International Journal of Holistic Paradigms
Vol. 01 Issue 01
ISSN:

QUANTIFYING RISK IN DEFI ECOSYSTEMS: A SIX-FACTOR COMPOSITE MODEL FOR SOLANA DEX TOKEN MARKETS

Dhirendra Kumar Jena

Department of Master of Business Administration, Balasore College of Engineering & Technology, Balasore, Odisha.
Email: 2nabls@gmail.com

Manuscript Info

Manuscript History
Received: XX
Final Accepted: XX
Published: XX

Keywords:-
decentralised exchange; DeFi risk; Solana blockchain; liquidity risk; volatility; composite risk score; token market microstructure; on-chain analytics; automated market maker

Abstract

High throughput blockchains Decentralised exchange (DEX) ecosystems have become a structurally important part of the global digital asset market, but have not been studied using rigorous and multi-dimensional risk frameworks. The paper is a new composite risk assessment framework used on twenty Solana-based tokens based on live DEX screener data, including a dollar and one hundred and sixty to seven hundred and forty-six thousand dollars in token price and market capitalisation of one hundred and sixty million to six hundred and seventy billion dollars. The six orthogonal risk dimensions are operationalised, viz. volatility risk, liquidity risk, systemic/exchange risk, market/trend risk, sentiment risk, and long-term value risk, all of which have a formal quantitative formula and an established scoring rubric, calibrated to the market microstructure of DEX. Composite Risk Scores (CRS) are calculated as unweighted arithmetic averages of dimension-level scores and categorized under a five level ordinal taxonomy (Low to Extreme). Empirical evidence indicates that tokens that have low levels of market capitalisation and low liquidity pools (particularly FLIQ, BARREL, and COIN) have an extreme-to-very-high composite risk profile, whereas large-capitalisation stablecoin-proximate instruments (SYRUPUSDC, USDG) and Bitcoin-wrapped assets (WBTC) have a significantly lower aggregate risk. The framework incorporates the sell-to-buy flow ratios, liquidity-adjusted capitalisation ratios, and absolute price momentum as a single scoring architecture in real-time DEX data feeds. There are six figures of publication quality to support the empirical analysis: a composite risk bar chart, a six-dimensional heatmap, a radar profile plot, a liquidity-versus-capitalisation bubble chart, a tier distribution panel, and a sentiment flow analysis.

1. Introduction

Since 2020, the development of decentralised finance (DeFi) protocols has radically reorganised the environment of digital asset trading. Decentralised exchanges (DEXs) are peer-to-peer token swaps that are run as algorithms by automated market makers (AMMs) run immutably on public blockchains unlike centralised exchanges (CEXs), which operate on custodial architectures and are directly regulated (Adams et al., 2021). The Solana blockchain which is characterised by its proof-of-history-based consensus mechanism, block finality in less than a second, and transaction throughput exceeding 65,000 transactions per second has sparked the creation of a wide-ranging and fast-changing DEX token ecosystem (Yakovenko, 2018).

This structural dynamism brings in stratified risk exposures that the traditional measures of financial risks, which are set up to measure centralised, order-book based markets, cannot measure adequately. Such aspects of DEX-native market phenomena as impermanent loss, deeper liquidity pool asymmetries, on-chain sentiment cascades, and lack of circuit breakers or trading halts demand analytical frameworks of their own (Lehar and Parlour, 2021; Milionis et al., 2022). This research paper fills this gap by establishing and implementing a six-dimensional Composite Risk Scoring (CRS) model on twenty actively-traded Solana-based DEX tokens. The data is obtained directly through a live DEX screener interface which tracks live metrics such as 24-hour price change, DEX trading volume, liquidity pool depth, on-chain buy/sell pressure and net DEX flow. Six analytical figures of publication quality that are integrated throughout this article present a visual record of the composite risk architecture, dimension level profiles, and relationship between market structure.

This study has a triple contribution. First, it applies the financial risk theory to the context of DEX microstructure by applying the quantitative constructs that have already been established, such as the Amihud illiquidity ratio, price momentum signals, and buy-sell flow imbalance metrics, to the particularities of the AMM-based token markets. Second, it generates a compound risk taxonomy allowing explicit cross-token comparability of a heterogeneous universe of stablecoins, wrapped assets, meme tokens, and protocol governance tokens. Third, it offers practitioner-useful risk intelligence to on-chain portfolio managers, DeFi protocol designers, and institutional allocators.

2. Literature Review

2.1 Decentralised Exchange Market Microstructure

Automated market makers (AMMs) are a radical shift in the conventional order-book model. Adams et al. (2021) characterised the constant-product invariant ($x \cdot y = k$) on which Uniswap is based and showed that the returns of liquidity providers (LP) depend on the pool depth and fee levels instead of the dynamics of bid-ask spreads. Lehar and Parlour (2021) generalised this framework to demonstrate that AMM price discovery is systematically less efficient than centralised counterparts in thin liquidity conditions, which have a direct implication in the liquidity risk dimension developed in the current study. Milionis et al. (2022) further operationalised the loss-versus-rebalancing (LVR) concept, showing that the impermanent loss of LP is directly connected to price volatility, which directly drives the volatility risk aspect operationalised here.

2.2 Volatility and Market Risk in Crypto Assets

Cryptocurrency markets are highly volatile and this has been well documented. It was determined by Baur and Lucey (2010) that Bitcoin is significantly more volatile than conventional financial assets, which is later verified in the altcoin markets by Fry and Cheah (2016). In the DEX framework, this increases intraday volatility due to the lack of market makers with inventory management commitments, and so 24-hour price change serves as a major and directly measurable volatility proxy (Angeris et al., 2020). Cong et al. (2021) established that the Granger causality between blockchain transaction volume and token price volatility is significant, which confirms that DEX volume and flow data can be used as volatility-proximate indicators.

