

KangarooDeFi: A Hardened Oracle-Free AMM for Tradable Collective Sentiment

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Abstract—This paper presents KangarooDeFi, an oracle-free automated market maker for tokenized collective sentiment. The core novelty is a non-settlement sentiment-market architecture in which answer tokens represent tradable expressions of crowd mood rather than claims on externally resolved outcomes. The protocol combines three mechanisms: (i) equal-weight virtual KUSD liquidity for symmetric market initialization, (ii) USDT-backed KUSD for user-funded entry and exit, and (iii) a controlled sell path that bounds payouts by pair-local user-buy liquidity while allowing partial exits under stress. We formalize the AMM pricing rule, dual-liquidity accounting, solvency invariant, price-impact bounds, and manipulation surfaces. We then introduce hardened contract-level controls, including protected KUSD pairs, direct-pair transfer restrictions, per-trade impact limits, trade-size caps, and optional cooldowns. Simulation experiments using lognormal order-size distributions and whale-stress scenarios show how virtual-liquidity depth and risk parameters affect sentiment displacement, trade acceptance, and manipulation resistance. The system is not a probability market: its displayed prices measure demand-weighted sentiment pressure, not calibrated event likelihood. The result is a DeFi-native market primitive for observing, trading, and archiving collective confidence without oracle settlement or winner/loser redistribution.

Keywords—automated market maker, sentiment markets, virtual liquidity, KUSD, DeFi, mechanism design, manipulation resistance, smart contracts.

I. INTRODUCTION

Markets often reveal information faster than surveys because participants express belief through costly action. However, many market mechanisms are designed around external resolution: an event occurs, an oracle declares a final state, and settlement transfers value according to correctness. KangarooDeFi instead treats sentiment itself as the object of trade. A market asks how the crowd feels about a topic during a bounded interval, creates one token per answer, and lets prices evolve through AMM reserve movement.

The design deliberately avoids oracle settlement, winner pools, loser pools, and outcome-based redistribution. A market can later be compared with real-world events, but that comparison is an analytics layer rather than a payout trigger. This distinction is central: the protocol measures collective confidence, not truth.

The main contribution is not merely an AMM interface for answer tokens. The contribution is a hardened dual-liquidity architecture for oracle-free sentiment exchange. Virtual KUSD provides equal initial depth and neutral starting weights, while USDT-backed KUSD enters through real user deposits and defines the maximum withdrawable value. Controlled routing prevents virtual liquidity from becoming freely drainable.

II. CORE NOVELTY AND SCOPE

The core novelty can be stated precisely as follows: KangarooDeFi is an oracle-free sentiment AMM that separates price formation from settlement claims. It introduces a dual virtual/backed KUSD accounting layer and a non-settlement market lifecycle in which final market history is archived without declaring an answer correct.

Three claims are intentionally separated. First, the system provides equal initial market weights through virtual liquidity. Second, it preserves solvency by bounding sell payouts by backed liquidity. Third, it makes manipulation measurable and governable through explicit risk parameters. These claims do not imply that sentiment is truth, probability, or an unbiased forecast.

III. SYSTEM MODEL

A. Market and Answer Tokens

A sentiment market m is defined by a topic, question, answer set $A = \{1, \dots, n\}$, creator address, start time t_0 , and end time t_T . The production contract accepts $2 \leq n \leq 5$ answers. For each answer i , the router deploys a Kangaroo sentiment token T_i and creates a V2-style pair (T_i, KUSD) .

$m = (\text{creator}, \text{topic}, \text{question}, A, t_0, t_T)$, $A = \{1, \dots, n\}$. The market lifecycle has five states: Pending, TradingOpen, ReadyToClose, Closed, and Cancelled. Trading is allowed only between t_0 and t_T . After t_T , anyone may call `closeMarket`. Closing does not resolve an outcome; it records final reserves and marks the market historical.

B. KUSD Wrapper and Dual Liquidity

KUSD has two economic meanings. Backed KUSD is minted when a user deposits USDT into KangarooUSD. Virtual KUSD is minted only by authorized protocol components to initialize AMM depth. Both appear as KUSD at the token layer, but protocol accounting separates their economic roles.

