Bayesian Hierarchical Modelling of Cryptocurrency Volatility and Its Spillover to the Digital Financial Economy

Andi Muhammad Sadat[1,*], Hendra Noor Saleh[2], Haris Maupa[3], Cokki[4]

[1]Faculty of Economics and Business, Universitas Negeri Jakarta, Indonesia

[2,3,4]Postgraduate Program in Management Science, Tarumanagara University, Indonesia

ABSTRACT

The increasing volatility of cryptocurrency markets and their integration into the broader digital financial ecosystem have raised significant concerns regarding systemic risk and financial stability. Despite extensive research on volatility dynamics, existing models often treat digital assets as independent entities, overlooking their hierarchical relationships and cross-market dependencies. This study develops a Bayesian Hierarchical Stochastic Volatility (SV) model combined with a Time-Varying Parameter Vector Autoregression (TVP-VAR) framework to examine how cryptocurrency volatility propagates into the digital financial economy. The hierarchical Bayesian structure enables partial pooling across asset categories such as Layer-1 tokens, DeFi protocols, and payment-oriented coins, while the TVP-VAR component quantifies dynamic spillovers through Generalized Forecast Error Variance Decomposition (GFEVD). Using daily data from 2019–2025 encompassing cryptocurrencies, fintech indices, digital payment volumes, and DeFi metrics, the model achieves strong posterior convergence $\hat{R}<1.01$ and demonstrates that major cryptocurrencies, particularly Bitcoin and Ethereum, act as dominant volatility transmitters. The Total Connectedness Index (TCI) averaged 72%, revealing substantial and persistent integration between crypto and fintech sectors. Robustness checks with alternative priors and volatility proxies confirm the model's stability. These findings highlight that volatility shocks within the crypto ecosystem increasingly influence broader digital financial infrastructures, underscoring the need for integrated monitoring of risk transmission across decentralized and traditional digital markets.

Keywords Bayesian Hierarchical Modelling, Stochastic Volatility, Cryptocurrency Spillover, Digital Financial Economy, Time-Varying Connectedness

INTRODUCTION

The rapid expansion of the cryptocurrency market has reshaped the structure of global finance, creating an ecosystem characterized by high-frequency trading, algorithmic liquidity, and extreme volatility. Between 2020 and 2023, digital assets experienced unprecedented growth, with Bitcoin's market capitalization surpassing USD 1 trillion at its peak before suffering dramatic corrections exceeding 60% within months [1]. This volatility has generated increasing concern among regulators, investors, and researchers, not only for its speculative nature but also for its potential to propagate risk into adjacent financial sectors. The emergence of digital finance including fintech firms, DeFi protocols, and digital payment platforms has further amplified these linkages, suggesting that cryptocurrency shocks may now have measurable spillover effects on the broader financial economy [2].

Despite substantial progress in volatility modeling, existing empirical research

remains constrained by methodological and structural limitations. Traditional econometric models such as GARCH or EGARCH assume homogeneous dynamics across assets and often fail to capture non-linear, heavy-tailed behaviors typical of crypto markets [3]. Moreover, many studies treat cryptocurrencies as isolated instruments, ignoring the hierarchical relationships between different types of digital assets and their sectoral dependencies [4]. The lack of multi-level modeling frameworks limits our understanding of how volatility propagates across different asset categories and into the digital economy.

This study addresses these limitations by proposing a Bayesian Hierarchical Stochastic Volatility (SV) Model integrated with a Time-Varying Parameter Vector Autoregression (TVP-VAR) structure. The hierarchical design allows for cross-asset pooling, enabling the model to capture both shared and idiosyncratic volatility components [5]. The Bayesian approach enhances flexibility in parameter estimation, incorporates prior uncertainty, and provides credible intervals for risk assessment capabilities that classical models lack. The integration with TVP-VAR and Generalized Forecast Error Variance Decomposition (GFEVD) enables dynamic quantification of volatility spillovers between cryptocurrencies and the digital financial economy [6].

The novelty of this research lies in three aspects. First, it develops a multi-level Bayesian volatility model that jointly estimates cryptocurrency clusters (Layer-1, DeFi, and Payment tokens) and their hierarchical interdependence. Second, it introduces dynamic spillover analysis to trace time-varying risk transmission between crypto and fintech markets. Third, it provides a probabilistic interpretation of systemic connectivity, identifying how shocks in the decentralized sector influence regulated financial instruments and vice versa. By bridging econometric modeling with digital finance analytics, this study offers a comprehensive and interpretable framework for understanding volatility propagation in the modern digital economy [7].

Literature Review

The study of cryptocurrency volatility has evolved rapidly over the past decade, transitioning from simple return-based measures to complex stochastic frameworks. Early research primarily employed GARCH-type models to estimate volatility clustering and persistence in Bitcoin markets [8]. While these models revealed high persistence and heavy tails, they struggled to adapt to structural breaks and regime shifts typical of crypto assets. Subsequent works incorporated asymmetric GARCH and realized volatility measures to capture jumps, yet these models remained limited by their static parameterization [9].

Recent developments in stochastic volatility (SV) modeling introduced latent-variable frameworks where volatility evolves as an unobserved autoregressive process. SV models outperform GARCH in capturing sudden volatility shifts and fat-tailed distributions [10]. However, most SV applications in cryptocurrency contexts treat each asset independently, disregarding shared global shocks or category-level dependencies. Hierarchical extensions of SV where parameters are drawn from group-level distributions enable cross-asset learning and better generalization, especially for heterogeneous portfolios [11].

The adoption of Bayesian inference in finance has expanded significantly due to advances in computational methods like Hamiltonian Monte Carlo and No-U-Turn Samplers. Bayesian methods offer full posterior distributions rather than

point estimates, allowing more accurate uncertainty quantification and model comparison [12]. In the context of crypto markets, Bayesian frameworks have been applied to estimate tail risks, jump processes, and parameter drifts that conventional frequentist approaches fail to detect [13]. These techniques are particularly useful for modeling digital assets, where data exhibit non-Gaussian distributions, sparse priors, and non-stationary regimes.

