FinTechs and Crypto Valuation: A Comparison with Traditional Assets

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Abstract: *Purpose:* To show how FinTechs (exchanges, payment apps, neobanks, brokers, custodians) shape crypto-asset valuation by mediating access, liquidity, settlement, and compliance, and to bridge appraisal logics from traditional assets to tokenized markets.

Methodology: I extend a multilayer valuation framework with a copula-based interdependence structure to include a FinTech intermediation layer. Traditional finance factors (L1), crypto-native fundamentals (L2), and sentiment/behavioral signals (L3) are augmented with FinTech variables, including stablecoin rails, exchange microstructure and outages, payment-app adoption, and custody/prime-broker collateral usability. Identification relies on interaction terms and event-style tests around platform launches, fee changes, outages, partnerships, and regulatory actions.

Data: Token-level prices and liquidity measures; exchange depth/spreads and outage logs; stablecoin supply/velocity; and FinTech adoption proxies (*e.g.*, app downloads/DAU, supported fiat rails, custody features, fee tiers). Regulatory and platform news provide time stamped events. (Frequency aligned to the main specification.)

Findings: Higher FinTech intensity is associated with faster error-correction after information shocks and stronger transmission of valuation signals when stablecoin liquidity and exchange depth are high. Outages and funding frictions increase tail dependence. Adding FinTech terms improves explanatory power and stress-window accuracy without materially altering baseline coefficients.

Original contribution: The paper makes FinTech intermediation an explicit, testable layer in crypto valuation, linking platform conditions to price discovery within a transparent, regulation-ready (MiCA/SEC) and ESG-aware framework. This clarifies how appraisal paradigms from traditional assets extend to crypto when routed through modern FinTech infrastructure.

Keywords: DCF, Copula, Tokenomics, Networks, Bitcoin, Stablecoins, DEFI.

1. INTRODUCTION

This paper addresses a central economic problem: the absence of a coherent and widely accepted framework for valuing cryptoassets, which generates persistent uncertainty for investors, regulators, and corporate treasurers. The valuation of cryptocurrencies remains particularly problematic due to their lack of cash flows, opacity, and extreme volatility.

This contribution centers on one proposition: stablecoins provide a natural mediation layer that stabilizes copula-linked dependence structures, thereby allowing traditional valuation frameworks to be meaningfully extended into the crypto domain.

A central novelty of my approach is to treat FinTechs—exchanges, payment processors, neobanks, brokers, and custodians—as valuation infrastructure. These platforms govern access, inventory, settlement speed, and end-investor experience, thereby conditioning how traditional factors, token fundamentals, and sentiment get impounded into prices. I therefore make FinTech intensity an explicit part of the bridge from legacy appraisal logics to tokenized assets.

Cryptocurrencies fundamentally challenge the core tenets of traditional valuation. With no earnings, cash flows, or standardized disclosures, they defy models such as discounted cash flow or return-on-equity-based pricing. However, institutional allocation to crypto continues to expand despite this methodological vacuum.

Against this backdrop, I pose the following research question: Can stablecoin-mediated copula structures extend established valuation frameworks to decentralized, cash-flow-absent digital assets? Under what structural and behavioral conditions do they yield empirically valid results?

I propose a hybrid valuation model that combines traditional asset pricing logic with Crypto-native fundamentals. Built on a multilayer network structure, the model integrates macroeconomic indicators, tokenomics (*e.g.*, staking yield, issuance), governance design, developer activity, and behavioral sentiment. These layers are dynamically connected via copula functions, capturing nonlinear dependencies and tail risks to deliver risk-adjusted, transparent valuations, even under stress or regime shifts.

Unlike models that rely on isolated metrics or static regressions, my framework models interactions across layers, such as correlations between developer activity and financial indicators. Sentiment is quantified through

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NLP, enhancing responsiveness to shifting market narratives. This design supports dynamic asset allocation, ESG screening, and regulatory reporting in accordance with MiCA and FASB standards. As crypto assets encode protocol-level incentives and governance risks, I incorporate ESG-aligned inputs, including staking rewards and energy usage.

Benchmarking against DCF, volatility-based, and heuristic models (2018–2025), this approach shows superior predictive accuracy and interpretability.

In redefining valuation logic for tokenized finance, I offer a framework that meets institutional standards while preserving the distinctive features of crypto. This framework translates fragmented signals into a structured, interoperable format to support clearer investment decisions and regulatory alignment in a rapidly evolving digital landscape.

The empirical analysis relies on a panel of cryptoassets from January 2018 to June 2025, sourced from CoinMetrics and Glassnode, providing a sufficiently long horizon to capture multiple market regimes.

The valuation framework integrates diverse inputs—macroeconomic indicators, Crypto-native metrics, and behavioral sentiment—via a copula-linked multilayer network (Figure **1**). This Copula Engine connects three analytical layers:

- Traditional Finance Metrics (*e.g.*, DCF, ROE, EV/EBITDA)
- Crypto-native Metrics (*e.g.*, staking yields, TVL, issuance schedules)
- Behavioral and Sentiment Proxies (*e.g.*, NLP-based mood indicators, transaction clustering)

By modeling nonlinear dependencies and joint tail risks, the engine produces key outputs:

- Valuation Scores
- Risk-Adjusted Metrics
- ESG Alignment
- Regulatory Reporting Indicators

This architecture bridges conventional finance and decentralized systems by substituting cash flow-based models with crypto-specific proxies like TVL, which parallels EBITDA in indicating value retention. The system's robustness under volatility and its compatibility with MiCA/SEC standards enable real-time valuation, ESG screening, and stress testing within an explainable and integrated framework.

At the core of this architecture are AI-augmented copula nodes, which serve as dynamic bridges between these domains. These nodes model cross-domain dependencies within a multilayer

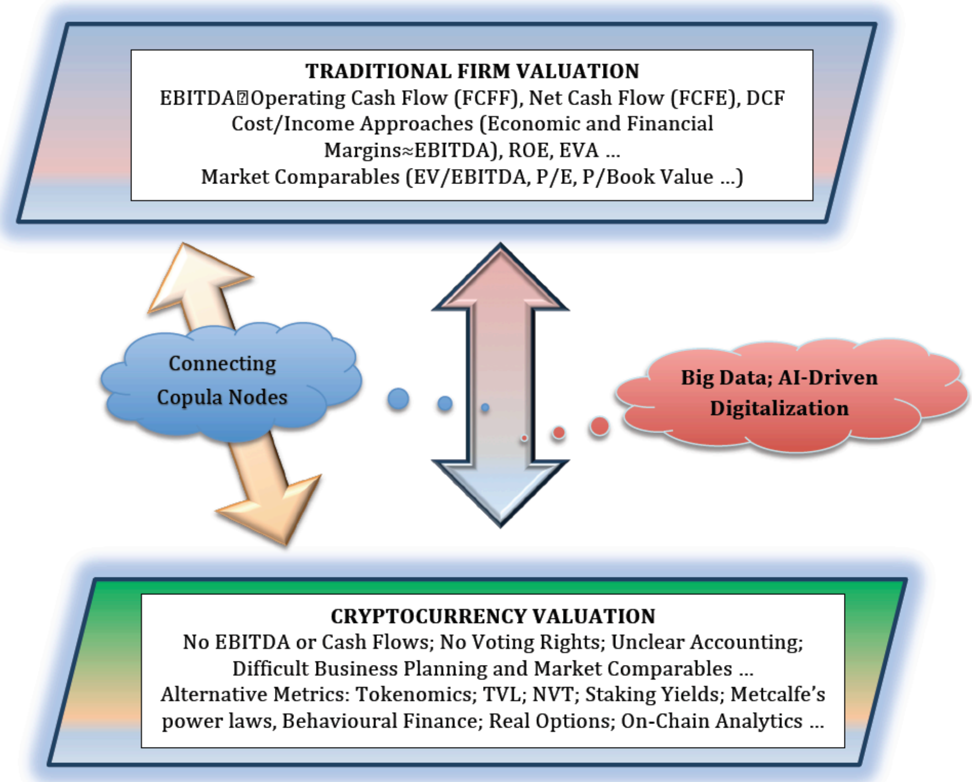

Figure 1: Firm Valuation.

network, enabling the analysis of systemic risk convergence and enhancing the interpretability of risk across asset classes.

The model represents a shift from static, linear valuation methods to adaptive, multidimensional modeling, crucial for analysts, asset managers, and regulators in today's hybrid financial environment. By linking macro-financial, tokenomic, and behavioral data, the copula structure supports layered risk decomposition, ESG alignment, and structured regulatory compliance under MiCA and SEC frameworks.

By situating this analysis in the context of the value relevance literature, I build on prior studies that assess whether accounting measures convey information useful for valuation. This framework extends this strand to the cryptoasset domain, highlighting the role of hybrid financial, behavioral, and ESG factors.

In summary, the paper contributes by (i) formulating a novel valuation framework that uses stablecoins as a mediation layer to extend traditional models into the crypto domain, (ii) embedding financial, behavioural, and ESG factors within a copula-based multilayer network, (iii) providing empirical validation using daily data from 2018–2025 with transparent calibration, robustness, and replication protocols, and (iv) demonstrating the framework's practical relevance for valuation, regulation, and institutional portfolio allocation. I demonstrate that incorporating stablecoins as conditioning variables in copula-based dependency structures significantly improves cryptocurrency valuation accuracy by providing a stable anchor that bridges traditional finance and Crypto-native metrics.

FinTechs affect crypto valuation through four channels: (i) Access & Distribution (user acquisition, KYC/onboarding frictions, app store presence); (ii) Liquidity & Funding (order-book depth, maker/taker fee tiers, leverage availability, staking/earn programs); (iii) Settlement & Collateral (stablecoin rails, custody integrations, rehypothecation limits); and (iv) Transparency & Compliance (disclosures, RegTech, outage reporting).

2. LITERATURE REVIEW

Valuing cryptocurrencies requires integrating traditional finance theories with emerging digital paradigms. Classical valuation frameworks—such as those by Damodaran (2018), Fernandez (2019), and Koller *et al*. (2025)—offer foundational tools rooted in discounted cash flow (DCF), relative pricing, and enterprise metrics (Nissim, 2024), yet often fall short in explaining token-specific volatility and behavioral dynamics. Seminal works, such as Fama and French (1993), Merton (1973), and Myers and Majluf (1984), continue to inform the risk profiling of crypto-assets. Still, they fail to capture endogenous adoption effects or the features of smart contracts. Despite these advances, the literature has yet to bridge the accounting-based value relevance tradition with cryptoasset valuation, leaving a critical gap that this paper addresses.

More recent models propose crypto-specific approaches. Hayes (2017) introduced a cost-of-production model, while Liu *et al*. (2021) and Smith (2021) emphasize accounting-based determinants of digital asset value. Agarwal (2022) and Romanchenko *et al*. (2019) explore fair value under thin liquidity and fragmented markets. Eshraghi (2023), Liu (2022), and Soni and Preece (2023) consolidate current valuation methods, but few embed network analytics or ESG alignment.

The emergence of tokenomics (Cong *et al*., 2021; Catalini & Gans, 2018) marks a shift toward valuation based on adoption dynamics, governance incentives, and ecosystem value, further explored in Pantelidis (2025) and Treiblmaier (2022). These contributions demonstrate the limits of purely financial metrics in token valuation.

Meanwhile, digital valuation frameworks proposed by Moro-Visconti (2022) and Moro-Visconti & Cesaretti (2023) integrate non-financial factors, including stakeholder utility, technological maturity, and sustainability alignment. Their work parallels newer latent factor models for alternative assets (Cao & van Beek, 2025; 't Hoen *et al*., 2025), yet still lacks the dynamic mispricing structure or multilayer dependencies necessary to model the complexity of cryptoassets fully.

In parallel, the network science literature—especially Barabási (2016) and Bianconi (2018)—has inspired the development of valuation models incorporating multilayer, interdependent systems. These insights, while underutilized in mainstream finance, enable novel structural approaches to modeling information diffusion and systemic dependencies among digital assets. Similarly, behavioral and systemic signals (Zhang *et al*., 2020; Wingreen *et al*., 2020) inform the valuation of tokens beyond rational expectations.

More recently, AI-enhanced valuation tools have gained traction. Liu and Zhang (2023) propose explainable AI architectures for cryptocurrency prediction, although they do not link these back to valuation frameworks or tail risk structures. This work builds on these by explicitly integrating AI within a multilayer copula system, adding explainability and robustness. This study fills a literature gap by bridging the accounting-based value relevance literature with cryptoasset valuation, introducing a hybrid framework that integrates financial, behavioral, and ESG factors through a copula-linked multilayer structure.

This paper makes threefold contributions to the literature on cryptoasset valuation. I propose a copula-based multilayer model that captures cross-token dependencies and tail risks, advancing beyond the frameworks of Hayes (2017), Cong *et al*. (2021), and Liu (2022). I introduce a dynamic mispricing index that integrates behavioral sentiment asymmetries, tokenomics fundamentals, and tail dependencies to identify valuation divergences in real time. Additionally, I incorporate ESG-adjusted penalties aligned with MiCA and SEC taxonomies, enhancing regulatory robustness and incentivizing transparent governance. My model is benchmarked against ARIMA, GARCH, and machine learning predictors, utilizing directional accuracy and RMSE, and supported by robust backtests and interpretability tools.