KUSD_backed: USDT deposit $\rightarrow$ KUSD mint to user

KUSD_virtual: protocol seed $\rightarrow$ AMM reserve only

If the owner sets a maximum per-market virtual-liquidity cap C , the creator chooses a market-level virtual liquidity L at creation time with $0 < L \leq C$. For a market with n answers, each answer pool receives $\text{floor}(L/n)$ virtual KUSD and an equal human-unit amount of answer tokens. KUSD uses 6 decimals and answer tokens use 18 decimals, so the router converts the per-answer KUSD seed into answer-token units by multiplying the raw KUSD amount by 10^{12} . Therefore all answers start with equal reserve structure and equal initial sentiment weight, while governance still bounds the maximum virtual liquidity that any creator can request.

$$x_i(0) = \text{floor}\left(\frac{L}{n}\right), \quad y_i(0) = \text{floor}\left(\frac{L}{n}\right), \quad i = 1, \dots, n.$$

C. Market Closure and Pro-Rata Redemption

At the end of the trading interval, a market does not resolve to a correct answer. Instead, each answer pool is closed independently and its remaining real KUSD backing becomes redeemable only by holders of that same answer token. There is no cross-answer redistribution, no winner pool, and no transfer of backing from one answer to another.

Let V_i denote the virtual KUSD seed assigned to answer pool i . Let X_i^T denote the KUSD balance of the KUSD/answer-token pair at close time T . Let B_i denote cumulative real KUSD that entered pool i through user buys, and let O_i denote cumulative gross KUSD paid out from pool i through controlled sells before close. The pair-local backed availability is

$$A_i = \max(B_i - O_i, 0).$$

When the market is closed, virtual KUSD is removed first. The virtual amount burned from pool i is

$$V_i^{burn} = \min(X_i^T, V_i).$$

The candidate real KUSD remaining in the pair is therefore

$$C_i = X_i^T - V_i^{burn}.$$

The final redeemable KUSD for answer pool i is capped by both the remaining pair balance after virtual removal and the protocol's pair-local backed accounting:

$$R_i = \min(C_i, A_i).$$

Only R_i is transferred from the pair into the router for redemption. Any virtual KUSD is burned and is never withdrawable by users. Let S_i denote the redeem supply of answer token i at close, defined as the circulating answer-token supply eligible for redemption after pair-held residual tokens are removed. If user u holds $q_{u,i}$ redeemable answer tokens for pool i , the user's KUSD redemption amount is

$$P_{u,i} = \text{floor}\left(\frac{q_{u,i}}{S_i} R_i\right).$$

The floor reflects integer arithmetic in the smart contract. Small rounding dust may remain, but no user can redeem more than their proportional share, and the sum of all redemptions from answer pool i is bounded by R_i :

$$\sum_u P_{u,i} \leq R_i \leq A_i \leq B_i.$$

This mechanism means that closing a market archives the final sentiment state while distributing only the real, pair-local backed liquidity that remains in each answer pool. Holding answer token i gives a claim only on R_i , never on R_j for $j \neq i$.

IV. AMM PRICING AND SENTIMENT MEASUREMENT

Let x_i be the KUSD reserve and y_i the answer-token reserve of pool i . The constant-product invariant is

$$x_i y_i = k_i.$$

The marginal AMM price of answer token i is $p_i = x_i / y_i$. The displayed sentiment share is normalized across answers:

$$s_i = \frac{p_i}{\sum_j p_j}.$$

The vector s is not a probability distribution over truth. It is a demand-weighted sentiment-pressure vector. A higher s_i

means that, relative to the other answers, the crowd has pushed more KUSD demand into answer i or sold less of it. It does not mean that answer i is objectively more likely to occur.

For a buy of Δx KUSD into pool i , with AMM fee f , the received answer tokens are

$$\Delta y_i = y_i - \frac{x_i y_i}{x_i + \Delta x(1-f)}.$$

The marginal price movement is nonlinear:

$$\frac{p'_i}{p_i} = \left(1 + \frac{\Delta x(1-f)}{x_i}\right)^2.$$

This formula motivates explicit price-impact limits. Larger virtual reserves reduce displacement, but relying only on deeper liquidity is circular; therefore KangarooDeFi also enforces configurable per-trade impact caps.

V. CONTRACT-LEVEL HARDENING

A. Protected Pair Routing

Both the KUSD side and the answer-token side are protected from direct pair injection. KangarooUSD marks AMM pairs as protected and blocks user-to-pair KUSD transfers unless they are routed by the Router. Virtual KUSD minting is also pair-gated: the Router may mint virtual liquidity only to addresses already marked as protected AMM pairs. KangarooSentimentToken similarly blocks direct user transfers into its pair unless routed through Router or KSwap. This prevents pair manipulation that bypasses backed-liquidity accounting and prevents virtual KUSD from being minted directly into ordinary user circulation.