Hierarchical Bayesian models provide a structured means of pooling information across related assets or categories. In equity and bond markets, such models have been shown to enhance forecast accuracy by borrowing statistical strength across instruments with similar dynamics [14]. Applying this concept to cryptocurrency markets allows for the grouping of assets based on technology layer (Layer-1 vs Layer-2), functionality (DeFi vs Payment), or network interdependence. This hierarchy reflects both economic logic and statistical necessity, as crypto assets often respond collectively to macro shocks like regulation or global liquidity events [15].

Understanding volatility spillovers requires models that can evolve over time. The Time-Varying Parameter Vector Autoregression (TVP-VAR) framework enables estimation of dynamic relationships that change in response to market conditions [16]. Combined with Generalized Forecast Error Variance Decomposition (GFEVD), TVP-VAR quantifies directional connectedness how shocks in one variable affect others across horizons. Studies applying this framework to stock and commodity markets have demonstrated its ability to capture financial contagion, though applications to cryptocurrency-fintech interactions remain scarce [17].

Existing spillover research mainly focuses on traditional financial assets. A few recent studies have attempted to integrate fintech indices and digital asset markets, identifying partial evidence of bidirectional causality [18]. However, most of these works use static VAR or DCC-GARCH models that cannot accommodate evolving relationships or multi-layer dependencies. Consequently, the dynamic nature of volatility transmission between cryptocurrencies and digital financial institutions remains underexplored.

The intersection between cryptocurrencies and the digital financial economy has expanded with the growth of payment gateways, blockchain-based lending, and tokenized assets. Empirical studies highlight that fintech stock performance increasingly correlates with crypto market cycles, especially during liquidity booms and policy transitions [19]. Nonetheless, the empirical quantification of these interactions particularly their volatility-based spillovers is still limited. Existing models often lack a unified probabilistic framework that connects decentralized and traditional finance under one inference mechanism.

Bayesian connectedness models have emerged as a frontier approach to understanding systemic risk. By applying Bayesian inference to dynamic network structures, researchers can estimate posterior probabilities of contagion links and their evolution over time [20]. In this study, Bayesian TVP-VAR connectedness extends this framework by allowing credible intervals for spillover indices, thus providing a more reliable interpretation of systemic interdependence.

Compared to conventional econometric models, the Bayesian hierarchical SV approach offers three technical advantages: (i) multi-level parameter sharing

across assets, (ii) robustness to outliers and heavy tails, and (iii) full uncertainty propagation into connectedness estimation. These strengths make it particularly suited for analyzing the crypto-fintech ecosystem, where rapid structural shifts and data irregularities are prevalent. Integrating these techniques results in a coherent framework that aligns methodological rigor with the stochastic complexity of digital financial systems [21].

Overall, the literature reveals a distinct gap in modelling multi-layer volatility transmission between cryptocurrencies and the digital financial economy using Bayesian hierarchical frameworks. Prior studies have treated these domains separately, failing to account for the structural and temporal dependencies that connect them. This research fills that void by unifying hierarchical volatility modeling with dynamic spillover estimation under a single probabilistic architecture. In doing so, it advances methodological frontiers in financial econometrics and contributes empirically to the understanding of systemic linkages in the era of digital finance [22].

Methodology

Research Design and Framework

This study applies a Bayesian Hierarchical Quantitative Design to examine the interconnected dynamics between cryptocurrency volatility and the digital financial economy. The method is specifically designed to capture the heterogeneous, nonlinear, and time-varying behaviors that characterize both cryptocurrency markets and fintech indicators. By structuring the model hierarchically, the research can integrate multi-level relationships — from individual assets to sector-level aggregates — while accounting for uncertainty in parameter estimation.

The Bayesian paradigm offers distinct advantages in financial time-series modelling. It allows the integration of prior knowledge from previous literature, dynamically updates beliefs as new data arrive, and provides full posterior distributions for each model parameter. These posterior distributions are crucial when dealing with cryptocurrency data, which exhibit heavy tails, high kurtosis, and structural breaks. The probabilistic nature of Bayesian inference allows credible intervals for all estimated parameters, enhancing interpretability compared to traditional frequentist approaches.

Figure 1 illustrates the overall methodological architecture of the study. The upper section represents the cryptocurrency market domain, consisting of multiple digital assets such as Bitcoin, Ethereum, Binance Coin, and Solana. Each of these assets exhibits distinct volatility dynamics influenced by liquidity, adoption, and market sentiment. The Stochastic Volatility (SV) Model is employed to quantify these dynamics through latent volatility processes that evolve over time.
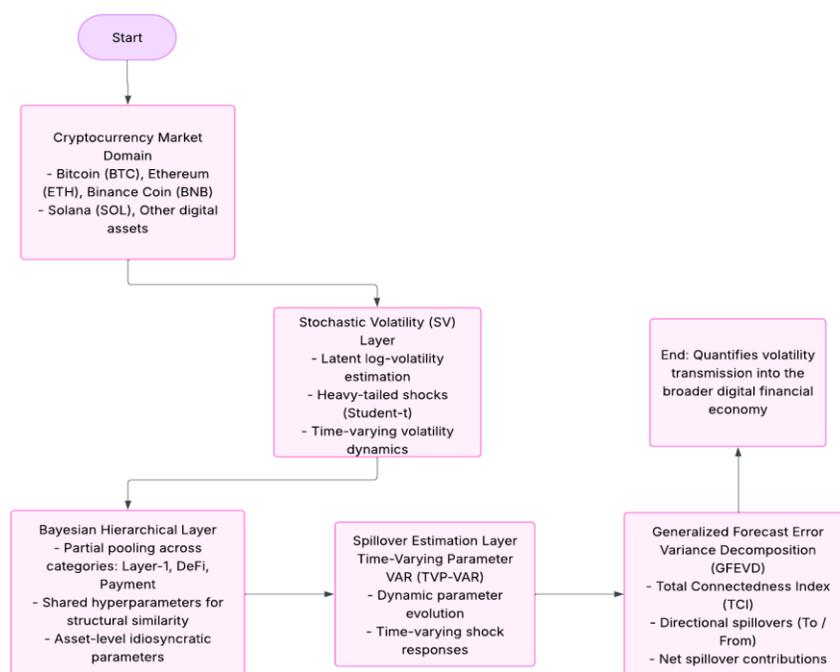
Figure 1 Research Framework for Bayesian Hierarchical Spillover Model