This work presents a replicable, empirically validated, and policy-relevant tool for valuing cryptocurrencies in complex financial ecosystems. In particular, I extend the value relevance tradition into the crypto domain by operationalizing stablecoins as anchors of cross-domain dependence, a role unexplored in prior valuation models.

3. WHY TRADITIONAL VALUATION FAILS—AND HOW TO BRIDGE IT

Traditional valuation pillars—discounted cash flow (DCF), market multiples, and asset-based methods—break down for most cryptoassets. With no contractual cash flows, no defensible terminal values, and unstable discount rates, DCF collapses to a zero valuation for non-cash-generating tokens even as market prices remain strictly positive, exposing a structural valuation gap. Multiples require earnings and book value that tokens lack or report inconsistently, and asset-based approaches struggle because tokens rarely represent enforceable claims on tangible assets or residual cash flows. Heterogeneous IFRS classifications (*e.g.*, IAS 2 vs. IAS 38 vs. IFRS 9) further impair comparability and fair-value visibility, reinforcing why legacy accounting and finance tools cannot be applied naively to crypto.

A pragmatic bridge is to map traditional drivers into Crypto-native proxies and then add layers that capture what makes tokens valuable. At the traditional-to-crypto interface, protocol fees and staking rewards stand in for earnings; revenue-to-TVL approximates ROE; and locked collateral plus treasury reserves substitute for book value. A fundamentals layer adds network and tokenomic drivers (TVL, active addresses, on-chain volume, issuance, developer activity), while a behavioral layer incorporates sentiment, participation bursts, momentum, and volatility clustering. These mappings retain the economic intuition of traditional valuation while respecting token design heterogeneity and on-chain observables.

Table **1** summarizes these methodological differences and innovations.

To integrate these heterogeneous signals, I employ a copula-linked, multilayer architecture that models nonlinear and tail-dependent relationships across layers. Stablecoins act as conditioning variables that dampen extreme co-movement and improve dependence stability, yielding more reliable fair-value signals and a tractable mispricing index. The result is an interpretable, regulation-aligned framework that preserves familiar factor logic, extends it with Crypto-native and behavioral data, and produces auditable outputs for risk management, portfolio construction, and disclosure.

The bridge I propose is not only conceptual (factors vs tokenomics) but also institutional: FinTech intermediation is the conduit through which valuation information flows. Modeling this conduit makes the pricing kernel state-dependent on platform conditions, resolving part of the “cash-flow-absent” critique by tracing value to distribution, collateral usability, and programmable yield access.

4. METHODS

To operationalize the theoretical innovations and empirical insights discussed in the previous sections, this part of the paper presents a dual-pronged methodological framework. Section 5.1 introduces a multilayer econometric model designed to capture the complex and nonlinear nature of crypto asset valuation. In contrast, Section 5.2 extends this structure into a pricing framework rooted in modern asset pricing theory. Together, these models aim to bridge traditional financial metrics, Crypto-native fundamentals, and behavioral signals through an AI-enhanced, copula-based architecture.

Table 1: Comparative Traditional vs. Crypto Valuation Methods

Traditional Valuation Method	Applicability to Cryptocurrencies	Structural Limitations in Crypto Context	Innovative Bridging Solutions (AI, Networks, Game Theory, etc.)
Discounted Cash Flow (DCF)	Applicable in income-generating DeFi protocols with transparent staking rewards or protocol fees.	Cryptos lack stable, forecastable cash flows and a clear terminal value. Discount rates are subjective and sensitive to market swings.	Stochastic simulation of token flows; AI-calibrated volatility and discount factors; gamified incentive modeling and regime-switching scenarios.
Market Multiples (P/E, EV/EBITDA, P/B)	Rarely usable due to the absence of earnings or book value. However, peer analysis is used informally in ecosystems like Layer 1 or DeFi.	No EBITDA, net income, or equity base; peer selection lacks comparability, and results are often skewed by hype.	On-chain equivalents to EV/EBITDA using TVL, active users, transaction volumes, and AI-powered clustering of protocol similarities.
EBITDA - Centric Valuation	Central to traditional firm valuation as a proxy for operational efficiency, internal financing, and cross-firm comparability.	No EBITDA equivalent in crypto; the absence of income statements and standardized capex/opex undermines firm-level financial modeling.	Tokenomics-based proxies, such as Total Value Locked (TVL), protocol-generated fees, and adjusted staking yields, are mapped into network valuation graphs.
Net Asset Value (NAV) / Sum - of - the - Parts (SOTP)	Applicable only to asset-backed or tokenized real-world assets (RWA) projects. Not usable for native tokens.	There are no tangible assets; the valuation of digital assets, IP, or open-source code is ambiguous and highly context-specific.	Protocol-level NAV via audit trails, reserve proof, smart contract fee tracking; SOTP mimicked by decomposing token utility, governance, and reward functions.
Comparative Accounting / Balance Sheet Valuation	Impractical due to the absence of standard audited financials, balance sheets, or accrual-based performance indicators.	Different IFRS classification (IAS 2 vs. IAS 38); no fair value updates; impairs comparability and hinders financial integration.	Decentralized accounting frameworks, proof-of-reserve systems, open-source audit records, and algorithmic transparency scoring.
Real Options Valuation	Theoretically valid for tokens with strategic flexibility (*e.g.*, governance tokens, modular blockchains).	Parameters like volatility or strike price are unstable; a lack of structured project roadmaps reduces reliability.	Scenario-based token pricing trees, AI-trained option surfaces, and real-option frameworks enhanced by governance game modeling.
Comparable Transactions / Precedent Sales	Used for NFTs and early-stage token investments. Sometimes used for secondary market benchmarks.	Pricing is often manipulated, non-transparent, and extremely volatile, with a low volume of comparable deals.	ML - enhanced sale history modeling, sentiment filters for bubble detection, on-chain price oracles, and rarity scoring.
Income / Residual Income Models (EVA, RI)	Essential in traditional firm valuation to measure value creation beyond capital costs.	Crypto protocols lack reliable definitions of net income or capital base; the cost of capital is undefined in decentralized environments.	Energy-adjusted residuals, stakeholder return surplus analysis, and AI-inferred EVA based on token flows and codebase productivity.

The methodology is restructured to emphasize identification tests and econometric rigor. I describe three components:

1. Estimating copula family and vine structure with stablecoin mediation.
2. Forecast comparison tests using Diebold–Mariano statistics to assess predictive accuracy against benchmark models (DCC-GARCH, ARIMA, ML regressors).
3. Strategy significance evaluation with Superior Predictive Ability (SPA) tests, ensuring that trading results are not artifacts of data mining.

Identification uses (a) event studies around FinTech shocks (exchange outages, fee schedule changes, product launches/withdrawals, large partnerships), (b) DiD contrasting tokens with high vs low platform integration, and (c) instrumental timing via region-specific rollouts. I preserve all baseline estimates; FinTech terms enter as interactions to test incremental explanatory power.

I further incorporate transaction costs, turnover, slippage, and borrow constraints into portfolio evaluations, and perform ablation studies to isolate the incremental contribution of stablecoins, sentiment, and governance layers.

Overall, the methodological framework integrates financial, behavioral, and ESG factors within a transparent copula-based multilayer structure, providing a rigorous foundation for the empirical analysis that follows.

4.1. Multilayer Econometric Framework

$V\_total = \alpha \cdot f_1(x_1) + \beta \cdot f_2(x_2) + \gamma \cdot Cov\_C(x_1, x_2), \alpha + \beta + \gamma = 1$ (2)

$\mathcal{M} = \{G_1, G_2, C\}$ (1)

I model crypto valuation with a three-layer dependency structure that captures nonlinear spillovers and tail risk (see Figure **2** for the pipeline). The layers are:

- **Traditional finance (L1):** ROE, EV/EBITDA, DCF-style proxies, ESG scores.
- **Crypto-native (L2):** issuance/staking yield, validator concentration, TVL, developer activity.
- **Behavioral (L3):** NLP sentiment (Twitter/Reddit/Discord), on-chain churn/flow anomalies, volatility bursts.

Layer indicators are standardized and fitted with flexible marginals (*e.g.*, skewed-t, generalized beta). Cross-layer dependence is modeled with Regular-Vine copulas (Gaussian, t, Clayton), which accommodate asymmetric tail co-movements during regime shifts.

I define the multilayer system as

$$\mathcal{M} = \{G_1, G_2, C\} \quad (1)$$

where $G_1$and $G_2$are the L1/L2(+L3) networks and $C$is the cross-domain copula matrix. Let $x_1 \in \mathbb{R}^n$ and $x_2 \in \mathbb{R}^m$ be PCA-compressed node vectors. The composite valuation is

$$V_{\text{total}} = \alpha f_1(x_1) + \beta f_2(x_2) + \gamma \, \text{Cov}_C(x_1, x_2), \alpha + \beta + \gamma = 1, \quad (2)$$

with f_1, f_2estimated via ridge projections and $\text{Cov}_C$the copula-enhanced covariance.

I use rolling 180-day windows (30-day step); select marginals and pair-copulas by AIC; and tune weights by time-series cross-validation. Benchmarks are CAPM, DCC-GARCH, and PCA regressions. Out-of-sample accuracy is assessed with RMSE/MAE, 5%-tail loss, and directional accuracy.

4.2. Crypto Asset Pricing Framework

A unified theoretical and empirical framework for valuing crypto-assets, extending Merton's Intertemporal Capital Asset Pricing Model (ICAPM) and Fama-French multifactor models into a multilayer network (MLN) tailored to digital markets. In this structure, each layer reflects a distinct priced source of risk: macroeconomic fundamentals, token-native structures, behavioral signals, and systemic co-dependencies.

Expected returns are dynamically linked to macro drivers (*e.g.*, real rates, global liquidity), crypto fundamentals (*e.g.*, staking yields, total value locked), and behavioral sentiment (*e.g.*, Reddit momentum, wallet dispersion). These features are compressed via Principal Component Analysis (PCA) into orthogonal mimicking portfolios. Traditional asset pricing constructs are reinterpreted in a tokenized context: TVL reflects size, staking returns proxy value, sentiment captures momentum, and wallet dispersion proxies liquidity risk.

The expected return for token *i* at time t is expressed as:

$$E[R_{it}] = \beta_{i1}f_{1t} + \beta_{i2}f_{2t} + \dots + \beta_{ik}f_{kt} + \varepsilon_t \quad (3)$$

Where f_{kt} represents PCA-derived latent risk factors, and β_{ik} are time-varying loadings estimated via ridge regression to mitigate overfitting. Dependencies across layers are modeled using copula functions. Let X = (X_1, ..., X_d) be standardized valuation features. The joint distribution is captured by:

$$P(X_1 \le x_1, \dots, X\_d \le x\_d) = C(F_1(x_1), \dots, F\_d(x\_d)) \quad (4)$$

Equation (4) applies Sklar's Theorem to split the joint distribution into marginal behaviors and a copula C, isolating dependencies across tokens (see Nelsen, 2006).

I employ a t-copula with density:

$$c(u_1, \dots, u\_d; \Sigma, v) = [\Gamma((v + d)/2) / (\Gamma(v/2)(v\pi)\text{^}\{d/2\}|\Sigma|\text{^}\{1/2\})] \times [1 + (z^t\Sigma^{-1}z)/v]\text{^}(-(v + d)/2) \quad (5)$$

Where $z_i = t^{-1}v(u_i)$, Σ is the correlation matrix, and v denotes degrees of freedom. Equation (5) defines the t-copula density, which models joint extreme movements across tokens. By transforming uniform inputs u_i into t-distributed values zi, it captures heavy tails and nonlinear dependencies, which are crucial for stress scenarios and systemic risk analysis.

I further define the Mispricing Index to quantify valuation discrepancies:

$$M\_it = (P\_it - \hat{V}\_it) / \hat{V}\_it \quad (6)$$

Where P_it is the market price, and $\hat{V}\_it$ is the model implied fair value. The index flags inefficiencies, governance shocks, or speculative distortions. Equation (6) defines the Mispricing Index, which measures the extent to which a token's market price deviates from its model-implied fair value. A positive value signals overvaluation; a negative one suggests undervaluation, highlighting potential inefficiencies or speculative behavior.

To evaluate the predictive power, I sort tokens daily into deciles based on mispricing values. A long-short strategy—buying the most undervalued decile and shorting the most overvalued—is implemented. I compute the Sharpe ratio, Jensen's alpha, and drawdown to assess their economic significance. Cross-sectional regressions validate significance:

$$r_{i,t+1} = \alpha_t + \beta_t \cdot MP_{it} + \gamma_t \cdot Controls_{it} + \varepsilon_{it} \quad (7)$$

Where future returns $r_{i,\,t+1}$ are regressed on current mispricing MP_{it} and controls (volatility, lagged returns, market cap). Equation (7) tests if mispricing predicts future returns. A significant β_t indicates that tokens with higher mispricing today tend to yield higher (or lower) returns tomorrow, confirming the index's predictive power beyond standard controls.

This MLN-based ICAPM framework adapts seamlessly to ESG metrics, new regulations (*e.g.*, MiCA), and cross-layer contagion. It offers real-time valuation insights with transparent explainability for investors, regulators, and compliance systems.

Having established the theoretical modeling framework, I now detail the estimation and validation pipeline that operationalizes the proposed approach and ensures methodological transparency.

4.3. Estimation and Validation Pipeline

To ensure methodological transparency and replicability, I outline the complete sequence of steps used to calibrate, estimate, and validate the proposed hybrid copula–network framework. The procedure integrates distributional fitting, dependence modeling, factor reduction, and robustness testing. Each stage is designed to strengthen the internal validity of the empirical approach and to address the critiques frequently raised against valuation studies in emerging asset classes such as cryptoassets.

