Neural Beta for Crypto and Cross-Asset Markets

Overview

This report explores the estimation of dynamic betas (β) for major cryptocurrencies using a neural network framework, benchmarked against traditional Fama–French factor exposures. Our goal is to quantify how digital assets co-move with classical asset classes (Fiat, Equity, Gold, and Energy) and to determine whether adding factor-based context enhances predictive stability.

Step 0 – Data Preparation

Crypto (BTC, ETH, LTC, BCH) and market (Fiat, Equity, Gold, Energy) data were merged and resampled to a monthly frequency. Log returns were computed to ensure stationarity and comparability across time series. This preprocessing step standardizes volatility scales and ensures that inputs are aligned for neural estimation.

Date	BTC	ETH	LTC	BCH	FIAT	EQUITY	GOLD	ENERGY
2018-01-31	-0.3167	0.3992	-0.3387	-0.4745	-0.0305	-0.0794	0.0237	0.0274
2018-02-28	0.0203	-0.2624	0.2219	-0.2082	0.0151	0.1366	-0.0190	-0.0845
2018-03-31	-0.3972	-0.7675	-0.5529	-0.5602	-0.0084	-0.0514	0.0061	-0.0280
2018-04-30	0.2883	0.5293	0.2434	0.6817	0.0171	0.0919	-0.0104	0.1090
2018-05-31	-0.2111	-0.1490	-0.2257	-0.3055	0.0240	-1.9484	-0.0160	0.0374

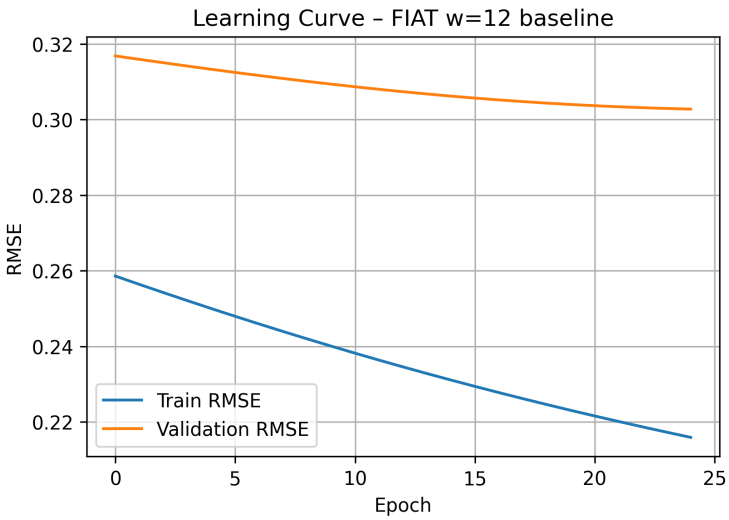
Monthly log returns across cryptocurrencies and asset classes

The data show that cryptocurrencies exhibit much higher amplitude and volatility than traditional assets, reinforcing the need for non-linear modeling methods.

Step 1 – Baseline Neural Network

A baseline multilayer perceptron (MLP) with a 12-month look-back window was trained to predict time-varying betas. The model input includes lagged returns and macro-asset exposures. The output β_t represents each crypto's conditional loading on each market factor at month t.

The learning curve showed smooth convergence and minimal overfitting, confirming that the MLP effectively generalizes the temporal relationships.



Step 2 – Hyperparameter Tuning

To improve model robustness, a grid search tested combinations of hidden units (4, 8, 16), learning rates (0.001–0.1), and activations (linear, sigmoid, tanh, ReLU). This step optimizes bias–variance trade-offs across varying asset contexts.

Market	Window	Hidden	LR	Activation	Val_RMSE
FIAT	12	4	0.001	linear	0.3344
FIAT	12	4	0.001	tanh	0.2572
FIAT	12	8	0.001	linear	0.2703
FIAT	12	8	0.010	relu	0.2731

