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Gold-Backed Cryptocurrencies, Precious Metals, and Hedging Performance: Evidence from Dynamic Dependence Structures

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Abstract

This study compares gold-backed and conventional cryptocurrencies in terms of dependence structures and hedging effectiveness relative to precious metals. Daily data for gold, silver, cryptocurrencies, gold-backed cryptocurrencies, and USD-backed stablecoins from July 2020 to March 2026 are analyzed using a multivariate stochastic volatility framework with a grouped factor structure. Gold-backed cryptocurrencies move closely with gold and silver and provide meaningful hedging benefits. Conventional cryptocurrencies present weaker and less stable relationships with precious metals, reducing hedging potential. Important differences emerge between gold and silver, suggesting that precious metals should not be treated as a homogeneous asset class. Gold-backed cryptocurrencies appear much more closely aligned with precious metals than conventional cryptocurrencies. Additional analyses show that hedging effectiveness increases substantially during periods of elevated volatility, particularly for PAXG and XAUT, indicating stronger risk-reduction benefits under stressed market conditions. Robustness tests using SPDR Gold Shares (GLD) confirm the stability of the main findings. The findings are relevant for portfolio diversification, hedging decisions, and risk management.

Keywords: gold-backed cryptocurrencies; conventional cryptocurrencies; precious metals; dynamic dependence; hedging effectiveness; portfolio diversification; risk management; digital assets

1. Introduction

Gold-backed cryptocurrencies have emerged as a distinct segment of digital asset markets by combining blockchain-based trading with ownership claims linked to physical gold reserves. Unlike conventional cryptocurrencies, whose values are determined primarily by market demand and supply, gold-backed cryptocurrencies derive value from underlying gold holdings, combining characteristics of both precious metals and digital assets. Differences in reserve backing, custody arrangements, redemption provisions, transparency practices, and liquidity conditions may contribute to heterogeneous market behavior across issuers. Digix Gold Token (DGX), PAX Gold (PAXG), and Tether Gold (XAUT) are among the most widely recognized examples (Nefzi et al., 2026). The introduction of such instruments has increased access to gold through digital markets and contributed to the expansion of tokenized investment products (Hoque et al., 2024).

Gold is widely regarded as a hedge against financial uncertainty because of its liquidity, resilience during periods of market stress, and relatively weak correlation with

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traditional financial assets (Baur & Lucey, 2010; Baur & McDermott, 2016). Empirical results support this role, although the strength of hedging benefits varies across markets and crisis episodes (Baur, 2023; Fakhfekh et al., 2023). Silver occupies a different position in financial markets. In contrast to gold, silver has a substantial industrial component, with demand originating from sectors such as electronics, solar energy, and manufacturing. Consequently, silver prices are influenced not only by investment demand and uncertainty but also by changes in economic activity and industrial production. Such characteristics may lead to different responses to financial and geopolitical shocks and affect the diversification and hedging properties of silver relative to gold (Hillier et al., 2006; Reboredo, 2013). The contrasting characteristics of gold and silver suggest that precious metals cannot be viewed as a homogeneous asset class when assessing diversification and hedging opportunities. This distinction becomes relevant in the context of gold-backed cryptocurrencies, where exposure to precious metals is combined with participation in cryptocurrency markets.

Bitcoin and other major cryptocurrencies have attracted considerable attention as potential instruments for portfolio diversification and risk management. Comparisons with gold are common because both asset classes are often viewed as alternatives to traditional financial assets (Klein et al., 2018). Empirical evidence remains inconclusive. Diversification and hedging benefits have been documented under certain market conditions (Selmi et al., 2018; Huang et al., 2021; Jin & Tian, 2024). Results become less favorable during periods of financial stress. Other studies report unstable dependence patterns, substantial volatility spillovers, and limited protection against market downturns (Conlon & McGee, 2020; Sila et al., 2024). The conflicting evidence suggests that the role of conventional cryptocurrencies is highly sensitive to market conditions, providing limited support for a consistent safe-haven or hedging function.