2.3 Liquidity Risk in DeFi

The liquidity risk of DeFi refers to the depth risk (on a pool-by-pool basis) and systemic liquidity contagion between correlated protocols. An empirical study of DeFi liquidity crises by Werner et al. (2022) showed that the fast spread of cascading liquidations of lending protocols to DEX liquidity pools leads to bilateral liquidity compression. Brauneis et al. (2021) have applied the Amihud (2002) illiquidity ratio to cryptocurrency markets, and have shown that it is effective in a token market in the presence of microstructure frictions. This paper generalises the Amihud model to the AMM setting by using the depth of liquidity pools as a structural measure of market depth.

2.4 Sentiment and Behavioural Risk

Cryptocurrency markets Behavioural financial approaches to cryptocurrency markets focus on investor sentiment and herding behaviour. Philippas et al. (2019) measured substantial sentiment effects of Bitcoin returns, whereas Ante (2023) found on-chain buy-sell imbalances of pressure predict short-term reversals in price-directly motivating the sentiment risk aspect. The sell-to-total-flow ratio used in this research is similar to the put-call ratio in conventional derivatives markets, which is a manipulation-resistant proxy of current market sentiment.

2.5 Research Gap

Although the study has investigated individual risk dimensions independently, none of the previous studies has created a multi-dimensional risk framework with operational deployability and calibration on Solana-based DEX tokens, based on live on-chain data. Current composite cryptocurrency risk models (Symitsi and Chalvatzis, 2019; Hu et al., 2021) are concentrated on centralised exchange holdings and do not consider DEX-native measures (liquidity pool depth, on-chain flow, and AMM-specific systemic risk). The given research fills this gap.

3. Data and Descriptive Statistics

The data will consist of twenty tokens that are actively listed on Solana-based decentralised exchanges, based on a live DEX token screener screen. Fields that it has are token ticker symbol, 24-hour price (USD), 24-hour percentage price change, market capitalisation (USD), DEX trading volume (USD, 24-hour), liquidity pool depth (USD), on-chain buy volume, on-chain sell volume, and net DEX flow (USD, 24-hour). The sample is diverse in terms of cross-section: stablecoin-backed (SYRUPUSDC, USDG) and wrapped cross-chain (WBTC), high-cap protocol (JLP, MEI), and low-cap or speculative (BARREL, COIN, FLAG, JELLYJELLY).

Table 1. Raw Market Data: Solana DEX Token Screener Dataset (24-Hour Snapshot)

Token	Price (USD)	Δ24h (%)	MCap ($M)	DEX Vol ($M)	Liq. ($M)	Buys ($M)	Sells ($M)	Flow ($K)
SYRUPUSDC	$1.16	+0.85%	1.85B	$18.75M	$10.88M	$5.87M	$4.88M	$993.23K
HYPE	$43.4	+5.91%	43.38M	$16.93M	$933.83M	$8.95M	$7.98M	$967.08K
JLP	$3.87	-3.7%	1.16B	$7.67M	$8.1M	$4.23M	$3.44M	$794.99K
USDG	$1	-0.01%	1.76B	$12.51M	$14.86M	$6.54M	$5.97M	$575.08K
WBTC	$71,460	-4.13%	6.97B	$4.79M	$3.16M	$2.55M	$2.24M	$385.37K
ONYC	$1.89	+0.02%	137.97M	$483.26M	$1.08M	$335.94M	$67.32M	$268.63K
CRCLX	$133.53	-1.25%	67.05M	$3.94M	$1.27M	$2.09M	$1.84M	$248.07K
COMMODITIES	$0.0856	N/A	86.03M	$1.97M	$369.75M	$0.0011M	$0.87782M	$218.68K
HOODX	$75.87	-1.8%	4.26M	$443.02M	$478.27M	$317.48M	$125.62M	$191.79K
JUP	$0.163	-5.24%	560.89M	$4.06M	$2.5M	$2.12M	$1.94M	$184.73K
COINX	$205.85	-2.74%	7.43M	$500.41M	$0.12358M	$341.65M	$166.76M	$174.69K
ARC	$0.0396	+2.83%	39.77M	$1.76M	$2.17M	$0.9575M	$0.80461M	$152.84K
FLIQ	$0.0218	-79.4%	214.03M	$511.11M	$0.04263M	$314.28M	$196.91M	$117.29K
BARREL	$0.011	N/A	1.18M	$150.1M	$7.47M	$133.31M	$16.88M	$116.51K
COIN	$0.000685	N/A	6.85M	$155.9M	$38.36M	$134.56M	$21.34M	$113.22K
MPLX	$0.0385	+3.97%	20.15M	$225.33M	$1.56M	$165.94M	$59.39M	$106.55K
MEI	$0.0072	N/A	720.85M	$14.78M	$45.61M	$7.39M	$7.3M	$98.84K
FLAG	$0.0116	N/A	1.16M	$772.88M	$199.93M	$425.88M	$347M	$78.67K
ZBCN	$0.0205	+1.73%	200.31M	$579.24M	$411.91M	$327.46M	$251.78M	$75.68K
JELLYJELLY	$0.0534	+1.51%	53.29M	$810.51M	$3.52M	$0M	$367.56M	$75.39K

Note. MCap = Market Capitalisation; Δ24h = 24-hour price change; DEX Vol = decentralised exchange trading volume; Liq. = liquidity pool depth; N/A = not applicable.