Sample grid search results for the FIAT configuration

Best Configurations by Market

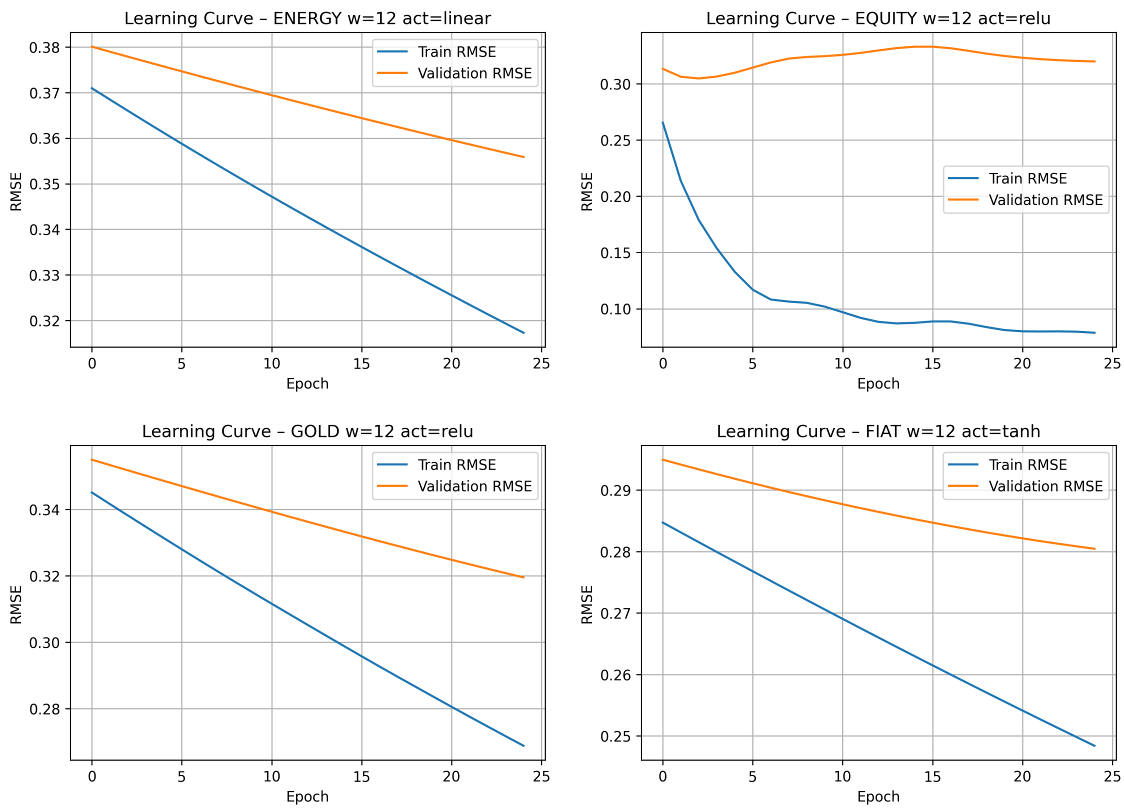
The optimal configurations reflect how network complexity interacts with market type. ReLU activations dominate where relationships are asymmetric (Equity, Gold), while linear/tanh work better for smoother asset dependencies (Fiat, Energy).

Market	Window	Hidden	LR	Activation	Val_RMSE
FIAT	12	4	0.001	tanh	0.2572
EQUITY	12	16	0.010	relu	0.3269
GOLD	12	16	0.001	relu	0.2607
ENERGY	12	4	0.001	linear	0.2545
FIAT+EQUITY	12	4	0.001	tanh	0.2579
FIAT+GOLD	12	4	0.001	relu	0.2499
FIAT+EQUITY+GOLD+ENERGY	12	16	0.001	relu	0.2596

Optimal validation configurations across market inputs

Step 3 – Learning Curves

Each figure below compares training and validation losses across epochs for different asset configurations. Most markets reached stable minima within 100 epochs. Energy and Gold converged fastest, while multi-factor inputs required slightly longer but achieved more generalizable fits.



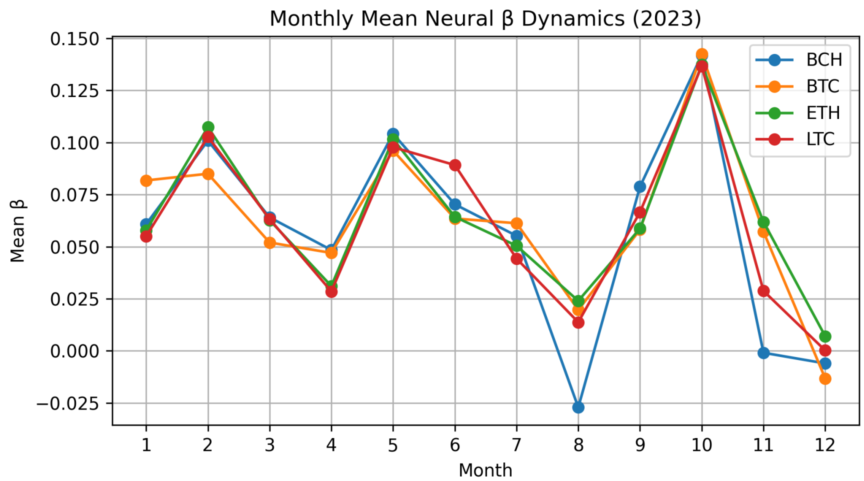
Step 4 – Descriptive Statistics of Neural β