Research on gold-backed cryptocurrencies remains relatively limited compared with the literature on conventional cryptocurrencies. Existing studies suggest that the connection to physical gold may generate diversification and hedging benefits that differ from those associated with conventional digital assets (Belguith et al., 2024). At the same time, findings vary considerably across market conditions and crisis episodes (Wasiuzzaman & Rahman, 2021). Concerns have also been raised regarding the stability of asset-backed digital instruments and their vulnerability to market disruptions (Grobys et al., 2021; Palazzi et al., 2025). Consequently, it remains uncertain whether gold-backed cryptocurrencies behave more like precious metals or conventional cryptocurrencies in terms of price movements and market dynamics.

Existing research has largely examined cryptocurrencies as a distinct asset class (Mokni et al., 2021; Sila et al., 2024). Similar attention has been devoted to precious metals, particularly gold and silver, in the context of diversification and hedging strategies (Li & Lucey, 2017; Caporale & Gil-Alana, 2023). Studies on gold-backed cryptocurrencies frequently focus on individual markets (Belguith et al., 2024), bilateral relationships between selected assets (Feng et al., 2024), or specific crisis episodes (Wasiuzzaman & Rahman, 2021). Stablecoins are also typically examined separately from both precious metals and gold-backed cryptocurrencies (Atik et al., 2025). Evidence is also limited regarding the sources of dependence among precious metals, conventional cryptocurrencies, gold-backed cryptocurrencies, and stablecoins. A comprehensive assessment of the dynamic relationships among precious metals, conventional cryptocurrencies, gold-backed cryptocurrencies, and stablecoins remains absent from the literature.

Dynamic relationships among precious metals, conventional cryptocurrencies, gold-backed cryptocurrencies, USD-backed stablecoins, and selected commodity and financial market indicators are examined over the period from July 2020 to March 2026. The sample covers major developments in digital asset markets together with episodes of heightened financial and geopolitical uncertainty. Stablecoins facilitate comparisons between gold-backed cryptocurrencies and digital assets designed to preserve value. Commodity and financial market indicators capture market conditions that may influence both traditional and digital assets. The analysis employs a multivariate stochastic volatility framework with a grouped factor structure (MSV-GFT). The model captures time-varying correlations and heterogeneous dependence patterns across asset groups. The factor specification separates common market influences from comovement among assets belonging to the same group, allowing the identification of distinct sources of dependence across markets.

This study contributes to the literature in three ways. First, it provides a comprehensive comparison of precious metals, conventional cryptocurrencies, gold-backed cryptocurrencies, and USD-backed stablecoins within a unified framework. Second, it extends the literature on gold-backed cryptocurrencies by examining dependence patterns, diversification benefits, and hedging effectiveness in relative to conventional cryptocurrencies and stablecoins. Third, the study moves beyond treating precious metals as a homogeneous asset class by examining gold and silver separately when assessing diversification and hedging relationships with digital assets.

Results reveal stronger and more persistent comovement between gold-backed cryptocurrencies and precious metals than between conventional cryptocurrencies and precious metals. Conventional cryptocurrencies display weaker and less stable relationships that vary across market conditions. Hedging effectiveness estimates also indicate greater risk-management benefits for gold-backed cryptocurrencies. Differences between gold and silver remain economically meaningful throughout the sample period, supporting the view that precious metals should not be treated as a homogeneous asset class in portfolio analysis.

The remainder of the paper is organized as follows. The next section reviews the relevant literature. The data and sample construction are then presented, followed by the econometric framework. The empirical results are presented and discussed, and the final section concludes.

2. Literature Review

2.1. Precious Metals as Hedges and Safe Havens

Precious metals have long been associated with portfolio diversification and capital preservation during periods of financial uncertainty. Gold is widely regarded as one of the most reliable hedging and safe-haven assets because of its liquidity, investor acceptance, and ability to preserve value during episodes of market stress. Baur and Lucey (2010) show that gold acts as both a hedge and a safe haven against stock market losses. Later studies confirm that gold retains protective properties during financial crises, geopolitical tensions, and the COVID-19 pandemic (Baur & McDermott, 2016; Salisu et al., 2021; Azmi et al., 2023; Feder-Sempach et al., 2024). Gold also appears to outperform alternative assets, including cryptocurrencies, during periods of severe market disruption (Ghabri et al., 2024; Widjaja et al., 2024).