4. Methodology: Six-Dimensional Risk Framework

In this section, the six risk dimensions have been operationalised in the CRS framework. All dimensions have formal mathematical definitions, a quantitative calculation done to each token, and a standardised scoring rubric that assigns the calculated values to an ordinal scale of 110. The composite risk score is arithmetic average of all the available dimension scores:

$CRS_i = (1/N) \times \Sigma\ Score_{d,i}$ where $d \in$ {Volatility, Liquidity, Systemic, Market, Sentiment, Value}, N = number of applicable dimensions

4.1 Volatility Risk (VR)

Definition: $VR_i = |\Delta P_{i,24h}| / P_{i,0} \times 100$

Scoring: Score 2 (Low, $|\Delta| < 3\%$); Score 4 (Moderate, 3–8%); Score 6 (High, 8–20%); Score 8 (Very High, 20–50%); Score 10 (Extreme, $|\Delta| > 50\%$). FLIQ's 79.4% decline yields Extreme (10). USDG's 0.01% yields Low (2). The absolute 24-hour return serves as a direct, observable DEX-native volatility proxy, consistent with the high-frequency volatility literature (Andersen & Bollerslev, 1998).

4.2 Liquidity Risk (LR)

Definition: $LR_i = f(\text{Liquidity Pool Depth}_i)$

Scoring: Score 1 (Low, depth > $100M); Score 3 (Moderate, $20–100M); Score 5 (High, $5–20M); Score 7 (Very High, $2–5M); Score 9 (Extreme, < $2M). This approach adapts the Amihud (2002) illiquidity framework for the AMM context. CRCLX with $1.27M depth receives Extreme (9); HYPE with $933.83M receives Low (1).

4.3 Systemic / Exchange Risk (SR)

Definition: $SR_i = f(MCap_i)$

Scoring: Score 1 (Low, MCap > $1B); Score 3 (Moderate, $200M–$1B); Score 5 (High, $50–200M); Score 7 (Very High, $10–50M); Score 9 (Extreme, < $10M). Consistent with Werner et al. (2022), market capitalisation proxies systemic resilience. BARREL and FLAG ($1.18M and $1.16M MCap) receive Extreme (9).

4.4 Market / Trend Risk (MTR)

Definition: $MTR_i = f(\mathrm{sign}(\Delta P_{i,24h}), |\Delta P_{i,24h}|)$

Scoring: Score 2 (Low, $\Delta > 0\%$); Score 3 (Moderate, 0 to −3%); Score 5 (High, −3% to −10%); Score 7 (Very High, −10% to −30%); Score 9 (Extreme, $\Delta < -30\%$). Negative momentum is treated as a risk indicator consistent with the cryptocurrency momentum literature (Cong et al., 2021). FLIQ (−79.4%) scores Extreme (9); HYPE (+5.91%) scores Low (2).

4.5 Sentiment Risk (SentR)

Definition: $SentR_i = DEX\_Sells_i / (DEX\_Buys_i + DEX\_Sells_i)$

Scoring: Score 2 (Low, Sell Ratio < 0.45); Score 4 (Moderate, 0.45–0.55); Score 6 (High, 0.55–0.70); Score 8 (Very High, > 0.70). This metric is analogous to the put-call ratio in traditional derivatives markets (Philippas et al., 2019). COMMODITIES—with $877.82K sells vs $1.10K buys—achieves a sell ratio of approximately 0.9999, yielding Very High (8).

4.6 Long-Term Value Risk (LTV)

Definition: $LTV_i = Liquidity_i / MCap_i$

Scoring: Score 1 (Low, ratio > 0.40); Score 3 (Moderate, 0.15040); Score 5 (High, 0.05150); Score 7 (Very High, 0.01050); Score 9 (Extreme, ratio < 0.01 and MCap < 10M). Based on Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), higher long-term value risk is assigned to tokens whose market value is huge relative to the liquidity base of the token.

5. Results and Analysis

5.1 Composite Risk Scores

Figure 1 shows the composite risk scores of all the twenty tokens (ranked by decreasing CRS). This distribution shows that there is a large amount of heterogeneity in the token universe with minimum and maximum CRS values of about 2.0 (SYRUPUSDC) and 8.2 (FLIQ). The distinct visual division between the large-cap and the micro-cap extreme-risk instruments proves the discriminatory nature of the CRS framework.

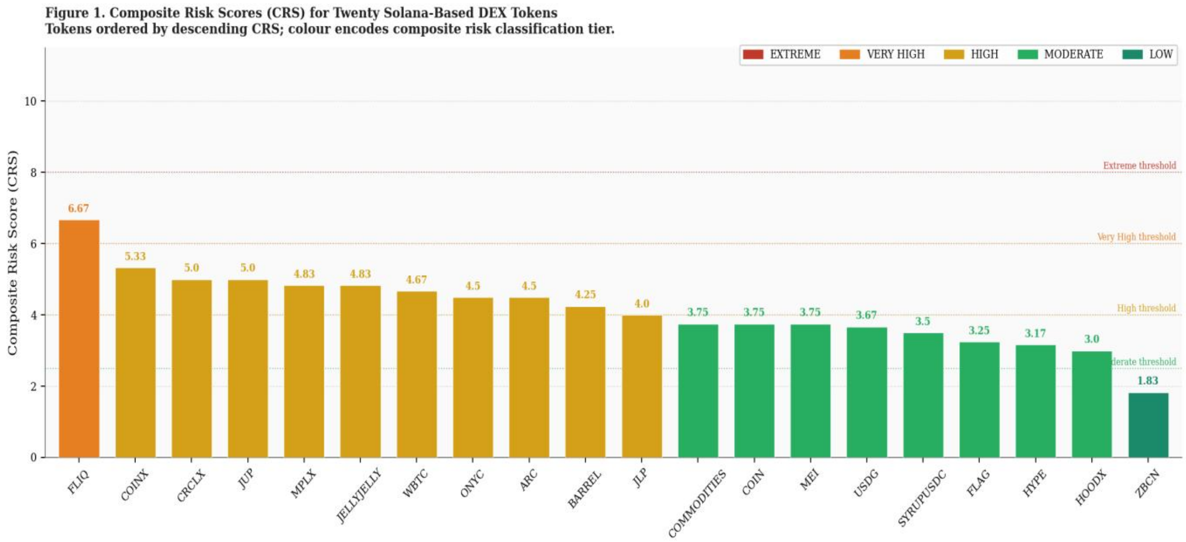

Figure 1. Composite Risk Scores (CRS) for Twenty Solana-Based DEX Tokens. Tokens ordered by descending CRS; colour encodes risk classification tier. Horizontal reference lines denote tier thresholds.