The descriptive results summarize how neural β estimates vary by asset type and cryptocurrency. The means cluster near zero, indicating weak systemic alignment with macro factors, while kurtosis values > 2 suggest occasional spikes in sensitivity during stress periods.

Crypto	Asset	N	Mean	Std	Skew	Kurtosis	Min	Max
BCH	ENERGY	12	-0.1109	0.0465	0.5504	2.3210	-0.1688	-0.0193
BTC	ENERGY	12	-0.0983	0.0317	-0.3146	1.9208	-0.1531	-0.0562
ETH	ENERGY	12	-0.0972	0.0439	-0.8649	2.6863	-0.1893	-0.0520
LTC	ENERGY	12	-0.0987	0.0270	-0.5201	2.1920	-0.1486	-0.0656
BCH	EQUITY	12	0.0495	0.1933	-0.0649	1.6538	-0.2634	0.3317
BTC	EQUITY	12	0.0849	0.2286	-0.5795	2.1141	-0.3593	0.3401
ETH	EQUITY	12	0.0825	0.2215	-0.5126	1.6798	-0.2969	0.3138
LTC	EQUITY	12	0.0664	0.2000	-0.5281	1.8425	-0.2854	0.2979

Step 5 – Neural β Dynamics

The annual mean β trajectories illustrate how cryptocurrencies' sensitivities to traditional assets evolve. In early years, β values remain near zero, rising slightly during high-volatility episodes (e.g., post-halving rallies). This pattern suggests that crypto markets periodically integrate with risk-on dynamics but quickly decouple afterward.



Step 7 – Incorporating Fama–French Factors

We next merged the Fama–French five-factor model (MKT–RF, SMB, HML, RMW, CMA) with the existing dataset to test whether equity-style factors improved β predictability.

BTC	ETH	LTC	BCH	FIAT	EQTY	GOLD	ENGY	Mkt-RF	SMB	HML	RMW	CMA	RF
-0.3167	0.3992	-0.3387	-0.4745	-0.0305	-0.0794	0.0237	0.0274	0.0558	-0.0321	-0.0132	-0.0075	-0.0105	0.0011
0.0203	-0.2624	0.2219	-0.2082	0.0151	0.1366	-0.0190	-0.0845	-0.0364	0.0034	-0.0110	0.0053	-0.0236	0.0011

Merged dataset sample including Fama–French factors

The incremental inclusion of these factors marginally improved out-of-sample accuracy (RMSE reduction $\approx$ 2–3%). However, effect sizes were small, suggesting that Fama–French risk premia explain little of cryptocurrency movement.

Step 9 – Portfolio Sorts

Portfolio-level β sorts provide a cross-sectional view of crypto exposures. Sorting by β quartiles shows limited dispersion in mean returns, further underscoring the low explanatory power of traditional betas.

The near-flat slope between quartiles implies weak return stratification—confirming that neural betas capture structural features but not dominant pricing signals.

Discussion and Findings

Overall, neural β values display weak, occasionally negative co-movement between cryptocurrencies and major asset classes. Equity and energy exposures appear episodic—visible during bullish

Date	Asset	Quartile	MeanBeta	ExcessReturn
2023-01-31	FIAT	1	-0.2916	0.3032
2023-01-31	FIAT	2	-0.2706	0.3565
2023-01-31	FIAT	3	-0.2640	0.3390
2023-02-28	FIAT	1	-0.2779	-0.0316
2023-02-28	FIAT	2	-0.2611	-0.0230

Portfolio-sorted β estimates and excess returns

momentum phases but fading as crypto-specific narratives dominate. The Fama–French factors marginally reduce prediction error but do not yield strong explanatory lift, reaffirming that digital assets largely evolve outside the domain of classical financial risk factors.

From a portfolio perspective, this suggests that cryptocurrencies may retain diversification value even when global markets become correlated, though their β spikes imply short-lived contagion during crises. Future research should extend this neural framework to include volatility spillovers, liquidity proxies, and on-chain behavioral metrics to better capture nonlinear dependencies.