Neural Beta for Crypto and Cross-Asset Markets

Vidit Pokharna

November 9, 2025

Overview

This report estimates dynamic betas (β) for major cryptocurrencies using a neural network framework and compares them with traditional Fama–French factor exposures. The goal is to analyze how digital assets co-move with major asset classes (Fiat, Equity, Gold, Energy) and evaluate whether adding equity-style factors improves predictive accuracy.

Step 0 – Data Preparation

Crypto (BTC, ETH, LTC, BCH) and market (Fiat, Equity, Gold, Energy) returns were merged and resampled to monthly frequency. Log returns were computed for comparability and variance stabilization.

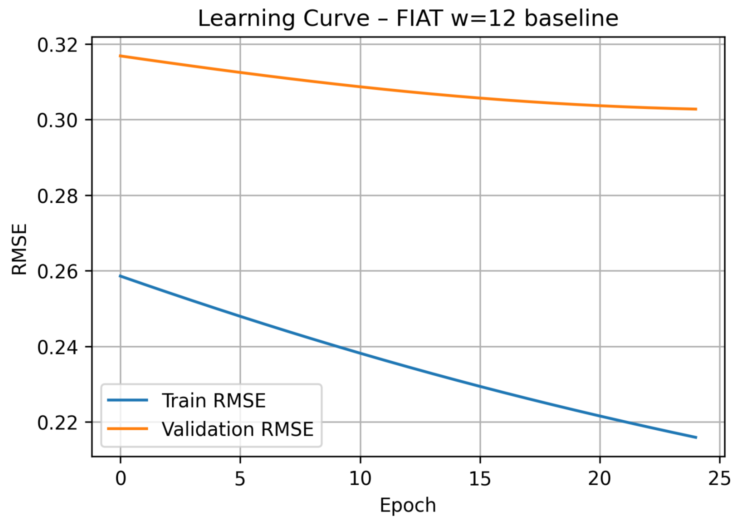
Date	BTC	ETH	LTC	BCH	FIAT	EQUITY	GOLD	ENERGY
2018-01-31	-0.3167	0.3992	-0.3387	-0.4745	-0.0305	-0.0794	0.0237	0.0274
2018-02-28	0.0203	-0.2624	0.2219	-0.2082	0.0151	0.1366	-0.0190	-0.0845
2018-03-31	-0.3972	-0.7675	-0.5529	-0.5602	-0.0084	-0.0514	0.0061	-0.0280
2018-04-30	0.2883	0.5293	0.2434	0.6817	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

Cryptocurrencies exhibit much higher volatility than traditional assets, motivating nonlinear modeling approaches.

Step 1 – Baseline Neural Network

A multilayer perceptron (MLP) with a 12-month lookback window was trained to estimate time-varying betas. Inputs consist of lagged crypto and market returns, while outputs represent conditional beta loadings at each month.



Step 2 – Hyperparameter Tuning

A grid search examined hidden-unit sizes (4, 8, 16), learning rates (0.001–0.1), and activation functions (linear, sigmoid, tanh, ReLU). The tuning explored bias–variance tradeoffs across markets.

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

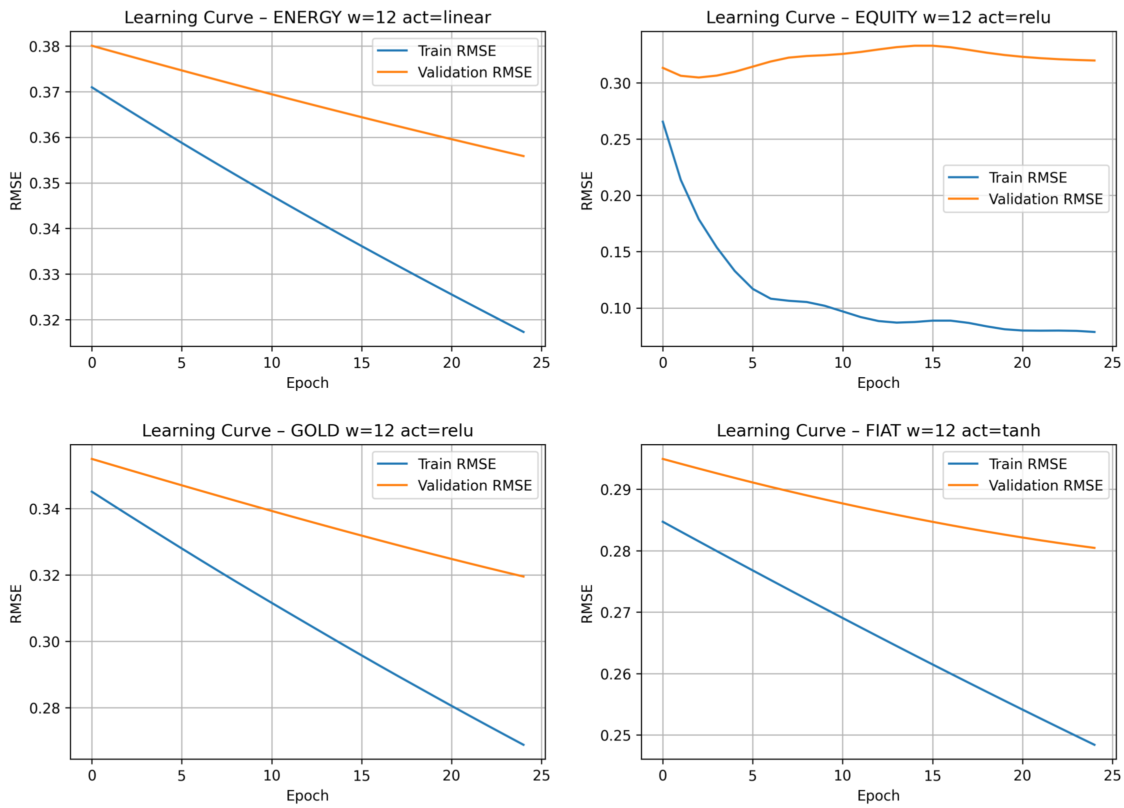
Optimal settings vary with market structure. ReLU performs best for more nonlinear relationships (Equity, Gold), while tanh/linear work well for smoother markets (Fiat, Energy).