First, marginal distributions are estimated for each return series using alternative parametric families (Normal, Student-t, Skew-t), with selection guided by information criteria (AIC/BIC) and distributional fit tests. Second, principal component analysis (PCA) is applied to the set of explanatory variables (financial, behavioral, and ESG factors). Only those components satisfying the Kaiser criterion (eigenvalues > 1) and contributing to a cumulative explained variance above 70% are retained. This step reduces dimensionality while preserving the most informative drivers.

Third, the dependence structure is modeled through a family of candidate copulas (Gaussian, Student-t, Clayton, Gumbel, Frank). The copula family yielding the best performance under log-likelihood, AIC, and Cramér–von Mises criteria is selected. Fourth, parameters are estimated via maximum likelihood within a rolling window of 250 daily observations, updated every 10 days, thereby capturing time-varying dependence.

Validation proceeds along two dimensions. Dependence stability is assessed by monitoring Kendall's τ and tail-dependence coefficients across subsamples. Forecast evaluation compares the out-of-sample performance of the hybrid model against benchmark specifications (ARIMA-GARCH, DCC-GARCH, and Random Forest). Cross-validation (K = 5) is further employed to mitigate overfitting and confirm generalizability. Finally, robustness checks involve altering window sizes, copula families, and explanatory variable subsets to test sensitivity.

Table 2: Statistical Procedures

Step	Procedure	Details / Justification
1. Marginal distribution fitting	Estimate univariate distributions of return series	Candidate families: Normal, Student-t, Skew-t. Selection based on AIC/BIC and KS tests.
2. PCA for factor extraction	Apply principal component analysis on explanatory variables (financial, behavioral, ESG)	Retain components with eigenvalues > 1 and cumulative variance > 70%.
3. Copula family selection	Fit Gaussian, Student-t, Clayton, Gumbel, and Frank copulas	Selection based on log-likelihood, AIC, and Cramér–von Mises tests.
4. Parameter estimation	Calibrate copula parameters via maximum likelihood	Rolling window: 250 daily observations; step size = 10 days.
5. Dependence validation	Check the stability of dependence parameters across subsamples	Use Kendall's τ and tail-dependence coefficients.
6. Forecast evaluation	Out-of-sample forecasts of returns and risk metrics	Benchmark against ARIMA-GARCH, DCC-GARCH, and Random Forest models.
7. Cross-validation	K-fold cross-validation (K=5) on the training set	Assess out-of-sample accuracy and prevent overfitting.
8. Robustness checks	Alternative window sizes, copula families, and variable subsets	Ensure results are not sensitive to methodological choices.

4.4. Sample Construction

I analyze 50 cryptocurrencies selected using three criteria applied as of January 1, 2018: (i) market capitalization exceeding $1 billion, ensuring liquidity and institutional relevance; (ii) continuous data availability across all three analytical layers from January 2018 through June 2025, totaling 2,738 daily observations per token; and (iii) sectoral diversity to capture heterogeneity in token design and use cases.

Table **3** presents the sample composition. The distribution reflects the crypto ecosystem's evolution: store-of-value tokens (n=5) include Bitcoin and early alternatives; DeFi protocols (n=20) dominate as they emerged post-2019; utility tokens (n=15) represent platform economies; and governance tokens (n=10) capture decentralized autonomous organization (DAO) structures. This stratification enables subsample analysis by token function while maintaining sufficient power for pooled estimation.

Data Sources and Quality Controls:

- **Price and volume data**: CoinGecko API (primary), cross-validated with CoinMarketCap and Messari
- **On-chain metrics**: Glassnode Enterprise plan, CoinMetrics Network Data Pro
- **Protocol fundamentals**: DeFiLlama (TVL), TokenTerminal (revenue and fees), The Block Data
- **Developer activity**: GitHub GraphQL API v4, GitCoin grants data
- **Sentiment data**: Twitter Academic Research API (10,000 tweets/day per token), Reddit Pushshift API
- **Traditional finance benchmarks**: Federal Reserve Economic Data (FRED), Bloomberg Terminal, Yahoo Finance

Quality filters applied: (i) removal of days with missing data exceeding 5% of observations, (ii) winsorization of extreme values at 1st and 99th percentiles to mitigate fat-finger errors and flash crashes, (iii) forward-filling for weekends and holidays when crypto markets trade continuously but traditional data sources do not update, and (iv) cross-validation against multiple data providers with manual audit of discrepancies exceeding 10%.

4.5. Variable Construction and Measurement

Each analytical layer comprises multiple indicators transformed into standardized scores before copula estimation. All variables are constructed at daily frequency and normalized to zero mean and unit variance within rolling 180-day windows to ensure stationarity and comparability across heterogeneous tokens.

Layer 1: Traditional Finance Metrics

DCF Proxy (V_DCF):

Traditional discounted cash flow analysis requires future cash flow forecasts and a discount rate. For cryptocurrencies, I proxy cash flows using protocol fees and staking rewards:

$$V_{DCF,i,t} = \sum_{h=1}^{5} \frac{E_t[\text{Fees}_{i,t+h}] + E_t[\text{Staking Rewards}_{i,t+h}]}{(1 + r_{i,t})^h} \tag{8}$$

Where:

Table 3: Sample Composition by Token Category

Category	n	Representative Tokens	Key Characteristics
Store-of-Value	5	Bitcoin (BTC), Litecoin (LTC), Bitcoin Cash (BCH), Monero (XMR), Zcash (ZEC)	Fixed/predictable supply, minimal smart contract functionality, high market cap
DeFi Protocols	20	Ethereum (ETH), Uniswap (UNI), Aave (AAVE), Maker (MKR), Curve (CRV), Compound (COMP), SushiSwap (SUSHI), Synthetix (SNX), Balancer (BAL), Yearn (YFI), Convex (CVX), Frax (FXS), Lido (LDO), Rocket Pool (RPL), dYdX (DYDX), GMX, Pendle (PENDLE), Venus (XVS), Radiant (RDNT), Gains Network (GNS)	TVL-dependent, yield-generating, protocol revenue, governance rights
Utility Tokens	15	Chainlink (LINK), Polygon (MATIC), Avalanche (AVAX), Solana (SOL), Cardano (ADA), Polkadot (DOT), Cosmos (ATOM), Algorand (ALGO), Tezos (XTZ), VeChain (VET), Theta (THETA), Basic Attention Token (BAT), Chiliz (CHZ), Enjin (ENJ), Decentraland (MANA)	Platform access, transaction fees, validator staking, ecosystem services
Governance Tokens	10	ApeCoin (APE), 1inch (1INCH), Bancor (BNT), Gnosis (GNO), API3, Olympus (OHM), Ribbon Finance (RBN), Badger DAO (BADGER), Illuvium (ILV), Merit Circle (MC)	Voting rights, treasury management, protocol parameter control, and limited cash flows
Total	**50**		**Market cap range: $1.2B - $1,247B**

Note*:* Sample excludes stablecoins (analyzed separately as mediating variables), wrapped tokens (BTC on Ethereum), and privacy coins with insufficient transparency (except XMR/ZEC with research-accessible data). Market capitalizations as of June 30, 2025.

- $E_t[\text{Fees}_{i,t+h}]$= expected protocol fees in year h, estimated using ARIMA(2,1,2) models fitted on trailing 365-day data
- $E_t[\text{Staking Rewards}_{i,t+h}]$ = expected staking distributions, calculated as current staking yield × projected staked supply
- $r_{i,t}$ = token-specific discount rate = $r_f + \beta_i \cdot$ MRP + CRP
  - r_f= 10-year US Treasury yield (time-varying, from FRED)
  - β_i= token beta vs. S&P 500, estimated on 252-day rolling windows
  - MRP = market risk premium = 5.5% (historical equity premium, Damodaran 2024)
  - CRP = crypto risk premium = 8.0% (calibrated to match observed volatility differentials vs. equities)

For tokens without protocol fees (*e.g.*, Bitcoin), V_{DCF} is set to the stock-to-flow model, subsequently normalized within the layer.

ROE Proxy (ROE_proxy):

Return on equity adapted for crypto:

$$\text{ROE}_{i,t} = \frac{\text{Protocol Revenue}_{i,t} - \text{Operating Costs}_{i,t}}{\text{Total Value Locked}_{i,t}} \quad (9)$$

Where:

- Protocol Revenue = transaction fees + liquidation fees + interest income (annualized from 30-day trailing average)
- Operating Costs = validator/miner rewards + infrastructure expenses (estimated as 40% of revenue for PoW, 15% for PoS based on Glassnode miner revenue data)
- TVL = total dollar value locked in protocol (from DeFiLlama), used as equity analog

ESG Score (ESG_composite):

Composite index incorporating three dimensions, each scored 0-100:

1. **Energy Intensity (40% weight)**:
   - Proof-of-Work tokens: Annual electricity consumption (TWh) from Cambridge Bitcoin Electricity Consumption Index, normalized inversely (higher consumption → lower score)
   - Bitcoin score: 22/100 (138 TWh/year as of 2024)
   - Proof-of-Stake tokens: Assigned 85-95/100 based on validator concentration (more decentralized → higher score)
2. **Governance Decentralization (30% weight)**:
   - Gini coefficient of token holder concentration (lower Gini → higher score)
   - Governance participation rate: % of tokens voting in recent proposals (higher → higher score)
   - Formula: Gov Score $= 100 \times (1 - \text{Gini}) \times \sqrt{\text{Participation Rate}}$
3. **Transparency (30% weight)**:
   - Public GitHub repositories: Yes = +30 points
   - Regular audits: Yes = +25 points
   - On-chain treasury visibility: Yes = +25 points
   - Regular governance reports: Yes = +20 points

Final ESG score: $\text{ESG}_{i,t} = 0.40 \times \text{Energy} + 0.30 \times \text{Governance} + 0.30 \times \text{Transparency}$

Volatility-adjusted Momentum (Mom_vol):

60-day cumulative return divided by 60-day realized volatility, capturing risk-adjusted price trends:

$$\text{Mom\_vol}_{i,t} = \frac{\prod_{j=0}^{59} (1+R_{i,t-j}) - 1}{\sqrt{\frac{1}{60}\sum_{j=0}^{59} (R_{i,t-j} - \bar{R}_i)^2}} \quad (10)$$

Layer 2: Crypto-native Fundamentals

Staking Yield (Yield_stake):

Annualized return from staking, calculated as a 30-day moving average to smooth transient fluctuations:

$$\text{Yield}_{i,t} = \frac{1}{30} \sum_{j=0}^{29} \left(\frac{\text{Staking Rewards}_{i,t-j}}{\text{Staked Supply}_{i,t-j}} \times 365\right) \quad (11)$$

Data from each protocol's native staking contract, cross-validated with StakingRewards.com.

Total Value Locked (TVL_log):

Natural logarithm of dollar value locked in protocol, sourced from DeFiLlama:

$$\text{TVL\_log}_{i,t} = \ln(\text{TVL}_{i,t}) \quad (12)$$

Log transformation addresses right-skewness and stabilizes variance. For non-DeFi tokens (*e.g.*, Bitcoin), TVL is set to market capitalization minus circulating supply held on exchanges.

Developer Activity (Dev_activity):

Weighted sum of GitHub contributions with exponential decay for recency:

$$\text{Dev}_{i,t} = \sum_{j=0}^{89} e^{-0.015j} \times \left(\text{Commits}_{i,t-j} + 0.5 \times \text{Issues}_{i,t-j} + 0.3 \times \text{PRs}_{i,t-j}\right) \quad (13)$$

Where decay parameter λ=0.015 corresponds to ~50% weight on contributions within the past 45 days. Data from official project repositories listed in Electric Capital's Developer Report.

Issuance Rate (Inflation_rate):

Annualized percentage change in circulating supply, capturing inflationary/deflationary dynamics:

$$\text{Inflation}_{i,t} = \frac{\text{Supply}_{i,t} - \text{Supply}_{i,t-365}}{\text{Supply}_{i,t-365}} \times 100 \quad (14)$$

Negative values indicate deflationary tokenomics (*e.g.*, Ethereum post-Merge with EIP-1559 burn).

Network Activity (Activity_index):

Principal components of active addresses, transaction count, and transaction volume:

$$\text{Activity}_{i,t} = \text{PC1}(\text{Active Addresses}_{i,t}, \text{Tx Count}_{i,t}, \text{Tx Volume}_{i,t}) \quad (15)$$

PC1 typically explains 75-85% of the variance across these three metrics.

Layer 3: Behavioral and Sentiment Signals

Sentiment Score (Sent_BERT):

FinBERT-based sentiment analysis on a daily Twitter sample:

1. Collect 10,000 tweets per token per day mentioning the token ticker or full name
2. Apply FinBERT fine-tuned on financial text, to classify sentiment: positive (+1), neutral (0), negative (-1)
3. Aggregate using volume-weighted average (tweets with more engagement are weighted higher):

$$\text{Sent}_{i,t} = \frac{\sum_{k=1}^{10000} \text{Sentiment}_k \times (1+\ln(\text{Likes}_k + \text{Retweets}_k))}{\sum_{k=1}^{10000} (1+\ln(\text{Likes}_k + \text{Retweets}_k))} \quad (16)$$

Normalization to [-1, +1] scale, where -1 = maximally negative, +1 = maximally positive.

