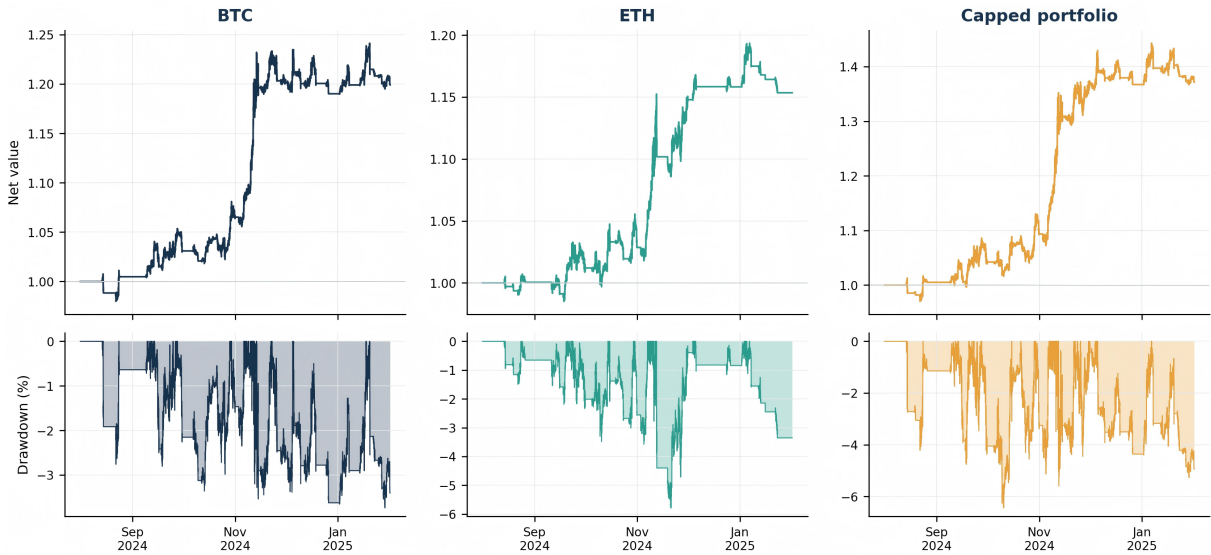


Figure 4: Cost-adjusted five-minute net value and drawdown paths for SwingGuard on BTC, ETH, and the exposure-capped joint portfolio.

action, and realized position over the subsequent decline.

Figure 4 shows shallow drawdowns throughout the five-minute paths. The BTC and ETH equity curves rise most during the shared November opportunity and then consolidate without surrendering the accumulated gain. The December trace complements this aggregate pattern: nonzero exposure precedes escalation, the state changes before the trough, and exposure remains zero during the decline. Together they connect state transitions to trading actions; the controlled comparison below then tests the incremental effect of pre-generation conditioning.

Controlled Ablation Results

Table 3 reports the configurations in Table 1 on the exposure-capped BTC–ETH portfolio. Full versus Post-hoc Risk tests when risk enters strategy generation; Post-hoc Risk versus No Risk Controller tests downstream governance; the final two variants measure the Analyst Team and debate components.

Mode	Sharpe $\uparrow$	Return (%) $\uparrow$	MDD (%) $\uparrow$
Full SwingGuard	2.98	37.16	-6.44
Post-hoc Risk	2.79	35.03	-8.62
No Risk Controller	1.87	23.02	-14.19
No Analyst Team	2.88	35.96	-6.71
No Bull/Bear Debate	2.82	34.90	-7.03

Table 3: Controlled ablation results for the exposure-capped BTC–ETH portfolio. Blue, orange, and green identify the top three results for Sharpe, return, and MDD, respectively; the best result is boldfaced. MDD is reported as a negative return, so higher is better.

Full SwingGuard ranks first on all three metrics. Against Post-hoc Risk, it increases Sharpe from 2.79 to 2.98 and return from 35.03% to 37.16%, while improving MDD from

-8.62% to -6.44%. Because these configurations share evidence, strategy machinery, audit, and controller, the observed difference is associated with placing risk before strategy finalization. Sharpe and return improve by 6.8% and 6.1%, while drawdown magnitude falls by 25.3%, indicating that conditioning has its strongest relative effect on downside quality.

With pre-generation conditioning absent, removing downstream governance produces the largest adjacent deterioration: Sharpe falls from 2.79 to 1.87, return from 35.03% to 23.02%, and MDD deteriorates from -8.62% to -14.19%. Removing the Analyst Team or debate yields smaller but directionally consistent losses: Sharpe declines to 2.88 and 2.82, respectively, with lower returns and higher drawdowns. This ordering associates the largest increment with five-minute governance, a further improvement to upstream conditioning, and complementary gains to specialization and deliberation. Together, these comparisons separate two sources of stability: downstream governance limits realized exposure between revisions, while pre-generation conditioning changes the proposal entering that layer. Their combined advantage reflects coordinated intervention timing and proposal formation.

Conclusion and Future Work

SwingGuard formulates cryptocurrency swing trading as dual-timescale control: daily multi-agent reasoning forms a risk-conditioned target, while the five-minute Risk Controller maintains the System Risk Context, constrains exposure, and records the path from evidence to execution. This coordination lets risk shape proposal formation and maintain exposure compatibility between daily revisions.

Across BTC and ETH, SwingGuard remains profitable with the highest Sharpe and lowest drawdown point estimates among reported methods. The capped portfolio also earns a

higher return than equal-weight buy-and-hold at lower exposure. Monthly results support cross-asset consistency, while the event trace establishes auditable state-to-position linkage.

Ablations support both risk pathways, with the largest deterioration after removing downstream governance. Supporting ablations distinguish this primary risk-governance contribution from the complementary effects of specialized analysis and deliberation.

Future work will test broader regimes and recovery efficiency.

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