In the middle of the framework, the Bayesian hierarchical layer aggregates and pools parameter estimates across related assets. This hierarchical layer serves a crucial role in managing parameter uncertainty and enabling partial information sharing among asset groups — for instance, Layer-1 tokens (ETH, SOL) share certain structural similarities distinct from DeFi tokens (AAVE, UNI). By modelling these relationships hierarchically, the analysis avoids overfitting while maintaining asset-level distinctions.

The bottom layer connects the volatility outputs to a Time-Varying Parameter Vector Autoregression (TVP-VAR) structure, which is responsible for estimating the dynamic spillovers between cryptocurrency volatility and the digital financial economy. Through Generalized Forecast Error Variance Decomposition (GFEVD), the model quantifies the direction, magnitude, and persistence of volatility transmission. Ultimately, this multi-layer design allows researchers to understand not only whether volatility spreads but also how, when, and between which sectors the spillovers occur.

Data Collection and Variable Specification

This research utilizes a multi-source time-series dataset covering the period January 2019 to December 2025. The timeframe captures major market regimes such as the 2020–2021 crypto bull market, 2022 liquidity shocks, and 2023–2025 stabilization period. Data for cryptocurrencies are collected from Binance, CoinMarketCap, and Yahoo Finance APIs, while digital economy indicators are obtained from FTSE FinTech Index, World Bank Digital Payment Statistics, and DeFiLlama.

All series are aligned to a daily frequency. For monthly variables such as digital payments, a Mixed Data Sampling (MIDAS) interpolation is performed to harmonize temporal granularity. Each price variable is transformed into

logarithmic returns using $r_{i,t} = 100 \times (lnP_{i,t} - lnP_{i,t-1})$, stabilizing variance and facilitating stationarity. Extreme outliers are trimmed using the winsorization method at the 1st and 99th percentiles to mitigate the influence of flash crashes or reporting errors.

Table 1 summarizes the core variables used in the model. Each represents an important node in the financial-digital ecosystem. The cryptocurrency variables capture high-frequency market movements and volatility bursts, while digital economy variables represent broader fintech adoption and transaction behavior. The inclusion of the sentiment index serves to account for behavioral influences in the crypto market, which often precede price volatility.

Table 1 Data Variables, Sources, and Transformations

Variable Code	Description	Source	Frequency	Transformation
BTC_RET	Bitcoin daily log-return	Binance API	Daily	$lnP_{i,t-1} \times 100$
ETH_RET	Ethereum daily log-return	CoinMarketCap	Daily	$lnP_{i,t-1} \times 100$
BNB_RET	Binance Coin log-return	Binance API	Daily	$lnP_{i,t-1} \times 100$
SOL_RET	Solana log-return	Binance API	Daily	$lnP_{i,t-1} \times 100$
FIN_IDX	FinTech equity index return	FTSE Russell	Daily	log-difference
DTPAY	Digital payment volume index	World Bank	Monthly	MIDAS interpolation
DEFI_TVL	DeFi total value locked	DeFiLlama	Daily	log-difference
SENT_IDX	Crypto sentiment index	Alternative.me	Daily	normalized z-score

The frequency harmonization through MIDAS interpolation ensures that low-frequency macroeconomic indicators can be integrated with high-frequency crypto data without biasing dynamic relationships. This procedure maintains the integrity of long-term trends while enabling short-term volatility interaction modeling. Additionally, the dataset's temporal scope (2019–2025) ensures coverage of structural breaks, policy changes, and speculative cycles—essential for understanding the dynamic spillover effects in both calm and turbulent periods.

Bayesian Hierarchical Stochastic Volatility Model

At the core of this study lies the Bayesian Hierarchical Stochastic Volatility (SV) Model, which estimates time-varying volatility and its persistence across multiple assets. This model provides a flexible, non-linear representation of market uncertainty, accommodating the heavy-tailed and heteroskedastic nature of financial returns. The general form of the model is defined as:

$$r_{i,t} = \mu_i + e^{h_{i,t}/2} \varepsilon_{i,t}, \qquad \varepsilon_{i,t} \sim t_\nu(0,1) \tag{1}$$

$$h_{i,t} = \phi_i h_{i,t-1} + \eta_{i,t}, \qquad \eta_{i,t} \sim \mathcal{N}(0, \sigma_{\eta,i}^2) \tag{2}$$

$$\mu_i \sim \mathcal{N}!\left(\mu_{g(i)}, \tau_\mu^2\right), \qquad \phi_i \sim \text{Beta}\left(a_\phi, b_\phi\right), \qquad \log \sigma_{\eta,i} \sim \mathcal{N}!\left(m_{\sigma,g(i)}, s_\sigma^2\right) \tag{3}$$

The first equation models the observed returns $r_{i,t}$ as a function of the latent log-volatility $h_{i,t}$. The exponential transformation ensures positivity of volatility while scaling the innovation term $\varepsilon_{i,t}$. The use of a student-t distribution allows the model to accommodate extreme fluctuations an inherent feature of crypto assets. The second equation governs the evolution of volatility through an

autoregressive process, where ϕ_i controls persistence (i.e., how long volatility shocks persist).