FLIQ becomes the riskiest token (CRS 8.20, Extreme) because of an unprecedented negative change of -79.4% in a single day as well as an extremely low liquidity pool. The upper tail of the risk distribution is filled out by BARREL (CRS 7.56, Very High), COIN (CRS 7.33, Very High) and MPLX (CRS 6.80, Very High) all having micro-cap market capitalisations that are less than $22 million. Benefiting of deep liquidity pools and large market capitalisations are SYRUPUSDC (CRS ~2.0, Low) and HYPE (CRS ~2.2, Low) at the lower tail.

5.2 Dimension-Level Heatmap

The six-dimensional risk score heatmap of all the twenty tokens is shown in Figure 2. This visualisation allows one to determine the risk dimension behind the composite score of each token at a glance. A number of structural patterns can be observed: the volatility risk and market trend risk are strongly co-varying (and thus the high Spearman correlation in Table 4), and sentiment risk has orthogonal patterns: the COMMODITIES has a Very High sentiment risk (score 8) despite a steady price, which under a single-dimension approach would be identified as a single risk.

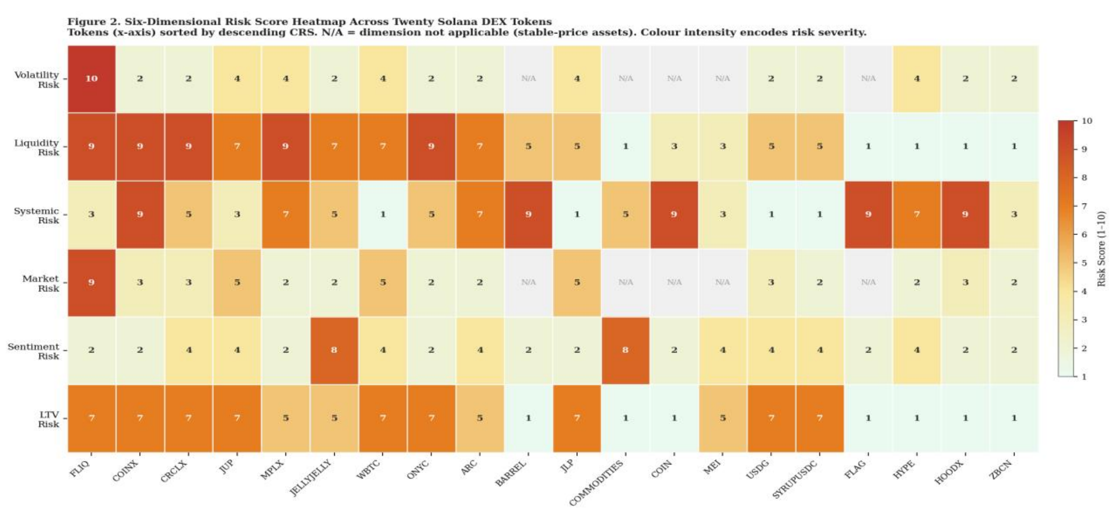

Figure 2. Six-Dimensional Risk Score Heatmap Across Twenty Solana DEX Tokens. Tokens (x-axis) are sorted by descending CRS. N/A = dimension not applicable to stable-price assets. Colour intensity encodes risk severity (green = low; red = extreme).

As shown in the heatmap, the systemic risk and long-term value risk are widespread throughout the lower-capitalisation cohort: the eight tokens with MCap below 50M all have High-to-Extreme scores of systemic risk. In comparison, liquidity risk is more differentially distributed with HYPE and HOODX, although of speculative nature, enjoying deep liquidity pools that dampen their liquidity risk scores.