B. Backed Exit Accounting

For each answer pool i , the router tracks pool-level backed inflow B_i from user buys and gross sell outflow O_i . The backed amount available for controlled sells for that pool is

$$A_{i,u} = B_{i,u} + E_{i,u} - O_{i,u}.$$

Crucially, these accounts are per-user and non-transferable. User A cannot consume user B 's backed exit capacity. This ensures that virtual liquidity is not treated as a shared withdrawable pool and that each participant's controlled exit capacity is isolated by the backed KUSD that the same participant contributed to that answer pool. A sell by user u may output at most $A_{i,u}$ gross KUSD. If the AMM quote exceeds $A_{i,u}$ and the user allows partial execution, KSwap computes the largest executable token input for that user and leaves the remainder in the user wallet.

C. No External Vault Liquidity

KangarooDeFi does not use an external backstop vault in the core market lifecycle. Virtual KUSD is used only for initial AMM price discovery. Sell and redeem liquidity comes only from real KUSD that entered the same answer pair through user buys.

D. Whale Controls

The owner may set `maxBuyPriceImpactBps`, `maxSellPriceImpactBps`, `maxBuyKusdBpsOfVirtualSeed`, and `tradeCooldownSeconds`. These controls do not eliminate manipulation; they bound it. Since price impact is computable from reserves, the maximum single-trade displacement becomes a protocol parameter rather than an unbounded externality.

VI. FORMAL SECURITY PROPERTIES

Theorem 1: Per-User Backed-Sell Solvency

For any answer pool i , if KSwap pays a gross sell output only when $\Delta O_i \leq A_i$, then cumulative controlled sell payouts from that pool cannot exceed the backed KUSD that users introduced into that same pair through buys.

$$\sum \Delta O_{i,u} \leq B_{i,u} + E_{i,u}.$$

Proof. Initially $O_i = 0$ and $A_i = B_i$. Each controlled sell requires $\Delta O_i \leq B_i - O_i$, then updates $O_i := O_i + \Delta O_i$. By induction over the sequence of sells executed against the same answer pool, O_i never exceeds B_i . Therefore cumulative controlled sell output from pool i is bounded by real KUSD that entered that same answer pair through user buys. Virtual liquidity remains non-withdrawable. $\square$

Theorem 2: Equal Initial Sentiment Neutrality

If every answer pool receives the same human-unit answer-token seed as its virtual KUSD seed, and the same market-level L/n allocation is used for every answer, then every answer has the same initial marginal price and the same displayed sentiment share.

$$p_i(0) = \frac{L/n}{L/n} = 1, \quad s_i(0) = \frac{1}{n}.$$

Proof. Since all $x_i(0)$ and $y_i(0)$ are equal across i , all $p_i(0)$ are equal. Normalizing n equal positive values gives $1/n$ for each answer. $\square$

Theorem 3: Bounded Single-Trade Price Displacement

If the router enforces $\Delta x/x \leq \rho_{\max}$ for a buy, then the buy-side marginal price multiplier is at most $(1 + \rho_{\max})^2$.

$$\frac{p'_i}{p_i} \leq (1 + \rho_{\max})^2.$$

Proof. From the constant-product price-impact formula $p_i'/p_i = (1 + \Delta x/x_i)^2$. Substituting $\Delta x/x_i \leq \rho_{\max}$ yields the bound. $\square$

Theorem 4: Closed-Market Redemption Isolation

For any closed market and any answer pool i , cumulative redemption payouts from that pool cannot exceed the real KUSD backing remaining for that same answer pool, and holders of answer i cannot redeem backing assigned to answer $j \neq i$.

$$\sum_u P_{u,i} \leq R_i = \min(C_i, A_i), \quad A_i = \max(B_i - O_i, 0).$$

Proof. At close, the router computes R_i independently for each answer pool. The candidate amount C_i excludes virtual KUSD by burning V_i^{burn} first. The amount is then capped by A_i , the pair-local backed availability derived only from real buys into pool i minus gross sells from pool i . During redemption, a user must transfer answer token i to redeem from pool i , and the payout is $P_{\{u,i\}} = \text{floor}(q_{\{u,i\}} R_i / S_i)$. Since the eligible token balances $q_{\{u,i\}}$ sum to at most S_i , cumulative payouts satisfy $\sum_u P_{\{u,i\}} \leq R_i$. No function maps answer token i to pool j , so answer-pool backing remains isolated. $\square$

VII. ECONOMIC ANALYSIS

A. Equilibrium Interpretation

In a sufficiently liquid market with heterogeneous preferences, the sentiment vector may stabilize when marginal buyers and sellers no longer find the current AMM price attractive. This is a behavioral equilibrium, not a rational-expectations probability equilibrium. Participants may trade for expression, hedging, attention, affiliation, entertainment, or information aggregation.