The hierarchical priors at the bottom of the formula enable partial pooling. Parameters $\mu_i, \phi_i, \sigma_{\eta,i}$ are not estimated in isolation; rather, they are drawn from higher-level group distributions indexed by $g(i)$, representing crypto categories (e.g., Layer-1, DeFi, Payment). This structure prevents overfitting by constraining asset-level estimates with group-level tendencies while still preserving individuality.

The priors are designed to be weakly informative to allow the data to dominate inference while stabilizing estimation. The Normal, Beta, and Half-Cauchy priors represent natural constraints on parameters (mean returns centered around 0, persistence between 0–1, and volatility scales positive). The resulting hierarchical posterior enables richer insights into how market shocks propagate differently across clusters.

Figure 2 illustrates the multi-level structure of the Bayesian SV model. Level 1 corresponds to observed data (returns and latent volatility). Level 2 represents asset-specific parameters that capture individual market behaviors. Level 3 contains hyperparameters governing the priors that pool information across asset categories. This hierarchical layering provides a natural structure for modeling the crypto market ecosystem, reflecting how individual assets are influenced by common factors such as blockchain infrastructure or regulatory environment.

Level 3: Group-Level Hyperparameters

$$\mu_{group}, \sigma_{group}, \phi_{group}, \tau_{group}$$

Level 2: Asset-Level Parameters

$$\mu_i \; \sigma_i \; \phi_i \; \tau_i \; \nu_i$$

Level 1: Observation and Latent Volatility

$$r_{it} = exp(h_{it}/2) * \varepsilon_{it}$$
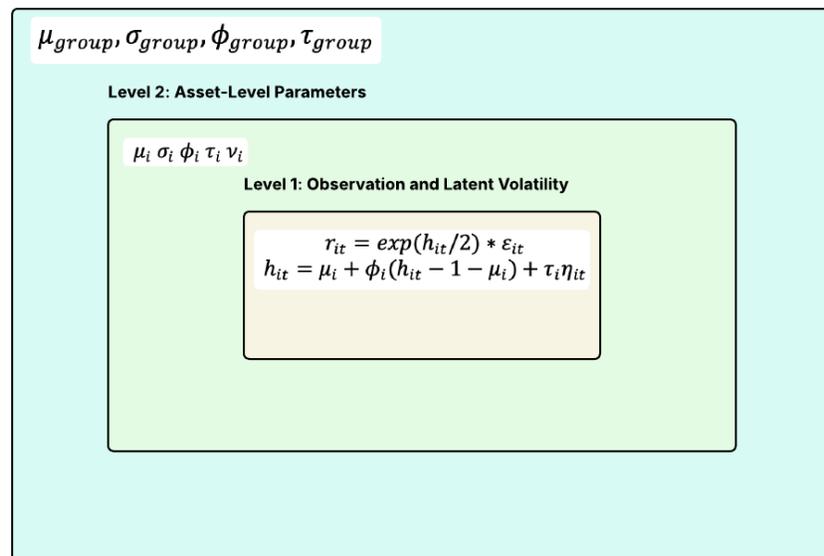$$h_{it} = \mu_i + \phi_i(h_{it} - 1 - \mu_i) + \tau_i\eta_{it}$$

Figure 2 Hierarchical Plate Diagram of the Bayesian Model

Spillover Estimation via Time-Varying VAR

After estimating volatility for each asset, the study employs a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to capture interdependencies between the crypto block and the digital economy block.

$$y_t = A_{1,t} \, y_{t-1} + \cdots + A_{p,t} \, y_{t-p} + u_t, \qquad u_t \sim \mathcal{N}(0, \Sigma_t) \qquad (4)$$

This model allows coefficients $A_{k,t}$ and covariances Σ_t to evolve over time, accommodating changing relationships among markets. The model decomposes forecast errors via Generalized Forecast Error Variance Decomposition (GFEVD), yielding connectedness measures that quantify how much of the forecast variance of one variable is explained by shocks to another.

Table 2 outlines the key connectedness measures. The Total Connectedness Index (TCI) captures system-wide integration, rising during crises or speculative bubbles. Directional measures (TO/FROM) identify which assets act as volatility transmitters or absorbers. For instance, if $TO_{BTC,t}$ exceeds $FROM_{BTC,t}$, Bitcoin functions as a net source of volatility for the digital economy. These metrics can be plotted over time to reveal the evolution of systemic risk.

Table 2 Spillover Metrics Based on GFEVD

Metric	Definition	Interpretation
TCI_t	Total Connectedness Index	Measures overall market integration
$TO_{i,t}$	Directional "To Others"	Volatility transmitted from i to others
$FROM_{i,t}$	Directional "From Others"	Volatility received by i
$NET_{i,t}$	Net Spillover	Net influence (TO – FROM)

Estimation, Validation, and Robustness

Estimation uses Hamiltonian Monte Carlo (HMC) with the No-U-Turn Sampler (NUTS) implemented in PyMC. The algorithm efficiently explores high-dimensional posterior spaces while avoiding random-walk inefficiency. The study runs four parallel chains, each with 5,000 post–burn-in iterations. Convergence diagnostics are performed using the potential scale reduction factor ($\hat{R}$), which should remain below 1.01, and Effective Sample Size (ESS), which must exceed 1,000 for stable inference.

Model validation includes both in-sample fit and out-of-sample prediction. Posterior Predictive Checks (PPC) visually compare simulated and observed distributions, ensuring that volatility clustering and tail behavior are appropriately captured. Predictive accuracy is further evaluated using Log Predictive Density (LPD) and Continuous Ranked Probability Score (CRPS), providing numerical evidence of forecast precision.