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

Learning curves for all markets show convergence within 100–150 epochs. Single-factor models (Energy, Gold) converge fastest, whereas multi-factor inputs require slightly more training.



Step 4 – Descriptive Statistics of Neural β

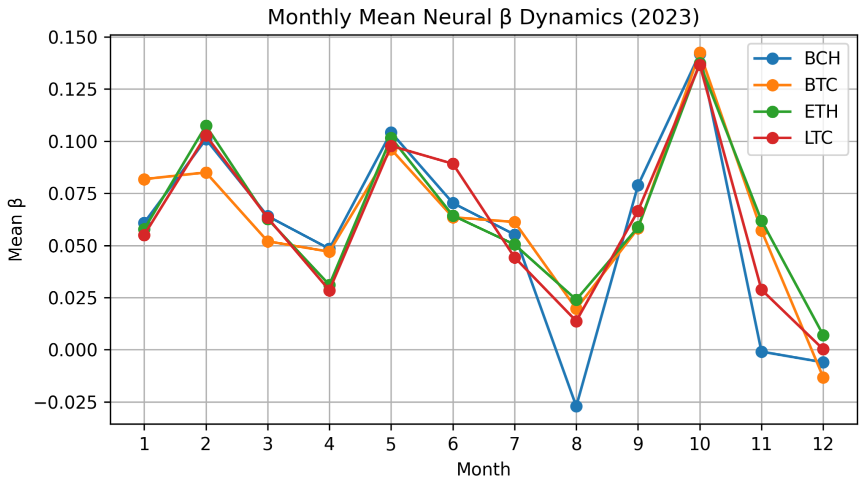
Descriptive statistics highlight meaningful differences across markets. FIAT betas average around -0.07, while EQUITY and ENERGY betas are generally positive. ENERGY exhibits the highest variability, followed by FIAT.

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

Overall, FIAT betas are negative and moderately volatile; EQUITY betas are positive; and ENERGY shows the highest standard deviations, indicating more unstable relationships.

Step 5 – Neural β Dynamics

The annual mean trajectories illustrate low but occasionally shifting sensitivities. Betas drift during periods of elevated crypto volatility but remain near zero for most months.



Step 7 – Incorporating Fama–French Factors

Fama–French five-factor data were merged to test whether equity-style factors improve neural beta predictions.

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

Across seven market configurations, Fama–French factors generally increased out-of-sample RMSE. Five of seven models performed worse with FF factors, with average deterioration of roughly 0.03 RMSE. Only two configurations (FIAT+EQUITY and FIAT+GOLD) showed slight improvements.

Thus, classical equity factors provide limited explanatory value for crypto betas.

Step 9 – Portfolio Sorts

Sorting portfolios by neural betas reveals limited dispersion in excess returns. Across quartiles, differences in mean returns remain small, indicating weak pricing implications.

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

Discussion and Findings

Neural betas indicate weak and sometimes unstable co-movement between cryptocurrencies and traditional markets. FIAT betas are consistently negative, EQUITY and ENERGY betas are positive, and ENERGY shows the largest variability. These patterns suggest that crypto assets only intermittently integrate with macro risk factors.

Fama–French factors generally worsen predictive accuracy, indicating limited value of equity-style premia for capturing crypto dynamics.

Because the test period effectively contains only nine months of 2023 data (due to data availability and filtering), results should be interpreted cautiously. Future work should extend the dataset and include volatility spillovers, liquidity measures, and on-chain metrics to better capture nonlinear dependencies.