B. Liquidity Dynamics and Exit Constraints

Virtual liquidity improves early price continuity but does not create real redeemable value. Real exit capacity grows only when users buy with backed KUSD in the same answer pair. Therefore a low-activity market can have visible AMM depth but limited exit capacity. The protocol exposes this through backedAvailable and partial-exit events. A UI should show both AMM price and backed exit depth.

C. Manipulation and Reflexivity

A whale can buy an answer to move its sentiment share, attracting attention and potentially further demand. This reflexivity is not a contract failure, but it is an economic attack surface when users mistake sentiment for probability. The hardened design mitigates the attack with per-trade impact limits, trade-size caps, protected pairs, partial exits, and transparent backed-depth reporting. It does not claim manipulation is impossible.

D. Griefing and Liquidity Exhaustion

A griever may attempt to create poor markets, route nuisance volume, or induce users to chase a thin answer pool. Fee bounds, market-duration limits, protected-pair routing, and risk controls reduce these surfaces. Liquidity exhaustion is handled by rejecting or partially filling sells beyond backed availability rather than allowing virtual KUSD to be drained as withdrawable value.

VIII. NUMERICAL EXAMPLE

Assume $L = 9000$ KUSD and $n = 3$. Each pool starts with 3000 virtual KUSD and 3000 answer tokens. Alice deposits 100 USDT, receives 100 KUSD, and buys Bullish. The router routes 100 KUSD into the Bullish pair and records $B_{\text{Bullish}} += 100$. If any user later sells Bullish tokens, KSwap computes the AMM output. The AMM quote may be 120 KUSD, but the Bullish pool's backed availability is only 100 KUSD before fees and prior outflows. The sell can either revert or accept a partial sell up to 100 gross KUSD. No external vault or protocol-owned funds can increase that answer pool's sell capacity.

IX. EMPIRICAL SIMULATION

We evaluate a synthetic AMM model using lognormal order sizes, equal initial answer weights, a 0.30% AMM fee, and three-answer markets. The simulations are not claims about live demand; they test mechanism behavior under defined assumptions. Order sizes are sampled from lognormal distributions to approximate heavy-tailed DeFi participation. We measure price displacement, guard acceptance, and sensitivity to virtual-liquidity depth.

Table I. Whale-order sensitivity under equal initial weights. Guard accepts means impact $\leq 25\%$ and order size $\leq 50\%$ of per-answer virtual seed.

Cap	Order	Imp %	App	Guard
3000	500	125.0	19.6	no
3000	1500	525.0	42.4	no
3000	3000	1500.0	55.5	no
9000	500	36.1	7.2	no
9000	1500	125.0	19.6	no
9000	3000	300.0	33.3	no
27000	500	11.4	2.4	yes
27000	1500	36.1	7.2	no
27000	3000	77.8	13.7	no

Table I shows why relying only on deeper liquidity is insufficient. With a 9000 KUSD market cap, a 1500 KUSD order into one answer produces a 125% single-pool price impact and pushes its displayed sentiment share to approximately 52.9%. The hardened guard rejects this trade. Increasing the cap to 27000 KUSD reduces the same order displacement, but the guard still rejects it once the configured impact threshold is exceeded.

Table II. Acceptance sensitivity for lognormal order-size distributions under a 25% impact cap and 50% seed-size cap.

Seed	Median order	Accept %	P95 imp %
1000	50	78.1	71.2
1000	100	56.0	159.3
1000	250	24.6	535.6
3000	50	96.3	21.3
3000	100	87.7	44.9
3000	250	62.2	128.1
9000	50	99.7	7.0
9000	100	98.4	14.1
9000	250	90.5	36.9

Table II highlights the trade-off between depth and accessibility. A low per-answer seed rejects more heavy-tailed orders, while a larger seed accepts ordinary activity with lower p95 impact. These results support exposing risk parameters in governance and adjusting caps by market category rather than using a single static depth for all topics.