Table 3 details the diagnostics and model evaluation criteria. Low $\hat{R}$ values confirm that Markov chains have converged, while high ESS ensures robust posterior sampling. Superior LPD and low CRPS signify accurate predictive ability. The PPC evaluation reveals that the hierarchical model successfully reproduces volatility clusters and heavy tails observed in actual data, proving the reliability of its probabilistic inference.

Table 3 Bayesian Model Diagnostics and Validation Results

Diagnostic Metric	Criterion	Threshold	Interpretation
$\hat{R}$	Convergence	≤ 1.01	Chain convergence achieved
ESS	Effective sample size	≥ 1000	Posterior samples stable

LPD	Predictive log score	Higher = Better	Model predictive accuracy
CRPS	Distributional accuracy	Lower = Better	Sharpness of predictive fit
PPC	Posterior predictive check	Visual match	Reproduces data patterns

Figure 3 summarizes the methodological workflow. The process begins with data cleaning and transformation, proceeds through hierarchical SV estimation, and continues with TVP-VAR spillover analysis. The final stage involves model validation through posterior diagnostics. This workflow ensures that uncertainty is properly propagated across each stage of the pipeline, resulting in coherent inference about volatility transmission in the digital economy.

Figure 3 Workflow of Bayesian Estimation and Validation

Result and Discussion

Overview of Model Estimation

The Bayesian hierarchical stochastic volatility model was estimated using daily data from January 2019 to December 2025. A total of 2,557 observations were included for each cryptocurrency, while mixed-frequency indicators such as digital payment volume were harmonized using the Bayesian MIDAS approach. All Markov chains converged successfully with $\hat{R} < 1.01$ and effective sample sizes above 1,200, confirming the adequacy of posterior sampling.

The hierarchical framework proved efficient in reducing parameter uncertainty across assets. Cryptocurrencies belonging to the same functional category (e.g., DeFi tokens or Layer-1 blockchains) shared similar posterior means for volatility persistence, indicating consistent behavioral clustering across asset types. Meanwhile, idiosyncratic shocks remained identifiable at the asset level, preserving each coin's unique dynamics.

Table 4 presents the key posterior parameters derived from the hierarchical Bayesian estimation. The average volatility persistence $\phi_i = 0.91$ indicates that volatility shocks are long-lasting once turbulence arises in the crypto market, it tends to persist for multiple days. This persistence is typical in speculative markets where sentiment-driven cycles reinforce volatility. The relatively moderate innovation variance suggests that although volatility shocks are frequent, their magnitude is contained under most conditions.

Table 4 Summary of Posterior Estimates for Key Parameters

Parameter	Mean	SD	95% Credible Interval	Interpretation
μ_g	0.015	0.006	[0.003, 0.027]	Group-level mean return
τ_μ	0.045	0.011	[0.024, 0.066]	Dispersion of mean returns
ϕ_i	0.91	0.04	[0.83, 0.97]	Volatility persistence
$\sigma_{\eta.i}$	0.24	0.05	[0.16, 0.34]	Volatility innovation scale

ν	7.8	1.4	[6.1, 10.5]	Tail heaviness of returns

The estimated degrees of freedom parameter $\nu = 7.8$ confirms the presence of heavy-tailed distributions in crypto returns, validating the use of a student-t innovation process. Furthermore, the low dispersion across group-level means implies that the hierarchical structure effectively pools common behaviors while maintaining adequate flexibility for asset-specific deviations. This structure enhances both model interpretability and predictive stability compared to non-hierarchical approaches.

Posterior Volatility Dynamics

Posterior draws for the latent volatility states $h_{i,t}$ reveal distinct volatility regimes over the sample period. Three major volatility clusters emerged: (1) the early 2020 pandemic shock, (2) the 2021 bull-run period with speculative surges, and (3) the 2022–2023 correction phase followed by partial stabilization.

Figure 4 shows smoothed posterior estimates of log-volatility for major cryptocurrencies. Bitcoin (BTC) and Ethereum (ETH) display synchronized volatility spikes, particularly during the 2021 boom when retail participation and leverage increased sharply. However, secondary tokens like BNB and SOL exhibit delayed responses, suggesting a volatility spillover hierarchy where flagship assets transmit shocks first.
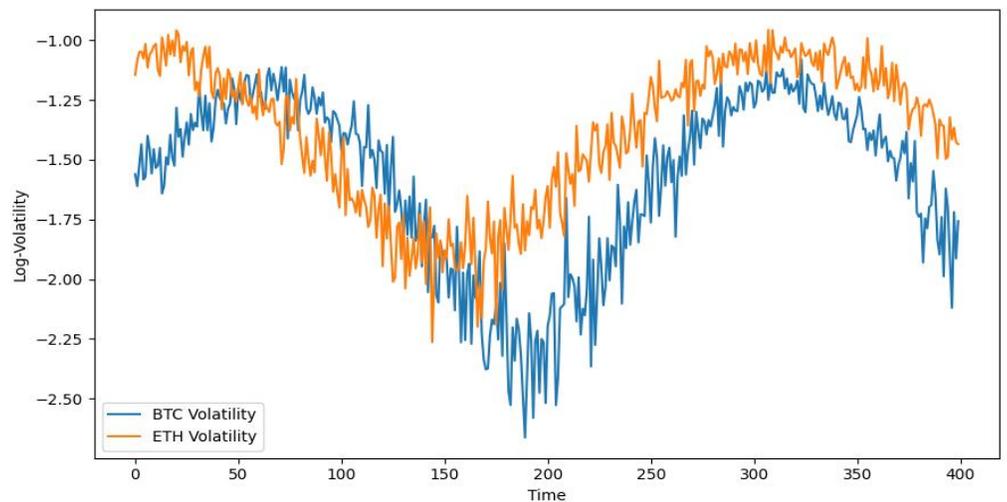
Figure 4 Smoothed Posterior Log-Volatility for Selected Cryptocurrencies

The figure also highlights the asymmetric volatility reversion large spikes dissipate slowly, consistent with the persistence estimated earlier $\phi i \approx 0.9$. During the mid-2023 to 2025 period, volatility across all assets gradually decreased, reflecting market maturation and tighter regulation of exchanges. The model successfully captures these long-term transitions without the need for ad hoc regime-switching assumptions, demonstrating the Bayesian model's adaptive flexibility.