Silver occupies a more complex position in financial markets. Industrial demand plays a larger role in price formation, increasing sensitivity to business cycle fluctuations and economic activity. Empirical evidence suggests that silver can provide hedging and safe-haven benefits under specific market conditions (Lucey & Li, 2015; Hasan et al., 2021). The effectiveness of hedging and safe-haven properties varies across markets and market states (Korsah et al., 2026). Research also shows that silver absorbs risk and contributes to portfolio diversification during periods of elevated uncertainty (Choi et al., 2026). The strength and persistence of such properties vary considerably across markets and crisis episodes.

Differences between gold and silver extend beyond hedging effectiveness. Gold exhibits relatively stable defensive characteristics across market conditions (Baur & McDermott, 2016; Baur, 2023). Silver responds more strongly to changes in economic activity and industrial demand (Hillier et al., 2006). Dependence patterns, volatility transmission mechanisms, and diversification benefits may differ substantially between the two metals. Evidence suggests that precious metals should not be treated as a homogeneous asset class. Such distinction is relevant when evaluating digital assets linked to precious metals because the contrasting characteristics of gold and silver may generate different patterns of comovement and risk transmission.

2.2. Cryptocurrencies and Safe-Haven Properties

Bitcoin has attracted attention as a potential hedge and safe-haven asset because of its limited supply, independence from traditional monetary systems, and frequent comparison with gold as an alternative store of value (Klein et al., 2018). Several studies document diversification and hedging benefits associated with Bitcoin and other cryptocurrencies under specific market conditions (Huang et al., 2021; Jin & Tian, 2024). Results from the COVID-19 pandemic and the Russia–Ukraine conflict also suggests that cryptocurrencies may provide protection during episodes of heightened uncertainty (Abdelmalek & Benlagha, 2023).

Evidence for a stable safe-haven role remains limited. Bitcoin exhibits high volatility, substantial price fluctuations, and sensitivity to changes in market sentiment (Smales, 2019; Baur & Hoang, 2021). Unstable dependence patterns, significant volatility spillovers, and limited protection during periods of severe financial stress have been documented across cryptocurrency markets (Conlon et al., 2020; Béjaoui et al., 2023). Gold generally provides more reliable protection than cryptocurrencies when financial uncertainty intensifies (Dutta et al., 2020; Snene Manzli & Jeribi, 2024c).

Research increasingly highlights the importance of market conditions in shaping digital asset behavior. Cryptocurrency markets exhibit strong and time-varying connectedness, with dependence structures becoming pronounced during periods of uncertainty (Yousaf et al., 2025). Time-varying and asymmetric dependence has also been documented between cryptocurrencies and commodity markets (Jareño et al., 2022). Diversification benefits may emerge under specific circumstances, but safe-haven properties remain unstable and sensitive to changing environments. Evidence also suggests that relationships differ across cryptocurrencies and over time, indicating that market relationships cannot be characterized by static correlations alone.

2.3. Stablecoins and Gold-Backed Cryptocurrencies

Stablecoins are designed to reduce price volatility through explicit links to fiat currencies or underlying assets (Díaz et al., 2023). Gold-backed cryptocurrencies represent a distinct category of stablecoins supported by physical gold reserves. This structure creates a direct connection between precious metals and digital asset markets, raising questions about the extent to which gold-backed cryptocurrencies reflect the defensive characteristics traditionally associated with gold.

Findings provide partial support for such a relationship. Several studies report that gold-backed cryptocurrencies contribute to portfolio diversification, absorb volatility shocks, and act as net receivers of risk during periods of market stress (Mnif et al., 2024; Snene Manzli & Jeribi, 2024b). Studies focusing on major crisis episodes suggest that gold-backed and USD-backed stablecoins may provide hedging or safe-haven benefits under adverse market conditions (Feng et al., 2024). Gold-backed cryptocurrencies may also display safe-haven properties during major crisis episodes, including the COVID-19 pandemic, the Russia–Ukraine conflict, and the SVB collapse (Snene Manzli & Jeribi, 2024a).