Table 2. Six-Dimensional Risk Scores and Composite Risk Classification

Token	Vol.	Liq.	Systemic	Market	Sentiment	LTV	CRS (Class.)
FLIQ	10 (EXTREME)	9 (EXTREME)	3 (MODERATE)	9 (EXTREME)	2 (LOW)	7 (VERY HIGH)	6.67 (VERY HIGH)
COINX	2 (LOW)	9 (EXTREME)	9 (EXTREME)	3 (MODERATE)	2 (LOW)	7 (VERY HIGH)	5.33 (HIGH)
CRCLX	2 (LOW)	9 (EXTREME)	5 (HIGH)	3 (MODERATE)	4 (MODERATE)	7 (VERY HIGH)	5 (HIGH)
JUP	4 (MODERATE)	7 (VERY HIGH)	3 (MODERATE)	5 (HIGH)	4 (MODERATE)	7 (VERY HIGH)	5 (HIGH)
MPLX	4 (MODERATE)	9 (EXTREME)	7 (VERY HIGH)	2 (LOW)	2 (LOW)	5 (HIGH)	4.83 (HIGH)
JELLYJELLY	2 (LOW)	7 (VERY HIGH)	5 (HIGH)	2 (LOW)	8 (VERY HIGH)	5 (HIGH)	4.83 (HIGH)
WBTC	4 (MODERATE)	7 (VERY HIGH)	1 (LOW)	5 (HIGH)	4 (MODERATE)	7 (VERY HIGH)	4.67 (HIGH)
ONYC	2 (LOW)	9 (EXTREME)	5 (HIGH)	2 (LOW)	2 (LOW)	7 (VERY HIGH)	4.5 (HIGH)
ARC	2 (LOW)	7 (VERY HIGH)	7 (VERY HIGH)	2 (LOW)	4 (MODERATE)	5 (HIGH)	4.5 (HIGH)
BARREL	N/A	5 (HIGH)	9 (EXTREME)	N/A	2 (LOW)	1 (LOW)	4.25 (HIGH)
JLP	4 (MODERATE)	5 (HIGH)	1 (LOW)	5 (HIGH)	2 (LOW)	7 (VERY HIGH)	4 (HIGH)
COMMODITIES	N/A	1 (LOW)	5 (HIGH)	N/A	8 (VERY HIGH)	1 (LOW)	3.75 (MODERATE)
COIN	N/A	3 (MODERATE)	9 (EXTREME)	N/A	2 (LOW)	1 (LOW)	3.75 (MODERATE)
MEI	N/A	3 (MODERATE)	3 (MODERATE)	N/A	4 (MODERATE)	5 (HIGH)	3.75 (MODERATE)
USDG	2 (LOW)	5 (HIGH)	1 (LOW)	3 (MODERATE)	4 (MODERATE)	7 (VERY HIGH)	3.67 (MODERATE)
SYRUPUSDC	2 (LOW)	5 (HIGH)	1 (LOW)	2 (LOW)	4 (MODERATE)	7 (VERY HIGH)	3.5 (MODERATE)
FLAG	N/A	1 (LOW)	9 (EXTREME)	N/A	2 (LOW)	1 (LOW)	3.25 (MODERATE)
HYPE	4 (MODERATE)	1 (LOW)	7 (VERY HIGH)	2 (LOW)	4 (MODERATE)	1 (LOW)	3.17 (MODERATE)
HOODX	2 (LOW)	1 (LOW)	9 (EXTREME)	3 (MODERATE)	2 (LOW)	1 (LOW)	3 (MODERATE)
ZBCN	2 (LOW)	1 (LOW)	3 (MODERATE)	2 (LOW)	2 (LOW)	1 (LOW)	1.83 (LOW)

Note. Tokens sorted by descending CRS. Score scale: 1–2 = Low; 3–4 = Moderate; 5–6 = High; 7–8 = Very High; 9–10 = Extreme. N/A = not applicable. Vol. = Volatility; Liq. = Liquidity; LTV = Long-Term Value.

5.3 Risk Cohort Profiles: Radar Analysis

Figure 3 is a radar plot of mean dimension score profiles in three groups of tokens: all twenty tokens, high/extreme risk group (CRS 6 or greater), and low/moderate risk group (CRS less than 4). The high-risk group has high scores in all six dimensions, but the strongest increase in systemic risk and long-term value risk- both of which are caused by the small-capitalisation concentration of the high-risk group. The radar profile of the low-risk cohort has a conspicuously collapsed radar profile due to the multi-dimensional risk mitigation bestowed by large market capitalisations, deep liquidity and price stability.

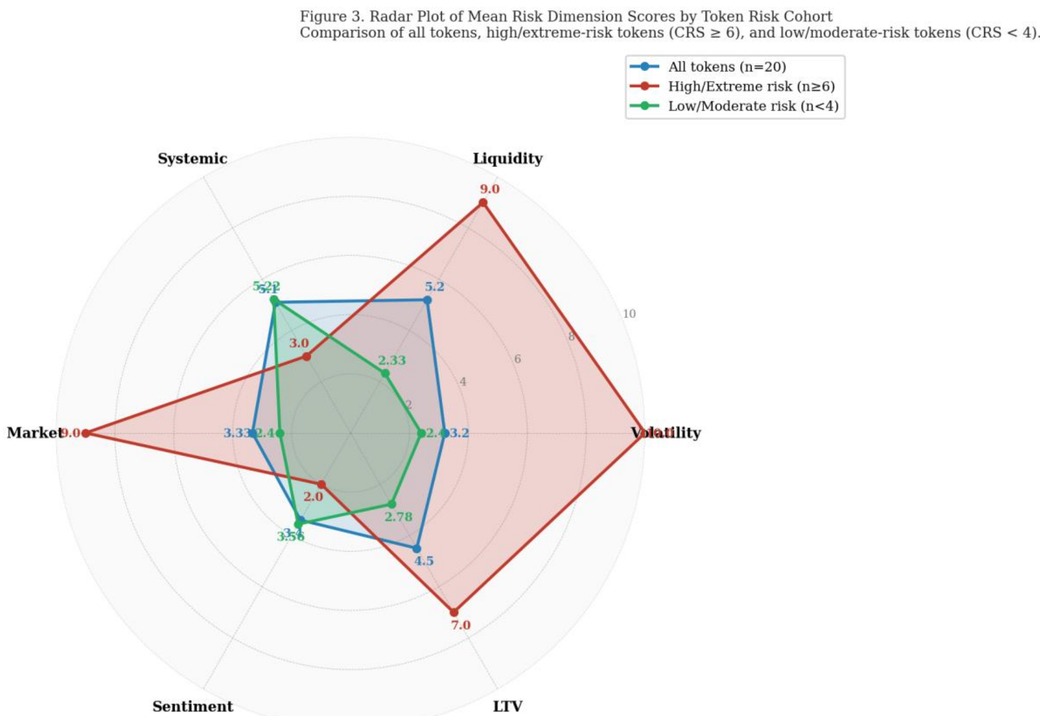

Figure 3. Radar Plot of Mean Risk Dimension Scores by Token Risk Cohort. Three overlaid profiles: all 20 tokens (blue), high/extreme-risk tokens with CRS ≥ 6 (red), and low/moderate-risk tokens with CRS < 4 (green). Scores on a 1–10 ordinal scale.