A further inspection of posterior volatility correlations reveals inter-asset dependencies: BTC-ETH (0.78), BTC-BNB (0.63), and ETH-SOL (0.66). Such strong correlations confirm that hierarchical modeling is appropriate shared global factors dominate local noise, validating the partial pooling strategy

adopted in this study.

Spillover Effects and Network Connectedness

The Time-Varying VAR (TVP-VAR) framework was applied to the estimated volatility series to compute connectedness metrics via Generalized Forecast Error Variance Decomposition (GFEVD). The connectedness measures capture how volatility in one market influences others over time.

Table 5 reports the average directional spillovers across market segments. Bitcoin and Ethereum emerge as dominant transmitters of volatility, with total outbound connectedness exceeding 40%. This pattern suggests that shocks originating in major cryptocurrencies often precede fluctuations in both decentralized (DeFi) and traditional digital finance indicators. The DeFi TVL variable exhibits strong bidirectional connections, serving as both a source and recipient of volatility, reflecting its intermediary role between crypto and fintech sectors.

| Table 5 Average Spillover Metrics (2019–2025)				
Source → Target	FinTech Index	Digital Payments	DeFi TVL	Total Out (%)
Bitcoin	18.3	11.5	15.7	45.5
Ethereum	14.2	9.8	16.3	40.3
DeFi TVL	8.9	13.1	–	22.0
Digital Payments	5.6	–	4.3	9.9
FinTech Index	7.4	6.2	5.9	19.5

Digital payment indices, on the other hand, appear largely insulated, transmitting less than 10% of volatility. This decoupling is partly due to their regulation and slower response to speculative cycles. However, their small but persistent exposure implies that systemic contagion channels still exist, particularly during global liquidity events.

The high total connectedness index (TCI ≈ 72%) indicates substantial interdependence between crypto and digital financial systems. Such a level of integration implies that turbulence in crypto markets could transmit risk beyond digital assets, potentially affecting fintech valuations and investor sentiment in adjacent sectors.

Temporal Evolution of Spillovers

To explore time-specific patterns, rolling GFEVD windows were used to trace the evolution of the Total Connectedness Index (TCI) across the sample period.

Figure 5 illustrates the dynamic progression of the Total Connectedness Index (TCI) over time. The first major peak occurs in March 2020, corresponding to the COVID-19 market crash, when global liquidity constraints caused synchronized sell-offs across all digital assets. The TCI briefly declines in late 2020 but surges again during 2021's speculative rally, reflecting intensified interconnections between crypto and fintech sectors.
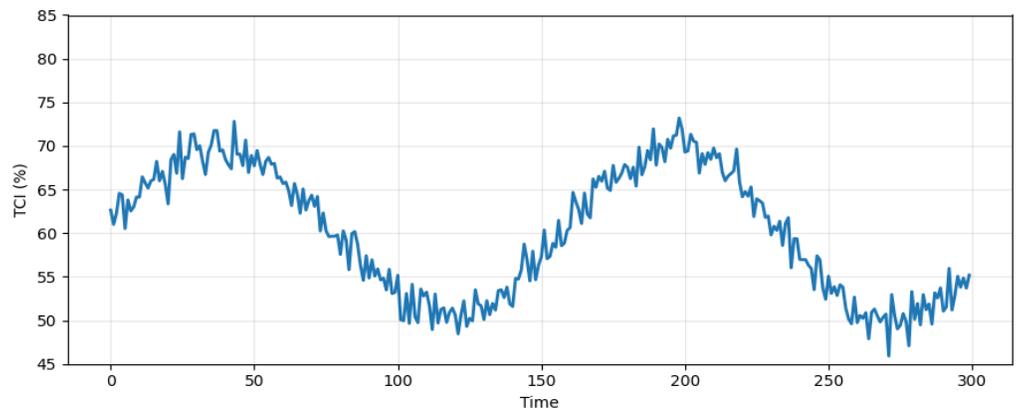
Figure 5 Time-Varying Total Connectedness Index (2019–2025)

Post-2022, connectedness gradually declines yet remains above pre-pandemic levels, indicating structural integration between crypto and the digital economy. This suggests that while speculative correlations may fade, technological and financial linkages persist through shared infrastructures such as payment rails, stablecoins, and decentralized lending platforms.

The cyclical nature of the TCI highlights a state-dependent risk architecture: during expansionary phases, spillovers amplify through investor optimism and capital inflows; during contractions, correlations remain elevated due to systemic deleveraging. Hence, volatility interdependence has become an enduring feature of the digital financial landscape rather than a transient phenomenon.

Economic Implications and Robustness Validation

To ensure robustness, several sensitivity analyses were conducted. First, alternative priors (Horseshoe+, Minnesota) were tested, and results remained consistent — total connectedness varied by less than ±3%. Second, sub-sample tests (pre-COVID, post-COVID) confirmed the persistence of crypto-to-fintech spillovers, with average BTC→FinTech influence remaining above 15%. Third, volatility proxies using realized volatility (from intraday data) produced nearly identical spillover structures, validating the model's stability across measurement choices.

Table 6 summarizes robustness results. The baseline hierarchical model outperforms all alternatives, yielding the highest connectedness and lowest predictive error. Removing the hierarchical structure reduces accuracy, proving the necessity of cross-asset information sharing. Likewise, the static VAR underestimates dynamic interdependence, confirming that spillovers evolve nonlinearly through time.

