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Market Risk Assessment of Tokenised Real-World Assets Using Forward-Looking Machine Learning Models

Zhamilya Abdildanova
Kazakh-British Technical University

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Zhamilya Abdildanova
Financial Risk Management & Data Science
Kazakh-British Technical University
Almaty, Kazakhstan
selena.jamilya@gmail.com

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Abstract: The rapid growth of tokenised real-world assets (RWA) has created an urgent need for robust, forward-looking risk measurement frameworks tailored to the structural characteristics of these emerging markets. Platforms dedicated to RWA tokenisation - spanning commodities, fixed-income instruments and institutional financial products - have expanded dramatically, with total on-chain RWA value exceeding tens of billions of dollars by 2025. Kazakhstan provides a particularly relevant empirical context: the country operates one of the world's most advanced digital finance ecosystems, including the live Digital Tenge CBDC integrated into national budget financing, a regulated crypto market that recorded $6.8 billion in transactions in the first nine months of 2025, and the recent launch of Central Asia's first regulated spot Bitcoin ETF.

Despite this growth, the risk measurement infrastructure for tokenised asset markets remains underdeveloped. Standard Value-at-Risk (VaR) models rest on assumptions of continuous liquidity and stable return distributions that do not hold in tokenised markets, where trading volumes are episodic, liquidity conditions shift abruptly in response to on-chain activity or regulatory developments, and price impact per unit of volume can diverge sharply from conventional markets. These features mean that standard VaR applied to tokenised portfolios will systematically understate tail losses during liquidity stress episodes - precisely the scenarios most relevant to financial stability oversight and macroprudential regulation.

This paper proposes and empirically validates a liquidity-adjusted Value-at-Risk (L-VaR) framework for a portfolio of tokenised real-world assets, combining gradient boosting machine learning with dynamic on-chain liquidity measurement. The framework is applied to a portfolio comprising PAX Gold (PAXG) - a regulated tokenised gold instrument in which each token represents one troy ounce of physical gold held in institutional custody - and Ondo Finance (ONDO), a leading RWA tokenisation protocol providing on-chain exposure to US Treasury securities and institutional fixed-income instruments. Daily price and volume data are sourced via Yahoo Finance API, covering April 2024 to April 2026, yielding 730 trading observations.

Volatility forecasting is performed using XGBoost, a gradient boosting algorithm well-suited to capturing non-linear dependencies and regime shifts in financial time series. The feature set encompasses standard volatility predictors - lagged portfolio returns and rolling volatility measures over 5-, 10- and 20-day windows - augmented by three features specifically designed for tokenised asset markets: a volume impulse indicator measuring the deviation of current trading volume from its 20-day moving average; a cross-asset volatility spread capturing divergence in risk levels between PAXG and ONDO; and a rolling 20-day return correlation serving as a market regime indicator. The target variable is the next-day absolute portfolio return, interpreted as a realised volatility proxy. The model is trained on a

chronological 75% subsample (June 2024 - October 2025) and evaluated out-of-sample on the remaining 25% (October 2025 - April 2026). The optimal VaR quantile multiplier $z^* = 2.70$ is calibrated on the training set, materially above the standard normal quantile of 1.65, reflecting the heavier return tails of tokenised assets.

Liquidity adjustment follows the Amihud (2002) illiquidity measure, adapted for on-chain trading volume data. The illiquidity ratio (|return| / volume) is standardised as a rolling 60-day z-score, and the VaR threshold is scaled by a factor of $(1 + k * \max(0, \text{amihud\_z}))$, where $k = 0.1$ is the liquidity sensitivity parameter. This specification allows risk thresholds to expand adaptively during illiquidity episodes while remaining unchanged under normal market conditions. Model performance is assessed using the Kupiec (1995) proportions-of-failure test, and tail loss severity is evaluated via Expected Shortfall. SHAP decomposition is applied to assess the marginal contribution of individual features to model predictions.

Out-of-sample backtesting over 168 trading days yields the following results. The baseline ML VaR achieves a violation rate of 2.38%, with a Kupiec POF test p-value of 0.084, confirming statistical adequacy at the 5% significance level. The liquidity-adjusted L-VaR specification reduces the violation rate to 1.19%. Expected Shortfall deepens from -6.90% under ML VaR to -9.40% under L-VaR, an increase of 2.50 percentage points in tail loss coverage. Liquidity regime analysis - partitioning the test sample into high-, medium- and low-liquidity terciles based on the Amihud z-score - reveals that all observed violations for both models are concentrated exclusively in the low-liquidity regime, where the ML VaR violation rate reaches 7.84%, nearly 60% above the theoretical 5% threshold. In high- and medium-liquidity regimes, the violation rate is zero for both models. This result constitutes direct empirical evidence that liquidity risk is the primary structural driver of tail risk underestimation in tokenised asset markets.

Feature importance analysis confirms that the two tokenisation-specific features - rolling cross-asset correlation and cross-asset volatility spread - rank as the most informative predictors alongside medium-term rolling volatility. SHAP decomposition corroborates this ordering, demonstrating that market structure features specific to decentralised environments contain substantial incremental predictive information. The volume impulse and Amihud z-score features also contribute meaningfully, confirming the value of on-chain liquidity data in risk forecasting.

The findings carry direct implications for the regulation and supervision of tokenised real-world asset markets. As central banks and financial regulators - including the National Bank of Kazakhstan - develop frameworks for CBDC integration, regulated crypto markets and RWA tokenisation platforms, the calibration of risk measurement tools becomes a first-order concern. The empirical evidence presented here demonstrates that standard VaR metrics, applied without liquidity adjustment, will systematically understate risk during market stress precisely when accurate measurement matters most. The low-liquidity regime - where all tail risk violations are concentrated - is the regime most likely to coincide with broader market dislocations and systemic contagion. The proposed L-VaR framework offers a tractable, interpretable and empirically validated alternative that can be implemented with publicly available market data, making it accessible to central banks and supervisory authorities across emerging economies. Its application to Kazakhstan's Digital Tenge ecosystem or regulated on-chain asset markets represents a natural extension of the current work.

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