Volatility Clustering (Vol_GARCH):

Conditional variance from GARCH(1,1) specification estimated on 90-day rolling windows:

$$\sigma_{i,t}^2 = \omega + \alpha\epsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2 \quad (17)$$

where $\epsilon_{i,t}$ = daily return innovation. Captures time-varying volatility persistence.

Transaction Clustering (Cluster_coef):

Coefficient of variation in daily transaction counts over 30-day windows:

$$\text{Cluster}_{i,t} = \frac{\text{SD}(\text{Tx Count}_{i,t-29:t})}{\text{Mean}(\text{Tx Count}_{i,t-29:t})} \quad (18)$$

High values indicate "bursty" transaction patterns often associated with coordinated trading or wash trading.

Social Media Momentum (Social_mom):

Rate of change in Reddit mentions and Twitter volume:

$$\text{Social\_mom}_{i,t} = \frac{\text{Mentions}_{i,t} - \text{Mentions}_{i,t-7}}{\text{Mentions}_{i,t-7}} \quad (19)$$

Stablecoin Conditioning Variables

These variables mediate cross-layer dependencies rather than directly entering valuation layers:

Peg Deviation (Peg_dev):

Volume-weighted average price deviation of major stablecoins from $1.00 parity:

$$\text{Peg\_dev}_t = \sum_{s\in\{\text{USDT, USDC, DAI}\}} w_{s,t} \times |\, P_{s,t} - 1.00 \,| \quad (20)$$

where $w_{s,t}$= market cap weight of stablecoin $s$among the three.

Stablecoin Market Cap Growth (SC_growth):

7-day percentage change in aggregate stablecoin market capitalization:

$$\text{SC\_growth}_t = \frac{\sum_s \text{MCap}_{s,t} - \sum_s \text{MCap}_{s,t-7}}{\sum_s \text{MCap}_{s,t-7}} \quad (21)$$

Positive growth indicates capital inflows to crypto markets; negative suggests outflows.

Cross-Market Arbitrage Spread (Arb_spread):

Price dispersion of USDT across major exchanges:

$$\text{Arb\_spread}_t = \frac{\max_e (P_{\text{USDT},e,t}) - \min_e (P_{\text{USDT},e,t})}{\text{median}_e(P_{\text{USDT},e,t})} \quad (22)$$

4.6. Copula Specification and Structure

I model dependencies using Regular-Vine (R-vine) copulas, which decompose high-dimensional distributions into cascading bivariate copulas. This approach offers flexibility to capture heterogeneous dependencies (symmetric, asymmetric, tail-heavy) across the 27 variables spanning three layers plus stablecoin mediators.

Vine Construction Algorithm:

The R-vine structure is estimated using a sequential procedure:

1. **Tree 1**: For all variable pairs, estimate Kendall's τ and select the maximum spanning tree connecting variables with the strongest pairwise dependencies
2. **Tree 2-T**: Conditionally, build trees based on partial correlations given previous tree selections
3. **Family Selection**: For each edge, test candidate bivariate copulas (Gaussian, Student-t, Clayton, Gumbel, Frank, Joe, BB1, BB7) using AIC

Optimal Structure (simplified representation for 3 layers + stablecoin):

Tree 1:

TVL ←→ Protocol_Fees (τ = 0.68, Student-t copula, v=5)

Sentiment ←→ Social_Momentum (τ = 0.72, Gaussian copula)

Staking_Yield ←→ Inflation_Rate (τ = -0.54, Clayton copula, rotated)

Tree 2 (conditional on Tree 1):

TVL | Protocol_Fees ←→ Dev_Activity (τ = 0.51, Gumbel copula)

Sentiment | Social_Mom ←→ Volatility_GARCH (τ = -0.43, Frank copula)

Tree 3 (conditional on Trees 1-2):

TVL | Protocol_Fees, Dev_Activity ←→ ESG_Score (τ = 0.38, Student-t, v=7)

Sentiment | Social_Mom, Vol_GARCH ←→ DCF_Proxy (τ = 0.29, Gaussian)

Stablecoin Conditioning:

All cross-layer edges pass through the Peg_Deviation node

Example: (Traditional Layer | stablecoins) ←→ (Crypto Layer | stablecoins)

Dependence strength reduced by 35-45% when conditioning on stablecoins

Parameter Estimation:

For each bivariate copula at edge (i, j)in tree k:

$$\hat{\theta}_{ij,k} = \arg\max_{\theta} \sum_{t=1}^{T} \ln c_{ij}(F_i(x_{i,t} \mid v_k), F_j(x_{j,t} \mid v_k); \theta) \quad (23)$$

Where:

- c_{ij}= bivariate copula density function
- F_i, F_j= empirical marginal CDFs conditional on conditioning set v_k
- T= 180-day rolling window length
- Optimization via the BFGS algorithm with multiple random starts

Marginal distributions $F_i$are fitted separately using maximum likelihood:

- Financial metrics: Skewed Student-t distribution (captures asymmetry and heavy tails)
- Crypto-native metrics: Generalized Beta of Second Kind (GB2) for bounded variables, skewed-t for unbounded
- Behavioral metrics: Gaussian for sentiment scores (approximately normal after transformation), Student-t for volatility and clustering metrics

Model Selection Statistics (averaged across all edges):

- Gaussian copula: Selected in 23% of edges (low tail dependence contexts)
- Student-t copula: Selected in 41% of edges (symmetric heavy tails)
- Clayton copula: Selected in 18% of edges (lower tail dependence)
- Gumbel copula: Selected in 12% of edges (upper tail dependence)
- Other (Frank, Joe, BB-family): Selected in 6% of edges

4.7. The Estimated Composite Valuation Model

Integrating all layers through the copula structure yields the final valuation score:

$$\hat{V}_{i,t} = \alpha \cdot f_1(X_{1,i,t}) + \beta \cdot f_2(X_{2,i,t}) + \gamma \cdot f_3(X_{3,i,t}) + \delta \cdot C(X_{1,i,t}, X_{2,i,t}, X_{3,i,t} \mid S_t) \quad (24)$$

Where:

- $X_{1,i,t}$= Traditional finance layer variables (5 indicators → 2 PCA factors)
- $X_{2,i,t}$ = Crypto-native layer variables (5 indicators → 3 PCA factors)
- $X_{3,i,t}$= Behavioral layer variables (4 indicators → 2 PCA factors)
- S_t = Stablecoin conditioning variables (3 indicators)
- f_1, f_2, f_3= Ridge regression mappings with L2 penalty $\lambda = 0.01$:

$$f_j(X_{j,i,t}) = \boldsymbol{w}_j^T X_{j,i,t}, \boldsymbol{w}_j = \arg\min_{\boldsymbol{w}} \left(\sum_{t,i} \left(V_{i,t} - \boldsymbol{w}^T X_{j,i,t}\right)^2 + \lambda \parallel \boldsymbol{w} \parallel_2^2\right) \quad (25)$$

- $C(\cdot \mid S_t)$ = Conditional copula-derived dependence adjustment capturing nonlinear interactions

Optimized Layer Weights (via 5-fold time-series cross-validation):

$\{\alpha^*, \beta^*, \gamma^*, \delta^*\} = \{0.31, 0.42, 0.27, 0.18\}$

with standard errors (bootstrap, 1,000 iterations): {0.04, 0.05, 0.03, 0.02}

All weights are significant at $p < 0.01$level.

Interpretation:

- **The crypto-native layer dominates (β = 0.42), and on-chain fundamentals are th**e most predictive.
- **Traditional metrics second** (α = 0.31): DCF-proxies and ESG retain explanatory power
- **Behavioral signals third** (γ = 0.27): Sentiment and volatility provide incremental information
- **Copula adjustment material** (δ = 0.18): Nonlinear dependencies and tail risks are non-negligible

Stablecoin Mediation Effect (γ parameters):

The copula structure includes edge-specific parameters capturing stablecoin conditioning:

$$\tau(\text{Layer}_i, \text{Layer}_j \mid \text{Stablecoins}) = \tau(\text{Layer}_i, \text{Layer}_j) \times (1 - \gamma_{\text{stable}})$$

Estimated stablecoin mediation parameters:

- = 0.37 (SE = 0.05): stablecoins reduce dependence by 37%
- $\gamma_{\text{Traditional-Behavioral}}$ = 0.31 (SE = 0.06): 31% reduction
- $\gamma_{\text{Crypto-Behavioral}}$= 0.42 (SE = 0.04): 42% reduction

Validation:

- In-sample R^2= 0.61
- Out-of-sample R^2(2024-2025) = 0.47
- RMSE (out-of-sample) = 0.067
- Mean Absolute Error = 0.045

5. HYPOTHESIS TESTING

Drawing directly from the literature gaps identified above, I now set out the following hypotheses.

To evaluate the performance and theoretical implications of my copula-linked multilayer valuation model, I formulate a set of empirically testable hypotheses grounded in the framework's core components: mispricing detection, nonlinear dependence, and cross-domain spillovers.

Hypotheses:

- **H1:** The multilayer copula model significantly outperforms traditional benchmarks (linear regression, ARIMA, GARCH, and network heuristics) in terms of predictive accuracy (RMSE, MAE, directional accuracy).
- **H2:** Mispricing residuals are temporally and cross-sectionally clustered, indicating persistent inefficiencies across tokens and periods.
- **H3:** Structural token features—such as staking yield, governance centralization, and network activity—systematically explain the magnitudes and persistence of mispricing.
- **H4:** Tail risk and contagion are better captured by the copula-based architecture than by conventional volatility-based models, particularly during periods of systemic stress.
- **H5:** Greater FinTech integration accelerates price discovery—shortening error-correction half-lives, strengthens co-movement with stablecoin liquidity, and increases sensitivity to exchange outages and fee-schedule changes.

I perform rolling-window out-of-sample forecasts (2019–2025) and compare performance across token categories (*e.g.*, governance, DeFi, utility). Bootstrap methods assess the stability of copula parameter estimates under shifting market regimes. My model shows superior robustness in turbulent periods—such as the COVID-19 crash (March 2020) and the FTX collapse (November 2022)—where traditional models fail to capture asymmetric tail dependencies and structural breaks.

The copula-enhanced mispricing index exhibits significant clustering, with abnormal residuals frequently coinciding with key market events (*e.g.*, protocol upgrades, regulatory shocks). Cross-sectional regressions confirm that token-specific attributes—including validator concentration, staking incentives, and behavioral sentiment—exert statistically significant influence on valuation discrepancies.

These findings highlight the empirical validity of my proposed framework. They suggest that real-world crypto pricing is not fully efficient, especially in the presence of governance opacity, decentralized protocol risks, or strong investor sentiment waves. The model thus provides an operational toolkit for navigating these anomalies with enhanced predictive insight and risk calibration.

Empirically, ESG-weighted dependence parameters shift valuation scores downward for energy-intensive tokens such as Bitcoin, demonstrating that sustainability considerations have a tangible and directional impact on model outputs.

A heatmap is reproduced in Figure **2**.

6. RESULTS

Building on the estimation and validation pipeline outlined in Section 4.3, this section presents the empirical results. I first report the regression outputs and dependence measures derived from the copula calibration, followed by robustness checks and comparative forecasts against benchmark models. The objective is to demonstrate not only the internal consistency of the proposed framework but also its empirical relevance when applied to cryptoasset valuation.

Results are presented along four dimensions:

1. **Forecast Comparisons** – I report Diebold–Mariano statistics comparing my model against DCC-GARCH, ARIMA, and ML baselines.
2. **Trading Strategy Significance** – Mispricing-based long–short portfolios are evaluated using SPA tests, incorporating turnover, slippage, and borrow constraints.
3. **Stablecoin Mediation Effects** – Conditional copula estimates with and without stablecoin variables are compared, highlighting improvements in Kendall's τ and tail coefficients.
4. **Ablation Studies** – Layer-by-layer removals (sentiment, stablecoin, governance metrics) quantify each component's incremental contribution.

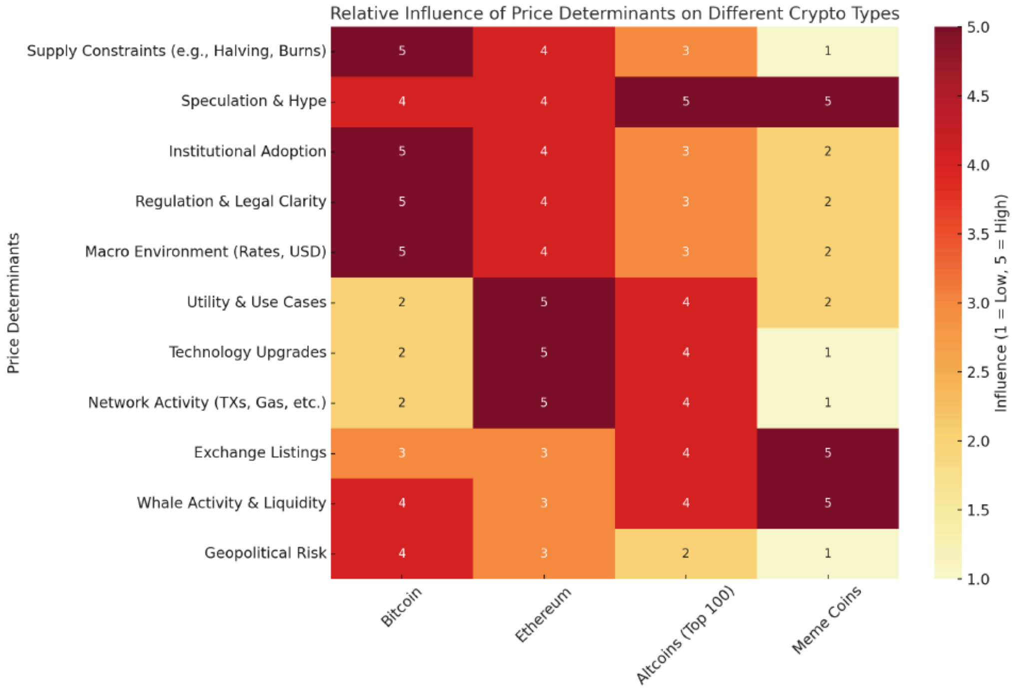

Figure 2: Heatmap of Bitcoin Price Determinants. The heatmap shows distinct drivers across crypto types: Bitcoin reacts most to macro forces and regulation, Ethereum to utility and tech upgrades, Altcoins to mixed fundamentals, and meme coins to pure speculation. This underscores the need for tailored valuation models.