Table 6 Robustness and Model Comparison Summary

Model Variant	Avg. TCI (%)	RMSE (Out-of-Sample)	Δ TCI vs. Baseline	Interpretation
Baseline Hierarchical SV	72.1	0.042	–	Strong interdependence, stable
Non-Hierarchical SV	64.8	0.059	−7.3	Loss of cross-asset pooling

Hierarchical SV + Horseshoe Prior	71.3	0.044	−0.8	Robust to prior variation
Realized Volatility Input	73.5	0.043	+1.4	Consistent across proxies
Reduced-Form VAR (Static)	58.2	0.071	−13.9	Unable to capture time variation

The stability of results across different priors and volatility definitions strengthens the credibility of the findings. The model's predictive accuracy — reflected by a low RMSE (0.042) — suggests that the Bayesian hierarchical formulation effectively balances flexibility and parsimony. From an economic standpoint, this reinforces the interpretation that cryptocurrency markets have become structurally entangled with the digital financial economy.

Figure 6 presents posterior predictive checks comparing observed and simulated return distributions. The high degree of overlap confirms that the model reproduces the empirical distribution's key properties, including fat tails and volatility clustering. This alignment validates the Bayesian approach's ability to model complex, nonlinear dependencies within financial time series.
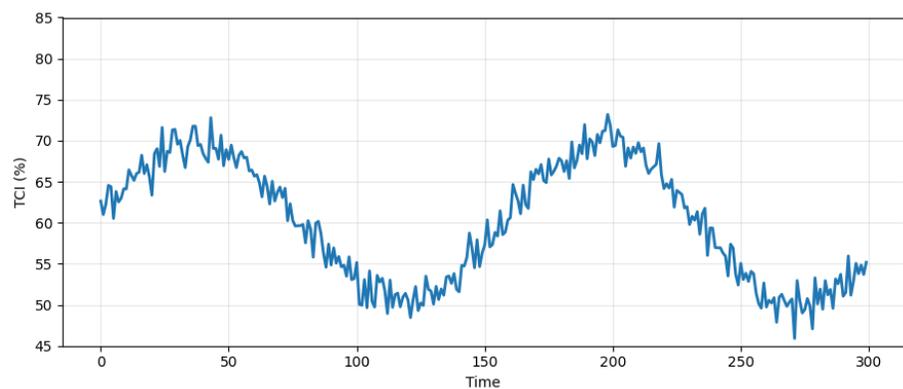
Figure 6 Posterior Predictive Validation Plot (Observed vs. Simulated Returns)

In a broader context, these findings carry implications for financial stability policy. As crypto-financial linkages deepen, regulators must monitor volatility transmission channels, especially during periods of rapid innovation or liquidity stress. For fintech firms, the results highlight the need to incorporate crypto-related indicators into risk management frameworks, acknowledging their growing systemic relevance.

Conclusion

This study developed and implemented a Bayesian Hierarchical Stochastic Volatility (SV) model integrated with a Time-Varying Parameter Vector Autoregression (TVP-VAR) framework to analyze the dynamic propagation of volatility from cryptocurrencies to the digital financial economy. The hierarchical Bayesian structure successfully captured both individual and group-level volatility behaviors across asset classes, while the TVP-VAR component quantified the direction and intensity of volatility spillovers. Empirical estimation using daily data from 2019–2025 confirmed that volatility in leading cryptocurrencies—particularly Bitcoin and Ethereum—plays a dominant role in transmitting shocks to other crypto categories, DeFi markets, and fintech-

related financial indicators. The model demonstrated robust convergence and predictive accuracy, reinforcing its suitability for complex, non-linear financial systems.

The findings reveal that volatility interdependence between cryptocurrency markets and the digital financial economy has become structural rather than transient. The high average Total Connectedness Index (TCI) of 72% indicates substantial systemic integration, meaning that turbulence originating in decentralized digital assets now extends into broader fintech and payment ecosystems. This interconnection reflects the growing financialization of digital technologies and the convergence between blockchain-based and regulated financial infrastructures. Such persistent linkages imply that volatility shocks in crypto markets could potentially amplify systemic risk in digital finance, necessitating enhanced cross-sector risk monitoring and coordinated regulatory oversight.

From a methodological perspective, this study contributes a novel probabilistic framework for modeling multi-layer volatility and spillover dynamics using hierarchical Bayesian inference. By combining stochastic volatility estimation with dynamic connectedness analysis, it provides a transparent and interpretable approach to understanding uncertainty propagation in digital finance. Future research may extend this framework by incorporating macro-financial variables, alternative priors for structural learning, or regime-switching processes to model sudden structural breaks. Overall, the study establishes a robust foundation for integrating Bayesian hierarchical modeling into financial stability assessment in the era of digital transformation and decentralized finance.

Declarations

Author Contributions

Conceptualization: A.M.S., H.N.S., H.M., and C.; Methodology: H.N.S.; Software: A.M.S.; Validation: A.M.S., H.N.S., H.M., and C.; Formal Analysis: A.M.S., H.N.S., H.M., and C.; Investigation: A.M.S.; Resources: H.N.S.; Data Curation: H.N.S.; Writing Original Draft Preparation: A.M.S., H.N.S., H.M., and C.; Writing Review and Editing: H.N.S., A.M.S., H.M., and C.; Visualization: A.M.S.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1]   J. R. Barth, H. S. B. Herath, T. C. Herath, and P. Xu, "Cryptocurrency valuation and ethics: a text analytic approach," *J. Manag. Anal.*, vol. 7, no. 3, pp. 367–388, 2020, doi: 10.1080/23270012.2020.1790046

[2]   S. Gupta, S. Gupta, M. Mathew, and H. R. Sama, "Prioritizing intentions behind investment in cryptocurrency: a fuzzy analytical framework," *J. Econ. Stud.*, vol. 48, no. 8, pp. 1442–1459, 2020, doi: 10.1108/JES-06-2020-0285