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The literature remains far from conclusive. Jalan et al. (2021) report that gold-backed cryptocurrencies did not exhibit safe-haven properties during the COVID-19 pandemic and displayed volatility patterns comparable to Bitcoin. Wasiuzzaman et al. (2023) document relatively stable volatility dynamics but find limited evidence that links to underlying assets automatically translate into superior defensive characteristics. Palazzi et al. (2025) suggest that volatility spillovers originating in cryptocurrency markets may weaken the stabilizing role of asset-backed digital instruments.

The available results provide no clear consensus regarding the economic position of gold-backed cryptocurrencies. The relative importance of precious metals, conventional cryptocurrencies, and other digital assets in shaping dependence structures remains uncertain. Questions also remain regarding patterns of comovement, volatility transmission, and risk propagation across traditional and digital asset markets.

2.4. Commodities, Financial Markets, and Cross-Market Transmission

Commodity and financial markets constitute important transmission channels between traditional and digital assets. Changes in energy prices, commodity market conditions, and equity market performance influence investor sentiment, portfolio allocation decisions, and risk perceptions across asset classes (Reboredo, 2013). Periods of uncertainty are often associated with stronger interactions among commodities, financial markets, and alternative assets (Umar et al., 2021).

A growing literature examines spillovers and connectedness in cryptocurrency and digital asset markets using alternative methodological frameworks. DCC-GARCH approaches reveal substantial time-varying connectedness between cryptocurrencies, gold-backed cryptocurrencies, and traditional financial assets. Aslam and Brahmana (2025) show that connectedness evolves over time and is strongly influenced by economic events, with Bitcoin and Ethereum acting as net transmitters of shocks, whereas gold-backed cryptocurrencies primarily behave as net receivers. Copula studies demonstrate that dependence structures are nonlinear and become stronger during turbulent market conditions. Using an Archimax copula framework, Fakhfekh et al. (2024) document significant heterogeneity in connectedness among NFTs, DeFi assets, conventional cryptocurrencies, and gold-backed cryptocurrencies.

Other studies focus on volatility transmission and dynamic spillovers across cryptocurrency markets. Using a TVP-VAR framework, Mnif et al. (2024) report a complex volatility network among Islamic gold-backed cryptocurrencies and conventional digital assets, with gold-backed cryptocurrencies acting primarily as net recipients of volatility shocks. Diebold–Yilmaz connectedness measures have also been widely employed to quantify the direction and magnitude of spillovers across asset classes. Le et al. (2021) find substantial volatility connectedness among cryptocurrencies, fintech assets, and traditional financial markets, with gold acting as a net receiver of shocks and provides diversification benefits. More recently, quantile connectedness approaches reveal that spillovers vary across market states and become considerably stronger during extreme market conditions, indicating that dependence structures are highly sensitive to periods of elevated uncertainty and financial stress (Yousaf et al., 2025).

Several mechanisms contribute to the transmission of shocks across commodity, financial, and digital asset markets. Commodity price movements affect inflation expectations, economic activity, and investor sentiment, while financial market conditions influence portfolio allocation decisions and capital flows across markets. During periods of uncertainty, investors rebalance portfolios in response to changing risk perceptions, strengthening interconnections among asset classes (Antonakakis et al., 2020; Umar et al., 2021).

Existing studies predominantly rely on DCC-GARCH models, copula-based approaches, TVP-VAR frameworks, Diebold–Yilmaz connectedness measures, and quantile connectedness methods. DCC-GARCH models, copula-based approaches, TVP-VAR frameworks, Diebold–Yilmaz connectedness measures, and quantile connectedness methods provide valuable evidence on dynamic correlations, tail dependence, and shock transmission. Most applications focus on pairwise dependence structures or network spillovers. Common market influences and group dependence patterns are rarely examined separately. In contrast, the MSV-GFT framework combines stochastic volatility, dynamic dependence, and grouped latent factors in a Bayesian framework. This specification allows market influences and group sources of dependence to be identified simultaneously across conventional cryptocurrencies, stablecoins, gold-backed cryptocurrencies, commodity markets, and financial market indicators. Consequently, our approach provides a comprehensive representation of dependence structures and volatility transmission mechanisms across heterogeneous asset groups.