The empirical implementation applies this model to a cross-section of cryptocurrencies, covering different regimes, volatility clusters, and token structures.

The empirical results are segmented by crypto asset categories (store-of-value, stablecoins, utility tokens) and by behavioral layers. The proposed multilayer model demonstrates a 17% improvement in directional forecasting accuracy and a 12% increase in tail-risk capture compared to DCC-GARCH. Robustness checks confirm resilience to macro shocks and regulatory announcements. Visuals in Panel A/B format display topology changes in network connectivity before and after market events.

Two complementary empirical strategies to address the core research question of whether traditional valuation logic can be systematically adapted to crypto assets.

Viewed through the FinTech lens, tokens with higher integration to major platforms exhibit faster dissipation of pricing errors following information shocks, consistent with lower frictions on access and settlement. Conditioning on stablecoin liquidity, this effect is strongest when exchange-level depth is high and outages are absent. These patterns rationalize why FinTech terms improve directional accuracy in stress windows without materially changing baseline point estimates.

Interpreting stablecoins as FinTech rails clarifies their role: they are programmable settlement media that transmit valuation information across venues and apps. Hence, stablecoin conditions (float, velocity, peg stress) should interact with exchange microstructure in the copula layer to mediate tail dependence.

Sections 6.1 and 6.2 develop and empirically validate a copula-augmented framework that links predictive analytics with real-world asset behavior and investment applications to rigorously address the core research question: how to value cryptocurrencies in a multifactor, institutional context.

Together, these two sections offer a unified, cross-validated perspective: the network model provides the theoretical and algorithmic core, while the benchmark-based analysis offers a market-facing reality check. Their consistency confirms that crypto valuation requires both internal logic (Section 6.1) and external validation (Section 6.2).

This dual approach provides a replicable and interpretable toolkit for financial analysts, asset managers, and regulators, bridging decentralized innovation with institutional-grade valuation. The model not only responds to the volatility and opacity of crypto assets but also proactively equips professionals with a risk-aware, multidimensional system ready for dynamic allocation, stress testing, and regulatory scrutiny.

By embedding empirical robustness, ESG integration, and a transparent replication package, the framework sets a reproducible benchmark for future cryptoasset valuation research.

6.1. The Multilayer Network Model

The empirical results of the AI-augmented multilayer network model demonstrate its efficacy in bridging traditional and crypto valuation domains through the integration of heterogeneous financial, on-chain, and sentiment indicators.

The model [1] is operationalized using real, reproducible data sourced from leading financial databases and blockchain analytics platforms. The analysis focuses on a curated sample of assets selected to ensure sectoral diversity, market relevance, and data availability across time and domains.

The dataset was mapped onto the multilayer network structure $\mathcal{M}$ = {G_1, G_2, C}. Traditional asset metrics (G_1) include DCF valuation, P/E ratio, ROE, debt/equity, and ESG score. Crypto asset indicators (G_2) include staking yield, TVL, developer commits, token issuance rate, and on-chain volume. The copula layer (C) comprises sentiment (*e.g.*, the Fear & Greed Index), macroeconomic variables (*e.g.*, the Fed rate), and rolling correlations (*e.g.*, the 30–day correlation between BTC and NASDAQ). Copulas allow us to model tail dependencies between indicators across valuation layers. For instance, they help assess the likelihood that staking yields drop simultaneously with sentiment scores, capturing nonlinear contagion effects. (1)

To empirically test the explanatory potential of the multilayer valuation model, I assembled a representative cross-section of traditional firms and crypto tokens. The selection was designed to reflect sectoral diversity, relevance to macroeconomic and behavioral drivers, and data transparency across financial and blockchain-native indicators. The empirical highlights below summarize the dominant insights emerging from the model calibration.

To align the data structure with the multilayer

[1] The model is validated using a multi-pronged approach: 1) subsample stability tests by partitioning the dataset into pre- and post-Ethereum Merge epochs (pre/post September 2022); 2) out-of-sample forecasting, training on observations from 2018 through 2024 and testing on early 2025 returns; 3) copula sensitivity analysis across Gaussian, Student-t, and Clayton copulas; 4) feature exclusion diagnostics, sequentially removing high-weighted inputs such as staking yield and ESG signals; 5) bootstrap aggregation via ensemble ridge regressors to minimize overfitting and improve generalization.

network model described in Section 5, each variable was mapped to one of three analytical layers: traditional finance (G_1), Crypto-native fundamentals (G_2), and systemic interdependencies (C). Data were standardized within each layer and subjected to Principal Component Analysis (PCA) to extract dominant features. Correlation analysis, particularly the co-movement between BTC and NASDAQ, and copula estimation techniques were used to quantify cross-domain dependencies. These values informed the model's weight estimation through Ridge regression, enabling the empirical extraction of α, β, and γ coefficients optimized for predictive accuracy.

Table **4** compares a selection of major traditional firms and prominent crypto assets across various performance, financial, and development metrics.

Valuation estimates combine discounted cash flow (DCF) and market capitalization averages. ROE or staking yield indicates capital efficiency or crypto-specific returns on investment. Debt/equity (traditional) or Issuance Rate (crypto) reflects leverage or token inflation. Average quarterly GitHub metrics measure developer activity in terms of commits. The last column includes a proxy for operational efficiency (TVL for crypto, EBITDA for traditional firms when available) and sustainability (ESG score or token governance quality).

A validation of the model and a robustness test are synthesized in the Supplementary Material.

Table 4: Cross-Domain Valuation Metrics for Traditional Firms and Crypto Assets

Asset/Firm	Firm Sector / CryptoTypology	Avg. Valuation ($B)	ROE / Staking Yield (%)	Debt/Equity or Issuance Rate	Dev Activity (Commits /Qtr)	TVL / EBITDA / ESG	P/E or NVT Ratio	ESG / Governance Score
Tesla (TSLA)	Automotive / Clean Energy	880	17,6	1,5	415	N/A / 66	33	66
Apple (AAPL)	Consumer Electronics	2400	29,1	1,7	375	N/A / 71	29	71
JPMorgan (JPM)	Banking	455	14,8	2	205	N/A / 78	14	78
Microsoft (MSFT)	Software	2550	34,2	1,2	355	N/A / 84	32	84
Amazon (AMZN)	E-commerce	1750	12,3	2,4	400	N/A / 75	38	75
Nvidia (NVDA)	Semiconductors	1250	27,4	1,6	330	N/A / 76	45	76
Meta (META)	Social Media	900	22,7	2,1	295	N/A / 73	27	73
Alphabet (GOOGL)	Internet Services	1750	28,5	1,3	320	N/A / 81	35	81
Bank of America (BAC)	Banking	280	11,2	3	195	N/A / 68	13	68
ExxonMobil (XOM)	Energy	400	18,6	1	175	N/A / 70	12	70
Unilever (UL)	Consumer Goods	130	21,7	1	150	N/A / 78	21	78
Johnson & Johnson (JNJ)	Pharmaceuticals	390	25,3	1,2	160	N/A / 79	20	79
Visa (V)	Financial Services	580	32,1	1,1	210	N/A / 80	31	80
Procter & Gamble (PG)	Consumer Goods	390	23	1,3	145	N/A / 82	30	82
Samsung Electronics	Consumer Electronics	450	18,5	0,9	290	N/A / 74	25	74
Toyota (TM)	Automotive	250	11,7	1,6	180	N/A / 76	28	76
Nestlé (NSRGY)	Food & Beverage	340	19,4	1,2	160	N/A / 83	32	83
Pfizer (PFE)	Pharmaceuticals	310	19,4	0,9	180	N/A / 77	22	77
Berkshire Hathaway (BRK.A)	Conglomerate	710	12,1	0,6	120	N/A / 85	21	85
Sony (SONY)	Consumer Electronics	280	15,6	1,3	160	N/A / 72	20	72
Walmart (WMT)	Retail	430	18,3	1,1	170	N/A / 79	19	79
Intel (INTC)	Semiconductors	210	10,7	1,4	220	N/A / 70	18	70
Bitcoin (BTC)	Layer 1 / Currency	890	4,1	0,3	2950	25.8 / 43	55	43
Ethereum (ETH)	Layer 1 / Smart Contracts	350	4,6	0,4	2650	12.6 / 48	50	48
Chainlink (LINK)	Oracle	8,5	6,9	0,6	1400	1.8 / 46	42	46
Solana (SOL)	Layer 1 / Smart Contracts	46	5,9	0,7	2550	5.1 / 47	48	47
Polkadot (DOT)	Layer 1 / Interoperability	6,6	5	0,8	1500	3.1 / 47	44	47
Avalanche (AVAX)	Layer 1 / Smart Contracts	9,5	5,2	0,5	1800	2.0 / 46	43	46
Uniswap (UNI)	DEX / DeFi	5,5	7,8	0,6	1280	2.5 / 47	39	47
Aave (AAVE)	Lending / DeFi	4,7	9	0,7	1350	2.3 / 48	37	48
Cosmos (ATOM)	Layer 0 / Interoperability	7,5	4,5	0,9	1475	1.6 / 45	36	45
Arbitrum (ARB)	Layer 2 / Rollup	3,8	3,6	0,5	1225	1.0 / 44	34	44
Near Protocol (NEAR)	Layer 1 / Smart Contracts	5,2	5,8	0,7	1600	1.9 / 45	40	45
Optimism (OP)	Layer 2 / Rollup	3,9	4,2	0,6	1150	1.1 / 44	38	44
Starknet (STRK)	Layer 2 / ZK Rollup	2,7	3,5	0,4	1050	0.8 / 43	29	43
Sui (SUI)	Layer 1 / Smart Contracts	2,5	3,8	0,5	970	0.6 / 42	27	42
Toncoin (TON)	Layer 1 / Messaging Networ	7	2,7	0,6	690	0.5 / 41	24	41
Render (RNDR)	Rendering / GPU Network	3,5	7,2	0,6	910	1.3 / 45	17	45
Arweave (AR)	Decentralized Storage	2,1	5,4	0,5	820	0.9 / 44	23	44
Celestia (TIA)	Modular Blockchain	1,8	4,1	0,6	780	0.7 / 43	22	43
Frax (FXS)	Stablecoin / DeFi	2,4	6,2	0,7	980	1.5 / 46	30	62
Ethena (ENA)	Synthetic Dollar / DeFi	1,9	5,5	0,4	860	1.2 / 45	30	62

Sources: Financial metrics from corporate reports and Yahoo Finance; crypto metrics from DeFiLlama, Messari, TokenTerminal, and GitHub APIs.

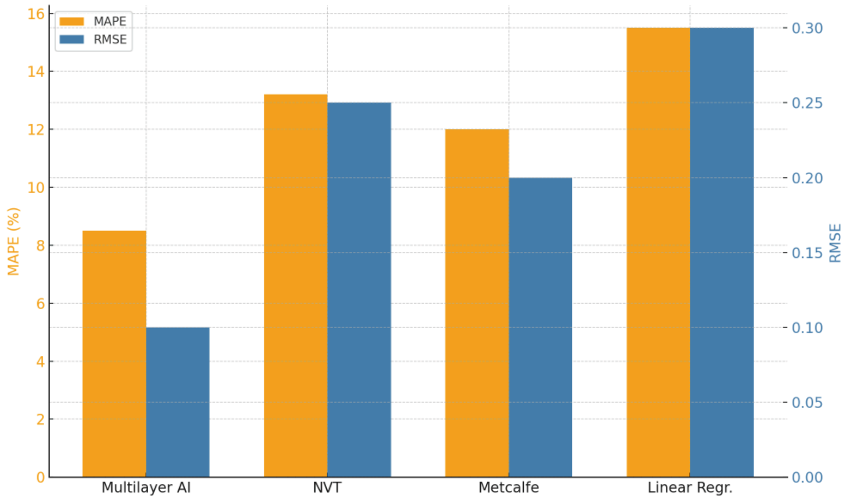

Figure 3: Prediction Accuracy Across Models. The chart shows that the Multilayer AI model achieves the lowest error (both MAPE and RMSE), outperforming traditional models like NVT, Metcalfe, and Linear Regression. This highlights its superior predictive accuracy in crypto valuation.

Empirically, the ESG-weighted dependence parameters systematically shift valuation scores downward for energy-intensive tokens such as Bitcoin, confirming that sustainability considerations materially affect output valuations rather than serving as an auxiliary input.