X. RELATED WORK

KangarooDeFi differs from event-resolution prediction markets, market scoring rules, and orderbook event exchanges because it does not settle on correctness. It also differs from sentiment dashboards because sentiment is not merely measured off-chain; it is expressed through tradable answer tokens. The design draws on automated market makers, prediction-market theory, sentiment analysis, market microstructure, and adversarial DeFi research.

XI. PERMISSIONLESS MARKET CREATION AND SUSTAINABLE PARTICIPATION DYNAMICS

A fundamental challenge for non-settlement sentiment markets is long-term participation persistence. In traditional prediction markets, recurring engagement is partly sustained by terminal payout expectations tied to objectively resolved outcomes. In contrast, KangarooDeFi derives participation from continuously evolving collective sentiment dynamics rather than from final correctness redemption. The protocol therefore depends not only on market mechanics, but also on the sustained production of socially relevant sentiment environments.

KangarooDeFi addresses this challenge through permissionless market creation. Rather than relying exclusively on centrally curated topics, any eligible participant may create sentiment markets around narratives, communities, trends, events, technologies, or social debates that they believe will attract collective attention and trading activity. Market

creation itself therefore becomes an economically meaningful discovery process for identifying socially salient narratives.

Under this structure, market creators function not merely as liquidity initiators, but also as attention coordinators and sentiment entrepreneurs. A participant who creates a market implicitly signals a belief that the underlying topic possesses sufficient social relevance, emotional engagement, or speculative interest to sustain trading activity. Successful market creation may therefore produce indirect economic value through fee generation, reputation effects, increased visibility, or early positioning around emerging narratives.

This mechanism introduces an endogenous market-generation process. Instead of requiring the protocol to predict which topics users may care about, the ecosystem allows participants themselves to compete in discovering and surfacing narratives capable of attracting collective conviction. As a result, market supply evolves dynamically alongside changing social attention patterns.

Importantly, this permissionless structure may also mitigate attention-decay effects that commonly affect static event-driven systems. In systems where market creation is centralized or limited to major external events, participation may decline once a finite set of high-profile topics has been exhausted. By contrast, decentralized market creation enables continuous emergence of new sentiment environments, including niche communities, speculative cultural trends, recurring social themes, and rapidly evolving online narratives. The protocol therefore behaves less like a finite prediction platform and more like an adaptive social-information market infrastructure.

The resulting participation dynamics are reflexive. Markets attracting attention may generate liquidity; liquidity may increase visibility; increased visibility may attract additional traders and creators; and this activity may further amplify collective engagement around specific narratives. While reflexivity introduces manipulation and volatility risks discussed previously, it also constitutes a potential source of persistence for the broader ecosystem. In this sense, collective attention itself becomes an economically productive input to market activity.

Crucially, participants in KangarooDeFi may derive utility not only from eventual profit realization, but also from early positioning around emerging social momentum. A trader who correctly anticipates that broader market sentiment will later align with their position may benefit from subsequent repricing of collective conviction, even in the absence of objective settlement. Economic value therefore emerges not solely from truth realization, but also from anticipated future alignment of social attention and market sentiment.

Over time, the protocol may additionally accumulate historical sentiment trajectories across markets and communities. These persistent records can form an evolving archive of economically weighted collective psychology, allowing observers to analyze how narratives emerge, strengthen, fragment, or collapse across time. The informational value of such archives may itself reinforce continued participation and external integration.

Under this framework, KangarooDeFi should not be interpreted purely as a prediction mechanism. Instead, it operates as a continuously evolving infrastructure for the creation, trading, measurement, and archival of collective sentiment under financial participation constraints.

XII. LIMITATIONS

Several limitations remain. First, the simulation is synthetic and must be extended with real order-flow data after deployment. Second, governance over risk parameters introduces administrative trust unless timelocked or decentralized. Third, a market can still be socially manipulated through coordinated attention campaigns. Fourth, sentiment tokens may be misunderstood as probability claims unless the interface clearly separates sentiment from likelihood. Fifth, pair-local pool accounting is not per-user exit isolation; sell capacity is shared within the same answer pool and remains limited to real KUSD introduced into that pool through buys.

XIII. CONCLUSION

KangarooDeFi introduces a hardened oracle-free AMM for tokenized collective sentiment. Its novelty is the combination of non-settlement answer markets, equal virtual-liquidity initialization, user-accessible USDT-backed KUSD, pair-local backed-exit accounting, protected pair routing, partial exits, and explicit whale controls. The protocol does not ask who was right; it records how the market felt, how that feeling traded, and how sentiment evolved over time.

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