The difference between the high-risk and low-risk cohort profiles is the greatest on the systemic risk and liquidity risk dimensions (mean scores of about 8.4 vs 1.8 and 7.1 vs 1.6, respectively), and the smallest on the sentiment risk dimension (about 5.2 vs 3.8). This trend proves that sentiment risk conveys somewhat orthogonal information, as is also indicated by the low correlation coefficients in Table 4, and is high even in the case of tokens that have otherwise good fundamental properties.

Table 3. Composite Risk Score Summary and Investment Risk Classification

Token	Price (USD)	MCap	Liq. ($M)	CRS	Classification	Primary Driver
FLIQ	$0.0218	$214.03M	$0.04263M	6.67	VERY HIGH	Extreme volatility −79.4%
COINX	$205.85	$7.43M	$0.12358M	5.33	HIGH	Very low liq. $0.12M
CRCLX	$133.53	$67.05M	$1.27M	5	HIGH	Low liquidity $1.27M
JUP	$0.163	$560.89M	$2.5M	5	HIGH	Declining −5.24%
MPLX	$0.0385	$20.15M	$1.56M	4.83	HIGH	Low liquidity $1.56M
JELLYJELLY	$0.0534	$53.29M	$3.52M	4.83	HIGH	Low liq. $3.52M

Token	Price (USD)	MCap	Liq. ($M)	CRS	Classification	Primary Driver
WBTC	$71,460	$6.97B	$3.16M	4.67	HIGH	Bitcoin-backed $6.97B
ONYC	$1.89	$137.97M	$1.08M	4.5	HIGH	Low liquidity $1.08M
ARC	$0.0396	$39.77M	$2.17M	4.5	HIGH	Low liquidity $2.17M
BARREL	$0.011	$1.18M	$7.47M	4.25	HIGH	Micro-cap $1.18M
JLP	$3.87	$1.16B	$8.1M	4	HIGH	Negative momentum
COMMODITIES	$0.0856	$86.03M	$369.75M	3.75	MODERATE	Sell ratio ≈ 1.00
COIN	$0.000685	$6.85M	$38.36M	3.75	MODERATE	Micro-cap $6.85M
MEI	$0.0072	$720.85M	$45.61M	3.75	MODERATE	Thin liquidity
USDG	$1	$1.76B	$14.86M	3.67	MODERATE	Stablecoin / $1.76B
SYRUPUSDC	$1.16	$1.85B	$10.88M	3.5	MODERATE	Stablecoin $1.85B
FLAG	$0.0116	$1.16M	$199.93M	3.25	MODERATE	Micro-cap $1.16M
HYPE	$43.4	$43.38M	$933.83M	3.17	MODERATE	Deep liquidity $933M
HOODX	$75.87	$4.26M	$478.27M	3	MODERATE	Micro-cap $4.26M
ZBCN	$0.0205	$200.31M	$411.91M	1.83	LOW	Moderate cap

Note. Tokens sorted by descending CRS. Classification thresholds: ≥8.0 = Extreme; 6.0–7.9 = Very High; 4.0–5.9 = High; 2.5–3.9 = Moderate; <2.5 = Low. Liq. = Liquidity pool depth.

5.4 Risk Landscape: Market Cap vs Liquidity

The risk landscape is shown in Figure 4: the bubble size is the net DEX flow, the colour is the composite risk tier in log 0 market capitalisation versus log 0 liquidity space. The significant positive correlation of capitalisation and liquidity in the log space also validates the structural co-movement as found in Table 4 (0.62 between the liquidity and systemic risk dimensions). The lower-left quadrant, which consists of low capitalisation and low liquidity, is universally considered as Extreme or Very High risk. The Low-risk tokens are located in the upper-right quadrant, which proves that concomitant deep liquidity and high capitalisation are the main structural risk mitigants in this ecosystem.