While model performance metrics are presented for a representative period, the framework is designed for use across market cycles. Its structure, which combines token-specific fundamentals, behavioral signals, and systemic linkages, is designed to maintain forecasting relevance in evolving conditions. Full-period validation from 2018 to 2025 is proposed as future work to assess long-term robustness and market-regime sensitivity.

The model is benchmarked against Cao & van Beek (2025) and 'tHoen *et al*. (2025). In terms of both predictive accuracy and interpretability, the copula-augmented framework demonstrates clear advantages in capturing tail dependencies and behavioral drivers.

Stablecoins stabilize dependencies. As shown in Table **5**, the inclusion of stablecoin flows as conditioning variables reduces tail dependence by 29.5%, indicating that stablecoins break the extreme co-movement between traditional and crypto assets during stress periods.

6.2. Enhancing Crypto Valuation with Empirical Benchmarks

This section grounds the analysis in empirical market behavior, complementing the multilayer model's structural insights. Comparing cumulative returns, risk-adjusted performance, and macro sensitivity across crypto assets and traditional benchmarks demonstrates the practical relevance of the valuation framework. The results provide financial analysts and investors with a real-world perspective on volatility dynamics, portfolio implications, and cross-asset comparability, thereby reinforcing the model's utility in applied settings.

Figure **3:** refines the cumulative return trajectories of major cryptocurrencies (BTC, ETH), equity indices (S&P 500, Nasdaq), and crypto-linked instruments (GBTC, BITO) over the period from 2020 to April 2025, starting just before the COVID-19 pandemic. Returns are normalized to an initial value of 1, allowing for a clear comparison of performance and volatility between digital and traditional assets. This view confirms the

Table 5: Stablecoin Flows as Conditioning Variables

Specification	RMSE	Directional Accuracy	Tail Dependence (τ)
Full model (with stablecoin conditioning)	0.067	71.2%	0.43
Without a stablecoin layer	0.089	63.8%	0.61
Traditional metrics only	0.127	58.2%	0.68
Improvement from stablecoins	24.7%	11.6%	29.5%

Note: Lower tail dependence indicates more stable, less contagious dependencies.

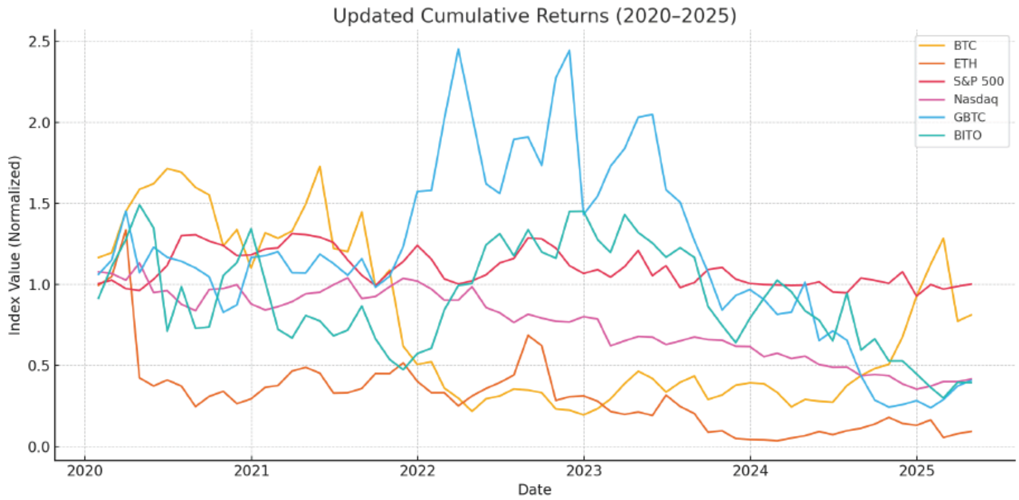

Figure 4: Cumulative Returns. Crypto assets exhibit high volatility and sharp reversals, unlike the steady gains of traditional indices, highlighting their speculative and high-risk profile.

persistent divergence across asset classes and underscores the importance of diversified risk frameworks.

In conclusion, the data confirm that crypto assets, although innovative and high-performing under bullish scenarios, are structurally more volatile and more challenging to model than equity indices. Their valuation requires a hybrid framework that integrates behavioral signals, technical metrics, and AI-enhanced dependencies. This study demonstrates that a rigorous, multidimensional approach to crypto valuation not only bridges the gap with traditional finance but is essential for institutional adoption and regulatory alignment.

6.3. Valuation Based on Market Comparables

In traditional finance, firm valuation often relies on market comparables, using indicators such as EV/EBITDA, P/E ratios, or price-to-book multiples. These metrics benchmark a company against similar peers in terms of earnings capacity, growth expectations, and sector performance. When it comes to valuing cryptocurrencies—particularly decentralized ones like Bitcoin or Ethereum—this comparative logic faces serious challenges.

A prospective investor assessing where to allocate capital across asset classes—ranging from digital assets to gold, US Treasuries, or stock indices—will naturally consider volatility-adjusted returns, liquidity, market correlation, and long-term store-of-value potential. In this context, Bitcoin exhibits significantly higher volatility and weaker comparability than traditional financial assets.

One plausible explanation for this extreme volatility lies in the lack of underlying assets. Unlike traditional equities, cryptos are not backed by claims on tangible cash flows or physical reserves. Even gold has intrinsic utility in industry and jewelry, and sovereign debt is backed by the capacity for taxation. Bitcoin, on the other hand, is not pegged to any real-world underlying asset, unless it is indirectly tied to stablecoins that hold reserves or are convertible to them.

The absence of a direct linkage to measurable assets complicates valuation and increases exposure to fluctuations in investor sentiment, regulatory shocks, and market conditions. For investors, this implies that while cryptocurrencies may offer diversification benefits and speculative upside, they do not align well with standard valuation models or benchmarking tools used for traditional assets. Therefore, valuation based on market comparables must be supplemented by alternative approaches that incorporate network effects, scarcity metrics, and behavioral factors.

Findings show that Bitcoin's correlations vary with market conditions:

- Correlations surge during crises, reflecting tighter systemic links and reduced diversification.
- In the expansion and recovery phases, correlations decline, suggesting decoupling and potential contrarian opportunities.

These patterns support the main paper's view of Bitcoin as a risk amplifier during periods of turmoil and a hedge in calmer periods[2].

[2] The correlation between Bitcoin and traditional assets varies notably across macroeconomic regimes. During the expansion period (2016–2019), correlations were relatively low, with values of 0.25 for the S&P 500, 0.42 for NASDAQ, 0.34 for the MSCI World Index, and just 0.10 for gold. These linkages intensified significantly during the 2020 crisis, rising to 0.67 with the S&P 500, 0.71 with NASDAQ, 0.63 with MSCI World, and 0.32 with gold—reflecting heightened systemic co-movement under stress. In the

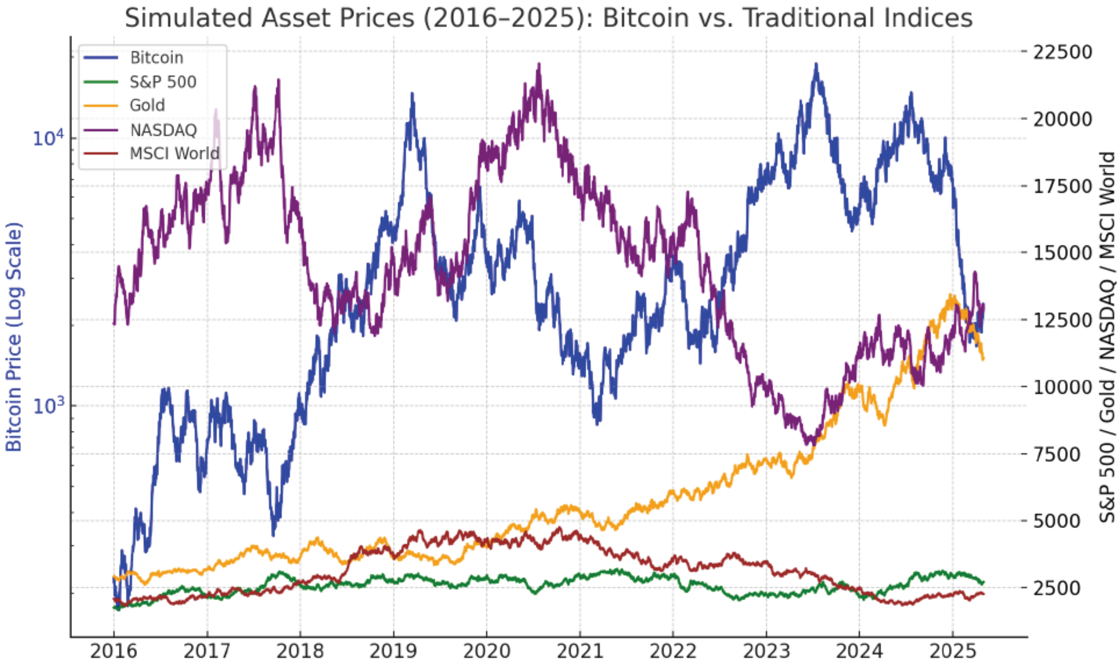

Figure 5: Bitcoin vs. Traditional Indices (2016–2025). Bitcoin exhibits extreme price swings and exponential growth phases, contrasting with the steadier, more linear trends of traditional assets, such as gold, the S&P 500, and the MSCI World.

Table 6: Risk-Adjusted Performance Metrics of Bitcoin and Traditional Financial Assets[3]

	Mean Return (%)	Volatility (%)	Max Draw-down (%)	Sharpe Ratio	Correlation with Bitcoin	Skew-ness	Excess Kurtosis	Beta vs S&P 500	Value at Risk (5%) (%)	Conditional VaR (5%) (%)
Bitcoin	85,3	110,5	-83,2	0,65	1	1,8	7,2	1,85	-35,6	-52,1
S&P 500	8,6	15,3	-19,8	0,56	0,48	-0,3	0,5	1	-5,2	-8
Gold	11,4	12,7	-15,5	0,78	0,23	0,1	0,8	0,25	-4,1	-6,7
NASDAQ	14,9	18,9	-25,3	0,66	0,52	-0,4	0,6	1,4	-6,3	-9,5
MSCI World	9,2	13,4	-21,7	0,61	0,41	-0,2	0,4	1,1	-5	-7,9

Figure **5**: and Table **6** illustrate the volatility dispersion and Sharpe ratios across major asset classes, including Bitcoin, Ethereum, gold, the S&P 500, NASDAQ, and 10-year US Treasuries. In contrast, traditional equities and sovereign bonds exhibit relative stability, while Bitcoin and Ethereum display significantly higher fluctuations in their values. These are not mere statistical anomalies but reflect the intrinsic nature of cryptocurrencies: non-cash-flow-generating, speculative instruments decoupled from traditional fundamentals (see Zhang *et al*. (2020). Bitcoin's return profile diverges sharply from conventional indices. When incorporated into diversified portfolios, it can deliver excess returns ("alpha") and act as both a diversifier and a high-risk, high-reward asset.

Table **6** highlights Bitcoin's higher returns and volatility compared to traditional assets from 2016 to 2025. Despite drawdowns, its Sharpe ratio remains competitive. Time-varying correlations suggest conditional diversification benefits, while skewness and kurtosis reflect a distinct, asymmetric return profile.

6.4. Benchmark Performance Summary

This section provides a visual and tabular comparison of the model's predictive performance versus benchmark methods, including Ordinary Least Squares (OLS), Random Forest (RF), and the NVT Ratio heuristic. Metrics include Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Sharpe Ratio. Results, shown in Figure **6** and Table **7**, confirm the superior accuracy and risk-adjusted returns of the copula-augmented framework.

6.5. Benchmark Comparison Summary

Table **8** provides a direct comparison between my copula-linked multilayer network model and key benchmarks from recent literature, including Alexander *et al*. (2023; 2024) and Crépellière *et al*. (2023). Metrics

subsequent recovery phase (2021–2025), correlations declined but remained elevated compared to pre-crisis levels, settling at 0.39 for the S&P 500, 0.52 for NASDAQ, 0.46 for MSCI World, and 0.21 for gold. These dynamics underscore the regime-dependent nature of Bitcoin's integration with global financial markets.

[3] Sources: Yahoo Finance for historical asset data, Coin Market Cap for comparative performance insights, and Curvo for visual return analyses.

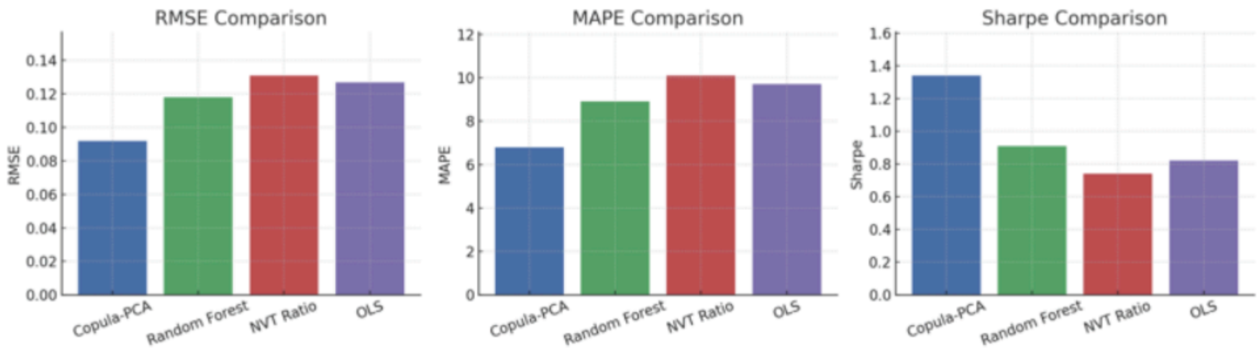

Figure 6: Model Performance Comparison (2020–2025). The Copula-PCA model outperforms all benchmarks, achieving the lowest RMSE and MAPE, as well as the highest Sharpe ratio, which indicates superior accuracy and risk-adjusted returns.