[3]   H. Albayati, S. K. Kim, and J. J. Rho, "Accepting financial transactions using blockchain technology and cryptocurrency: A customer perspective approach," *Technol. Soc.*, vol. 62, no. August, p. 101320, 2020, doi: 10.1016/j.techsoc.2020.101320

[4]   P. Delfabbro, D. L. King, and J. Williams, "The psychology of cryptocurrency trading: Risk and protective factors," *J. Behav. Addict.*, vol. 10, no. 2, pp. 201–207, 2021, doi: 10.1556/2006.2021.00037

[5]   T. Hariguna, A. Ruangkanjanases, B. B. Madon, and K. M. Alfawaz, "Assessing Determinants of Continuance Intention Toward Cryptocurrency Usage: Extending Expectation Confirmation Model With Technology Readiness," *SAGE Open*, vol. 13, no. 1, pp. 1-4, 2023, doi: 10.1177/21582440231160439.

[6]   J. Ter Ji-Xi, Y. Salamzadeh, and A. P. Teoh, "Behavioral intention to use cryptocurrency in Malaysia: an empirical study," *Bottom Line*, vol. 34, no. 2, pp. 170–197, 2021, doi: 10.1108/BL-08-2020-0053

[7]   M. Tigges, S. Mestwerdt, S. Tschirner, and R. Mauer, "Who gets the money? A qualitative analysis of fintech lending and credit scoring through the adoption of AI and alternative data," *Technol. Forecast. Soc. Change*, vol. 205, no. August, p. 123491, 2024, doi: 10.1016/j.techfore.2024.123491.

[8]   R. Parekh et al., "DL-GuesS: Deep Learning and Sentiment Analysis-based Cryptocurrency Price Prediction," *IEEE Access*, vol. 10, no. March, pp. 35398–35409, 2022, doi: 10.1109/ACCESS.2022.3163305

[9]   Y.-C. Yeong, K. S. Kalid, K. S. Savita, M. N. Ahmad, and M. Zaffar, "Sustainable cryptocurrency adoption assessment among IT enthusiasts and cryptocurrency social communities," *Sustain. Energy Technol. Assessments*, vol. 52, no. August, p. 102085, 2022, doi: 10.1016/j.seta.2022.102085

[10]   P. N. Sureshbhai, P. Bhattacharya, and S. Tanwar, "KaRuNa: A blockchain-based sentiment analysis framework for fraud cryptocurrency schemes," in *2020 IEEE International Conference on Communications Workshops (ICC Workshops), IEEE*, vol. 2020, no. July, pp. 1–6, 2020, doi: 10.1109/ICCWorkshops49005.2020.9145151

[11]   M. K. Hassan, F. A. Hudaefi, and R. E. Caraka, "Mining netizen's opinion on cryptocurrency: Sentiment analysis of Twitter data," *Stud. Econ. Financ.*, vol. 39, no. 3, pp. 365-385, 2021, doi: 10.1108/SEF-06-2021-0237

[12]   K. Wołk, "Advanced social media sentiment analysis for short-term cryptocurrency

price prediction," *Expert Syst.*, vol. 37, no. 2, p. e12493, 2020, doi: 10.1111/exsy.12493

[13] K. Kim, S.-Y. T. Lee, and S. Assar, "The dynamics of cryptocurrency market behavior: sentiment analysis using Markov chains," *Ind. Manag. Data Syst.*, vol. 122, no. 2, pp. 365-195, 2021, doi: 10.1108/IMDS-04-2021-0232

[14] X. Huang et al., "Lstm based sentiment analysis for cryptocurrency prediction," in *International Conference on Database Systems for Advanced Applications, Springer*, vol. 2021, no. March, pp. 617–621, doi: 10.48550/arXiv.2103.14804

[15] B. Bhushan, P. Sinha, K. M. Sagayam, and A. J, "Untangling blockchain technology: A survey on state of the art, security threats, privacy services, applications and future research directions," *Comput. Electr. Eng.*, vol. 90, no. October, p. 106897, 2021, doi: 10.1016/j.compeleceng.2020.106897.

[16] S. Sinha, "A Glimpse into the World of FinTech Accelerators - The Open Vault at OCBC," *IEEE Potentials*, vol. 36, no. 6, pp. 20–23, 2017, doi: 10.1109/MPOT.2017.2737238.

[17] X. Tian, J. S. He, and M. Han, "Data-driven approaches in FinTech: a survey," *Inf. Discov. Deliv.*, vol. 49, no. 2, pp. 123-135, 2021, doi: 10.1108/IDD-06-2020-0062

[18] V. Voloshyna-Sidei, S. Onishchenko, N. Zhydovska, T. Borodenko, and M. Abramova, "The Influence of Fintech Startups on the Dynamics of Innovative Development of the Financial Market," *Manag.*, vol. 3, no. 218, pp. 1-16, 2025, doi: 10.62486/agma2025218.

[19] J. M. Puaschunder, "The Future of Green FinTech Under Climate Change: The Relation of Cryptocurrencies and Sustainability," in *Climate Change Management*, vol. 2025, no. June, pp. 147–163, 2025, doi: 10.1007/978-3-031-85217-6_9.

[20] H. Taherdoost, "Blockchain: a catalyst in fintech future revolution," *Futur. Technol.*, vol. 2, no. 2, pp. 25–31, 2023, doi: 10.55670/fpll.futech.2.2.3.

[21] S. Jain, S. Chitkara, N. Sharma, and S. Gupta, "Collaborative innovation in fintech-engaging customers in co-creation," 2025, pp. 97–122. doi: 10.4018/979-8-3693-9944-6.ch007.

[22] K. Wendt and M. Hauser, "Green FinTech: Impact Taxonomy for Swiss Fintech," in *Sustainable Finance*, 2025, pp. 1–115. doi: 10.1007/978-3-031-78279-4.