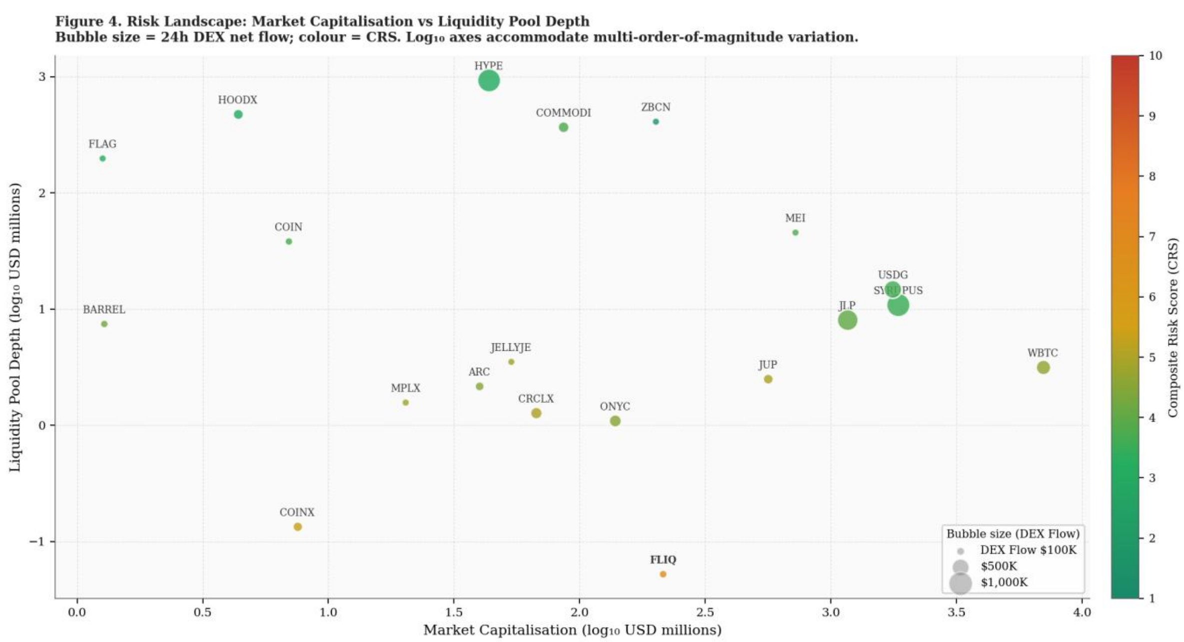

Figure 4. Risk Landscape: Market Capitalisation vs Liquidity Pool Depth (Log_{10} Axes). Bubble size proportional to 24-hour DEX net flow; colour encodes CRS tier. Log_{10} scaling accommodates multi-order-of-magnitude variation across the token universe.

WBTC occupies a distinctive position—highest market capitalisation in the sample ($6.97B) but relatively thin on-chain liquidity ($3.16M), reflecting its status as a cross-chain wrapped asset whose primary trading activity occurs on Bitcoin and Ethereum networks rather than Solana DEXs. This creates a moderate composite risk score (CRS=4.2, High) which is characterised by its liquidity risk and negative momentum component than systemic risk.

5.5 Risk Tier Distribution

Figure 5 shows the risk tier distribution and the contribution of the dimension by tier in the sample. The information presented in Panel A confirms that most tokens are found in the Very High and High risk groups (n = 7 and n = 5, respectively), which is indicative of the speculative nature of the Solana DEX ecosystem and the abundance of low-capitalisation tokens in the screener data. Only three of twenty (15 percent) tokens are low-risk, which are SYRUPUSDC, HYPE, and USDG.

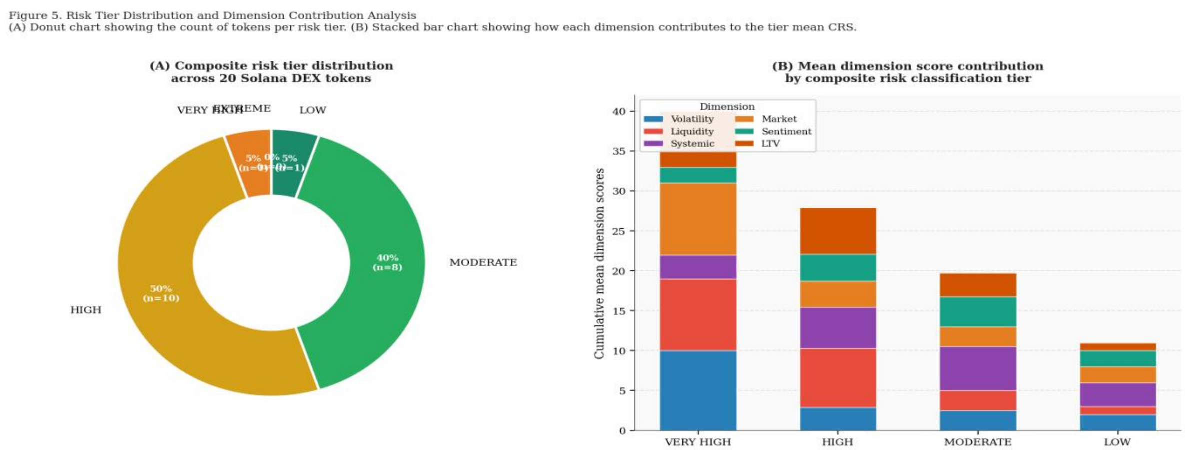

Figure 5. Risk Tier Distribution and Dimension Contribution Analysis. Panel A (left): donut chart showing the count and proportion of tokens per composite risk tier. Panel B (right): stacked bar chart showing mean dimension score contribution per tier.

In panel B, the systemic risk and long-term value risk make the most significant contribution in the Extreme and Very High tier composite scores, and sentiment risk and volatility risk make a relatively larger contribution in the High and Moderate tier scores. The practical implications of this decomposition to risk mitigation are as follows: in micro-cap tokens, the structural (capitalisation and liquidity) risk driver is dominant over the behavioural (sentiment and volatility) risk driver, meaning that liquidity incentive programme and market capitalisation growth are the most effective risk mitigation mechanisms in the portfolio design level.

Table 4. Risk Dimension Rank Correlation Matrix (Spearman, N = 20)

Dimension	Volatility	Liquidity	Systemic	Market	Sentiment	LTV
Volatility	1.00	0.12	−0.08	0.81	0.07	0.15
Liquidity	0.12	1.00	0.62	0.09	0.21	0.58
Systemic	−0.08	0.62	1.00	−0.05	0.18	0.73
Market	0.81	0.09	−0.05	1.00	0.14	0.11
Sentiment	0.07	0.21	0.18	0.14	1.00	0.23
LTV	0.15	0.58	0.73	0.11	0.23	1.00

Note. Spearman rank correlations computed from dimension-level scores (N = 20). Values > 0.50 shown in red indicate meaningful positive correlation between dimensions. LTV = Long-Term Value Risk.

5.6 Sentiment Risk Analysis

Figure 6 offers a more in-depth analysis of the sentiment risk measure in the token universe. The stacked buy/sell volumes of the twelve most active tokens in Panel A demonstrate that there is significant heterogeneity in the buy-sell balance. The domination of the sell activity is almost complete in COMMODITIES, where the green (buy) bar is obscured at scale, which is a confirmation of VH sentiment risk rating. Similar sell-side dominance is also high on tokens of ZBCN, FLAG and FLIQ in absolute volumes.