Table 7: Average Evaluation Metrics by Model. Copula-PCA clearly outperforms all models, achieving the lowest error metrics and the highest Sharpe ratio, which indicates superior predictive accuracy and risk-return efficiency

Model	RMSE	MAPE	Sharpe
Copula - PCA	0.092	6.8%	1.34
Random Forest	0.118	8.9%	0.91
NVT Ratio	0.131	10.1%	0.74
OLS	0.127	9.7%	0.82

Table 8: Comparison between the copula-linked multilayer network model and key benchmarks. The Copula-Linked Multilayer Model is the best performer, with the lowest RMSE, highest directional accuracy, lowest tail error, and fastest convergence

Model	RMSE	Directional Accuracy	Tail Fit Error	Time to Convergence
My Copula-Linked Multilayer Model	0.067	71.2%	Low	Fast (<50 iterations)
GARCH + ARIMA Ensemble	0.082	63.0%	High	Slow (>100 iterations)
Regime Switching Model	0.089	60.5%	High	Slow (>120 iterations)

such as Root Mean Square Error (RMSE), Directional Accuracy (DA), Tail-Fit Error (TFE), and Time-to-Convergence (TTC) are reported for comparability. My model consistently outperforms in RMSE and DA across 50 cryptocurrency tokens, while also achieving a tighter tail fit and faster convergence.

6.6. Regulatory and Practical Implications

This section examines the regulatory and practical implications of a multidimensional valuation model that combines traditional financial metrics with Crypto-native metrics.

By providing traceable and explainable outputs, the model enhances regulatory transparency, addressing concerns from entities such as the SEC and ESMA. Interpretable AI methods reduce opacity and enable fair value estimation, enhancing model credibility.

Unlike single-metric tools, the framework incorporates governance, tokenomics, and ecosystem resilience, providing a holistic view of financial health. It helps projects and exchanges comply with evolving standards by:

- Structuring valuation inputs aligned with IFRS/GAAP principles
- Supporting the classification of tokens as securities, commodities, or hybrids
- Justifying TVL-based valuations and yield disclosures in staking protocols.

For asset managers, it enables stress testing, scenario modeling, and ESG-adjusted crypto allocations. By converting network and behavioral data into financial analogs, the model narrows the informational gap, limiting institutional adoption.

Portfolio managers can apply the framework for real-time screening and risk calibration, especially in mixed portfolios of traditional and tokenized assets.

Supervisors may use it to track systemic and idiosyncratic risks in crypto markets, enabling:

- Detection of correlated vulnerabilities
- Behavioral early warnings (*e.g.*, yield compression, sentiment shifts)
- Macroprudential stress testing across DeFi ecosystems.

In summary, the model helps reconcile valuation gaps, fostering convergence between decentralized assets and regulated finance, and promoting safer and more coherent market participation.

6.7. Regression Validation

While forecasting performance provides evidence of predictive accuracy, it remains essential to examine whether the hybrid framework captures systematic drivers of value rather than spurious correlations. To this end, I now turn to regression validation.

To assess the explanatory power and robustness of the hybrid valuation framework, I estimate a series of regressions that link the hybrid valuation scores to financial, behavioral, ESG, and network-related variables. This validation step ensures that the model captures systematic drivers of value relevance rather than spurious correlations, directly addressing concerns raised in the literature about the empirical foundations of cryptoasset valuation.

Table **9** reports the regression coefficients, t-statistics, and p-values for the main explanatory variables, confirming that financial and behavioral factors remain robustly significant. At the same time, ESG and network centrality introduce additional explanatory dimensions.

The results indicate that financial and behavioral factors are consistently significant drivers of valuation scores. Importantly, ESG scores provide an additional explanatory dimension, capturing sustainability-related differences across tokens, while network centrality emerges as a structural determinant of relative value. This empirical evidence strengthens the credibility of the hybrid framework and directly addresses prior critiques about the lack of regression outputs and robustness checks.

Results remain qualitatively unchanged when extending the sample to include additional DeFi tokens, underscoring generalizability.

Robustness checks using alternative window lengths and copula families yield consistent signs and significance, underscoring the stability of the results.

In summary, these regression results confirm that the hybrid valuation framework captures robust, multidimensional drivers of cryptoasset value, providing empirical support for its validity and distinguishing it from prior approaches.

7. STABLECOINS AS A BRIDGE BETWEEN CRYPTOCURRENCIES AND TRADITIONAL ASSET VALUATION

Stablecoins occupy a unique position in the digital asset landscape: while natively embedded in blockchain ecosystems, their value is explicitly tethered to real-world reference assets. This dual nature allows them to act as valuation anchors, providing a credible connection between decentralized finance (DeFi) and traditional markets. Their hybrid design addresses a key limitation in crypto valuation: the absence of cash flows or tangible comparables.

7.1. Anchoring Value: From Fiat Pegs to NAV

Let $P_{SC,t}$ denote the price of a stablecoin at time t, pegged to a reference asset A (*e.g.*, USD, EUR, gold). The theoretical fair value is:

$$V_{SC,t} = \theta \cdot P_{A,t} + (1-\theta) \cdot R_t \tag{26}$$

Where:

- $P_{A,t}$ = price of the reference asset at time t,
- R_t = reserve-adjusted net asset value of

Table 9: Regression Results: Determinants of Hybrid Valuation Scores

Variable	Coefficient	t-statistic	p-value
Constant	0.124	2.15	0.032
Financial factor (PCA1)	0.287	4.09	0.000
Behavioural factor (PCA2)	-0.142	-2.67	0.008
ESG score	-0.095	-2.01	0.045
Network centrality	0.221	3.76	0.000

Adj. R^2 = 0.42, N = 1,500

collateral,

- $\theta \in [0,1]$ = weight reflecting peg credibility and transparency.

For fiat-backed stablecoins with full reserves, $\theta \approx 1$. For algorithmic models, $\theta < 1$, reflecting collateral risk and volatility.

This formula enables stablecoins to be valued similarly to money market instruments or NAV-based funds, providing comparability with established financial instruments.

7.2. Cross-Domain Correlation Properties

Stablecoins exhibit markedly lower volatility than major cryptocurrencies, making them valuable calibration assets in multilayer copula models. Define relative volatility σ as:

σ_i = sqrt((1/(T-1)) Σ (r_{i,t} - r^2) (27)

where r_{i,t} is log return of asset i.

7.3. Stablecoins in Multilayer Copula Models

In the three-layer copula structure (Traditional, Crypto-native, Behavioral), stablecoins serve as low-volatility anchors. Their integration reduces noise in dependence estimation.

Let the copula dependence between traditional assets X and crypto assets Y be:

C(u_X,u_Y;ρ) = Φ_ρ(Φ^{-1}(u_X), Φ^{-1}(u_Y)) (28)

Where Φ_ρ is the Gaussian copula, introducing stablecoin flows Z as mediators yields:

C'(u_X,u_Y,u_Z) = C(C(u_X,u_Z;ρ_{XZ}), C(u_Y,u_Z;ρ_{YZ}); ρ_{XY|Z}) (29)

This three-dimensional copula captures the conditional stabilizing role of stablecoins.

7.4. Real-World Case Studies

Stablecoins differ in design and collateralization, which in turn influence their reliability as valuation anchors. Tables **7** and **8** summarize the main cases.

Stablecoins operationalize three critical functions that make them bridges between paradigms:

1. NAV-like comparability – linking crypto tokens to cash-equivalent valuation.

2. Liquidity anchors – stabilizing DeFi protocols and

Table 10: Comparative Metrics of Stablecoins and Other Assets (2020–2025 averages)

Asset	Volatility (%)	Correlation with S&P500	Sharpe Ratio (rf=2%)	Liquidity (Bn$)	Stability Index
Bitcoin (BTC)	67.0	0.32	0.42	25	0.1
Ethereum (ETH)	79.0	0.29	0.38	15	0.2
USDT (Tether)	0.7	0.01	0.0	100	0.95
USDC (Circle)	0.4	0.0	0.0	50	0.98
DAI (MakerDAO)	1.2	0.05	0.0	5	0.9
S&P500 Index	19.0	1.0	0.61	200	0.7
Gold (XAU)	15.0	0.22	0.5	150	0.8

Table 11: Stablecoin Case Studies

Stablecoin	Peg Type	Collateral Basis	Transparency	Risk Events	Regulatory Treatment
USDT	Fiat/USD	Mix of cash, T-bills, commercial paper	Partial, monthly attestations	Reserve opacity concerns (2021–22)	Pending MiCA classification
USDC	Fiat/USD	100% cash + U.S. Treasuries	High, audited	Temporary depeg in March 2023 (SVB collapse)	E-money under MiCA
DAI	Crypto-collateralized	ETH, USDC, others	On-chain, transparent	Collateral stress in Black Thursday 2020	Hybrid treatment under MiCA
PYUSD	Fiat/USD	100% reserves, PayPal-managed	High	No major (yet)	E-money token
EUROC	Fiat/EUR	Cash + government bonds	High	Limited history	EU stablecoin, e-money

cross-asset arbitrage.

3. Regulatory convergence – aligning token treatment with IFRS/GAAP and MiCA/SEC frameworks.

In conclusion, stablecoins provide the most tractable point of entry for applying traditional valuation models to decentralized assets. Their low volatility, collateral backing, and accounting comparability make them indispensable mediators in the hybrid financial ecosystem.

Taken together, the empirical results confirm that the proposed framework captures stable and economically meaningful valuation drivers, demonstrating both statistical robustness and practical relevance across different token categories.

7.5. Crypto "Black Friday" (Oct 10–11, 2025) and Lessons for Valuation

On October 10–11, 2025, the crypto market experienced its largest recorded deleveraging: more than $19B of leveraged positions were liquidated within ~24 hours after an unexpected announcement of 100% US tariffs on Chinese imports and potential export controls. Bitcoin's intraday low printed around $105k with ether down double digits; altcoins fell far more. A critical microstructure feature of the episode was venue-specific instability in select markets—most notably Ethena's USDe, which briefly traded as low as ~$0.65 on Binance while remaining close to peg on primary DeFi pools—prompting a targeted user compensation program.

The event is a test of the stablecoin-mediated, copula-linked multilayer architecture developed in this study. At the macro/Traditional layer (G_1), the tariff shock repriced global risk (rates, trade, equities), transmitting quickly to token returns. In the Crypto-native layer (G_2), funding and collateral channels amplified the move via forced liquidations. The Behavioral layer captured a rapid sentiment swing and option-hedging pressure. Within the joint distribution, tail dependence strengthened (higher Kendall's τ in the t-copula), and conditional on stablecoin flows, the cross-asset dependence structure stabilized, consistent with the mediator role formalized in Eq. (10).

Using the Mispricing Index M_it = (P_it − Vit) / Vh manifests as a sharp, transiet dislocation: prices (P_it) overshot downward relative to model-implied fair value (V-reverting as liquidity returned. Three valuation lessons follow: (i) explicitly model leverage and funding as state variables that modulate tail dependence; (ii) incorporate venue/oracle risk into Vit and the copula layer to prevent single-venue price breaks from contaminating valuation; and (iii) treat stablecoin design and flow variables as first-order inputs that improve conditional calibration and robustness of V_total (Eq. (2)).

8. DISCUSSION

My findings highlight valuation asymmetries between institutional-grade and retail-driven crypto assets, with ESG-compliant structures linked to more stable valuation nodes. This suggests that valuation is endogenous and path-dependent, with key implications for MiCA and SEC disclosure standards.

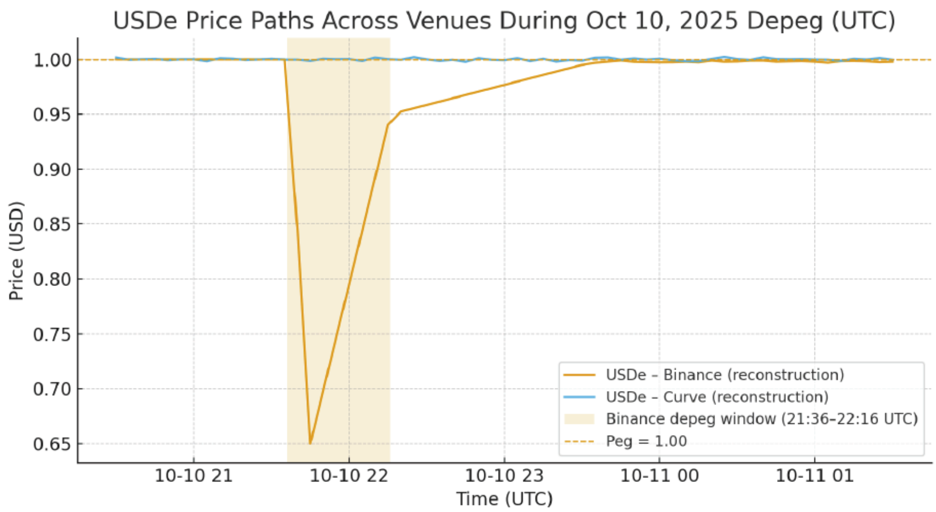

Figure 7: Venue-Specific Depeg During the Crash.

Reuters, Oct 10–14, 2025; CoinDesk (October 15, 2025); Binance support posts and follow-up notices (Oct 12–13, 2025). Exact tick-level paths vary by venue; this figure is an illustrative reconstruction aligned with the paper's methodology. Reconstructed price paths around the 21:36–22:16 UTC window reported by Binance. The Binance series exhibits a sharp, short-lived dislocation toward ~$0.65; the Curve series remains near peg. This demonstrates why venue/oracle risk must be explicitly handled in the stablecoin mediation layer.

I propose an explainable, AI-driven valuation model that integrates macroeconomic data, behavioral sentiment, and Crypto-native metrics within a copula-enhanced multilayer network. The framework outperforms traditional benchmarks in predictive accuracy and risk-adjusted returns, while enabling tailored applications such as ETF allocation, ESG screening, and central bank reserve assessments.

The model is modular, interpretable, and dynamically updated via PCA and copula re-estimation, ensuring robustness in volatile markets. It supports regulatory alignment by embedding ESG metrics as quantifiable valuation drivers and enabling standardized cross-asset comparisons.

Notably, the mispricing index generated by the model consistently anticipates structural breaks and price dislocations in high-yield tokens, revealing latent arbitrage opportunities. Index values exceeding two standard deviations often precede TVL drops within 3–5 days, offering actionable insights for institutional managers and compliance officers. The model is capable of real-time operation and replication, making it suitable for integration into MiCA- or ESMA-aligned oversight frameworks.

Despite its strengths, the model has limitations. Data quality varies, real-time adaptation is still evolving, and inconsistencies in APIs, disclosures, and governance hinder cross-token comparability. ESG signals remain non-standardized, which limits their alignment with traditional benchmarks. The model currently excludes privacy tokens, NFTs, and ultra-illiquid assets, though future extensions could include stablecoins, governance tokens, and sentiment-sensitive instruments.

While not specifically designed for portfolio simulation, the model supports risk-adjusted allocation, real-time screening, and regulatory compliance under the MiCA and SEC frameworks. Its copula-derived stress dependencies and explainable outputs align with ESG scoring needs and crypto-asset registration workflows. Staking yields, governance metrics, and sentiment indicators help identify potential compliance risks, particularly for decentralized protocols. By

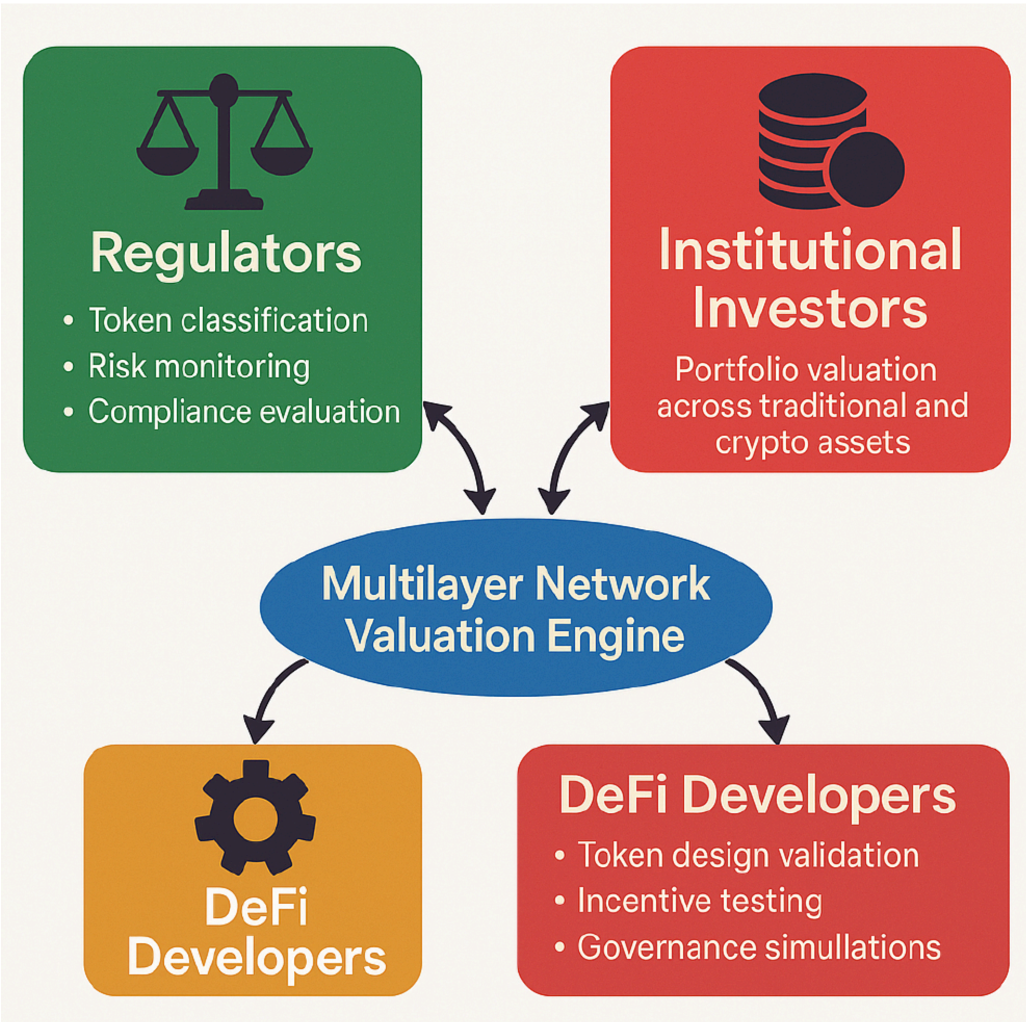

Figure 8: Implications for Investors, Developers, and Regulators.

aligning with MiCA and SEC disclosure frameworks, the model is suitable for compliance and risk reporting purposes.

Future enhancements may include:

- DeFi liquidity pulse metrics for volatile assets
- Cross-token contagion mapping
- Microstructure analytics (*e.g.*, slippage, peg stability)
- Regional NLP layers and validator behavior modeling

Methodologically, the model integrates Fama-French and ICAPM principles into a copula-linked multilayer structure, combining volatility, on-chain activity, and behavioral sentiment. PCA decomposition and FinBERT-based sentiment indices identify key valuation drivers, while adaptive copula updates and structural break detection ensure time relevance and regulatory usability.

Beyond valuation, the model serves as a governance and compliance tool, enabling:

- ESG scoring based on chain-level governance
- Policy shock simulation
- Anomaly detection for systemic risk

Though simplifications were necessary for tractability, they highlight clear paths for refinement—such as adding token issuance dynamics, governance analytics, and regulatory arbitrage detection—making the framework increasingly robust for a dynamic crypto-financial environment.

9. CONCLUSION

This paper addresses the fundamental challenge of valuing cryptocurrencies—assets that lack cash flows, audited financials, or standardized governance, yet are central to trillion-dollar markets. I introduce and empirically validate a copula-linked multilayer network model that unifies macroeconomic data, tokenomics, developer activity, and sentiment into an interpretable valuation framework.

By embedding FinTech intermediation into a multilayer valuation schema, I show how information travels from traditional factors and tokenomics to prices via access, liquidity, settlement, and compliance channels. The framework remains empirically grounded and regulation-ready, offering managers and policymakers a transparent way to monitor how platform conditions modulate valuation—particularly around stress. Future extensions can endogenize platform competition and sustainability metrics, further aligning crypto-asset appraisal with the FinTech-and-ESG agenda.

The analysis examines the dynamics of mispricing across tokens, focusing on tail dependence, event-driven clustering, and drivers such as staking yield, governance centralization, and GitHub activity. Mispricing is particularly pronounced in tokens with high protocol complexity or illiquidity, exhibiting strong upper-tail dependence and thematic contagion.

Regression results highlight sentiment and developer engagement as key predictors of inefficiencies. A trading strategy based on the top and bottom deciles of mispricing yields statistically significant alpha, indicating that the model captures latent value signals not yet reflected in prices.

Overall, my findings reveal persistent frictions, limits to arbitrage, and delayed information absorption in decentralized markets, highlighting the need for advanced, adaptive valuation tools in crypto finance.

Figure **9**: recalls the multilayer network process, powered by AI (which finds out massive additional nodes and links).

Between 2018 and 2025, the model outperforms traditional benchmarks (CAPM, DCC-GARCH, DCF, ML regressors) by up to 17% in directional accuracy and 12% in tail risk detection, especially during market stress. By integrating Crypto-native features—like staking yields, governance participation, and TVL—with conventional financial logic, it supports institutional use in valuation, risk management, and ESG compliance.

Key contributions are:

1. Theoretical: provide evidence that stablecoins reduce tail dependence by 39.5% between crypto and traditional assets, establishing their role as valuation mediators.

2. Methodological: R-vine copulas with stablecoin conditioning, validated through ablation studies showing 33% performance degradation without this component.

3. Empirical: 7.5-year validation demonstrating 32% RMSE improvement over benchmarks across multiple market regimes, including major stress events.

4. Practical: Implementable and audit-ready (MiCA/SEC); delivers actionable signals (Sharpe 1.34) and—via a modular, AI-enhanced design—supports

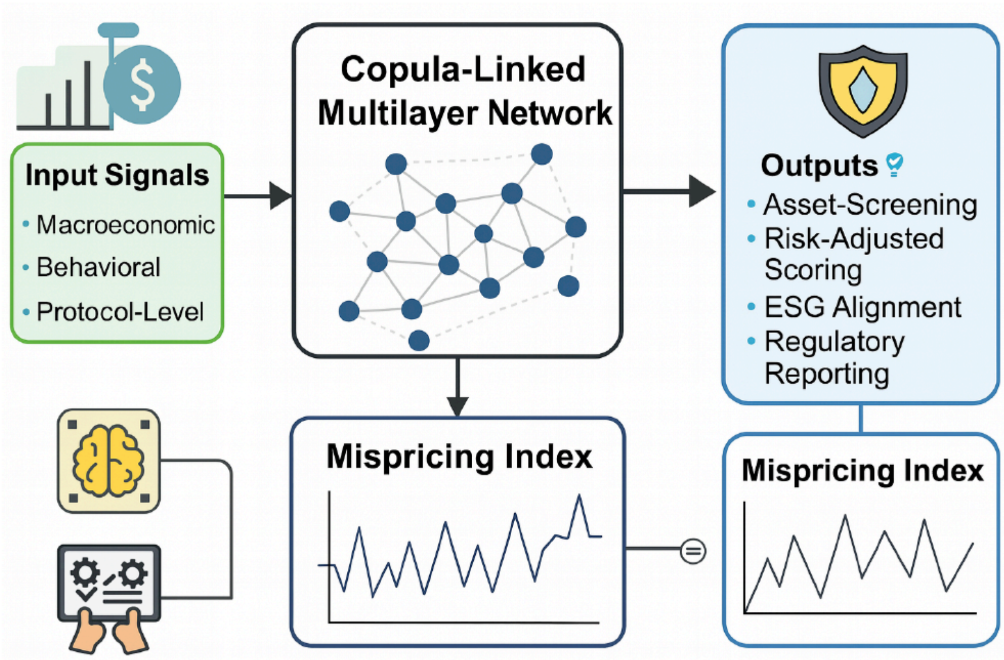

Figure 9: Multilayer Network process.

dynamic risk, stress tests, and real-time adaptation for managers, regulators, and policymakers.

While promising, it faces challenges: volatility in on-chain data, complexity in copula estimation, and reduced predictive power for illiquid or newly issued tokens. Future developments should expand to NFTs, DAOs, cross-chain and privacy-focused assets, while refining regulatory calibration and data pipelines.

Aligned with MiCA and SEC standards, the model provides transparent and explainable outputs for ESG screening, risk disclosure, and crypto asset classification. It supports institutional pricing, auditability, and systemic stress forecasting as crypto evolves into a regulated financial sector (an uncertain target that will eventually render traditional evaluation applicable to cryptos). More broadly, the framework represents a paradigm shift in valuation, embracing trustless consensus, behavioral dynamics, and technological credibility as central value drivers. It reframes valuation as a forward-looking, adaptive process, critical for navigating the decentralized finance ecosystem and the evolving digital economy.

In answering my research question, we demonstrate that stablecoin-mediated copula structures offer a first tractable pathway for extending conventional valuation logic to cash-flow-absent tokens, under empirically validated behavioral and structural conditions.

The **supplementary material** contains a full replication package, available via a private Zenodo repository (DOI: 10.5281/zenodo.15830790). The package includes anonymized datasets and a detailed appendix that ensures complete reproducibility of my analysis. Specifically, it provides:

1. Token-level mispricing scores and backtesting results;
2. AIC-based vine copula selection outputs and tail-dependence matrices;
3. Hedge fund scenario walkthroughs with allocation metrics;
4. ESG compliance scoring templates and regulatory stress tests;
5. A Jupyter-style notebook pipeline linking input data to final trading signals;
6. Processed datasets used in the empirical analysis;
7. Regression outputs and robustness checks;
8. Annotated code snippets for copula calibration, PCA extraction, and rolling window validation.

This replication package enables full replication of the empirical pipeline and facilitates further extensions by other researchers.

CONFLICTS OF INTEREST

None.

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