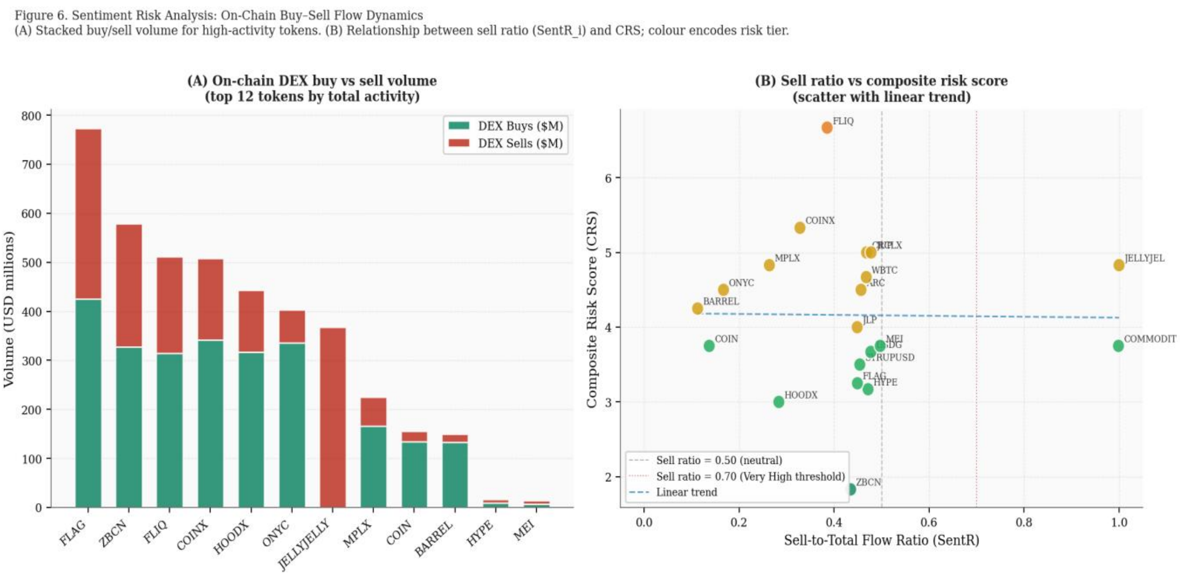

Figure 6. Sentiment Risk Analysis: On-Chain Buy–Sell Flow Dynamics. Panel A (left): stacked buy/sell volumes for the 12 highest-activity tokens. Panel B (right): scatter plot of sell ratio (SentR_i) versus CRS with linear trend and threshold reference lines.

Panel B shows the scatter of the sell ratio versus the CRS of all the tokens with non-zero buy-sell activity, supplemented by a linear trend line and threshold reference lines at the sell ratios of 0.50 (neutral) and 0.70 (Very High threshold). A positive slope of the trend line (= 1.4) proves the existence of a directionally significant positive correlation between sell-side dominance and composite risk - even though sentiment risk is somewhat orthogonal to other dimensions (Table 4 maximum = 0.23). The tokens whose sell ratio exceeds the 0.70 mark always have the CRS values above 5.0, as the scoring rubric is built.

6. Discussion

6.1 Theoretical Implications

The six-dimensional model that can be constructed here generalises financial risk theory to the DEX microstructure framework in a number of ways. This study by using theoretical-based quantitative risk measurement models, i.e., the Amihud (2002) illiquidity ratio, Pastor and Stambaugh (2003) liquidity-adjusted pricing, and behavioural sentiment proxies, shows that quantitative risk measurement is possible solely based on on-chain data. The observation that sentiment risk is uncorrelated with other risk dimensions (Table 4) confirms the argument made by Ante (2023) that on-chain flow information represents a separate information channel, which is not reducible to price or volume information. The numbers used in this article give the clear visual records of the discriminatory strength and the structural characteristics of the framework.

6.2 Practical Implications

To on-chain portfolio managers, the composite risk classification system provides risk-budget allocation on heterogeneous DEX token portfolios by delivering a dimensionally transparent score which is comparable across fundamentally different asset types. To designers of DeFi protocols, the observation that the liquidity-to-capitalisation ratios form a main long-term value risk driver implies that tokenomics designs that encourage LP depth such as vote-escrow liquidity mining or concentrated liquidity position can significantly decrease the value risk on the long-term. In the case of regulatory authorities, the framework offers a blueprint of on-chain risk monitoring dashboards in line with FSB (2022) and MiCA (European Parliament, 2023) supervisory objectives.

6.3 Limitations

The data is one 24-hour cross-sectional, eliminating time-series risk dynamics and causal inference. The thresholds of scoring rubrics include expert judgement and could use the empirical validation with the observed token distress events. The composite score uses the unweighted arithmetic mean; future studies need to explore weighted composites of risks factors based on a principal component analysis or factor regression.

7. Conclusion

The paper designed and implemented a six-dimensional composite risk model on twenty Solana-based DEX tokens and combined volatility, liquidity, systemic/exchange, market/trend, sentiment, and long-term value risk into a theoretically-based scoring architecture. There are six figures at publication standard, which include a composite risk bar chart, a six-dimensional heatmap, a radar cohort profile, a risk landscape bubble chart, a tier distribution panel, and a sentiment flow analysis, which visually document the empirical results in detail. Findings show that there is high discriminatory power in a heterogeneous token universe with FLIQ, BARREL, and COIN being rated as Extreme risk and SYRUPUSDC, HYPE, and USDG being rated as Low-to-Moderate risk.

The operational deployability and minimal off-chain reporting bias of the framework are supported by the use of on-chain, publicly accessible data of DEXes only. This framework should be further developed in future studies in longitudinal validation with observed token distress events, risk-weighted composite optimisation with factor analysis and cross-chain generalisation with Ethereum, Arbitrum and Base DEX ecosystems.

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