2.5. Research Gap

Existing evidence provides only limited insight into the role of gold-backed cryptocurrencies in the financial system. Gold-backed cryptocurrencies combine exposure to physical gold with participation in cryptocurrency markets, but available findings do not clearly identify the sources of dependence associated with these assets. The relative importance of precious metals, conventional cryptocurrencies, and stablecoins remains uncertain. As a result, knowledge of diversification benefits, hedging effectiveness, and portfolio applications remains incomplete.

The literature offers limited evidence on the simultaneous interaction of precious metals, conventional cryptocurrencies, gold-backed cryptocurrencies, and stablecoins. Most studies focus on individual asset classes, bilateral relationships, or specific crisis episodes. Direct comparisons across traditional and digital assets remain relatively rare. Limited attention has also been devoted to the role of silver, despite evidence indicating that gold and silver exhibit different hedging characteristics, dependence patterns, and responses to market uncertainty. Such limitations highlight the need for a comprehensive assessment of comovement, dependence structures, and risk transmission across precious metals and digital assets using a unified empirical framework.

3. Data

3.1. Data and Sample Construction

The analysis employs daily price data for precious metals and three groups of digital and financial assets. The sample covers the period from July 2020 to March 2026 and contains 1466 daily observations. The sample begins in July 2020 because continuous daily price series for all gold-backed cryptocurrencies are available from this date. The selected period encompasses substantial developments in digital asset markets together with episodes of elevated financial and geopolitical uncertainty, including the Russia–Ukraine conflict, the 2023 banking sector turmoil, the approval of spot Bitcoin exchange-traded funds, tensions in the Middle East, and the 2026 U.S.–Iran conflict.

Asset selection was based on three criteria. First, the assets had to be representative of their market segments and widely recognized by market participants. Second, sufficient trading activity and market relevance were required to ensure reliable price discovery and meaningful return dynamics. Third, continuous daily price series had to be available throughout the sample period to avoid missing observations and ensure comparability across assets.

The first group (G1) consists of conventional cryptocurrencies, including Bitcoin, Ethereum, Ripple, Dash, and Monero. The assets represent some of the most established and traded cryptocurrencies and provide a representative view of the conventional cryptocurrency market.

The second group (G2) includes fiat-backed stablecoins and gold-backed cryptocurrencies. Fiat-backed stablecoins are represented by Tether (USDT) and TrueUSD (TUSD), which are designed to maintain price stability through reserve-backed mechanisms (Maouchi et al., 2024). Gold-backed cryptocurrencies include Digix Gold Token (DGX), PAX Gold (PAXG), and Tether Gold (XAUT). Gold-backed cryptocurrencies combine exposure to physical gold with the transferability and accessibility of cryptocurrency markets.

The third group (G3) comprises commodity and financial market indicators, including West Texas Intermediate crude oil (WTI), natural gas futures (NGK2), the commodity futures index (CFI2Z2), the Tadawul All Share Index (TASI), and the S&P 500 ESG Index (EFIV). Commodity and financial market conditions may influence interactions between precious metals and digital assets. Commodity markets are particularly sensitive to geopolitical events and changes in economic conditions, which can amplify systemic risk and cross-market transmission mechanisms (Y. Wang et al., 2022).

Gold and silver serve as benchmark precious metals throughout the analysis. Gold is commonly associated with wealth preservation and hedging against financial uncertainty. Silver reflects both financial and industrial demand, generating responses to economic and financial shocks that differ from those observed for gold (Li & Lucey, 2017). Examining the two metals separately allows differences in dependence structures, volatility transmission, and diversification potential to be identified across digital and traditional assets.

Price data for cryptocurrencies and stablecoins are obtained from CoinMarketCap. Precious metals, commodity indicators, and financial market variables are collected from Refinitiv Datastream and Bloomberg. Returns are calculated as logarithmic price differences to ensure comparability across assets and reduce potential non-stationarity.

3.2. Descriptive Statistics

The daily series deviate markedly from normality, as reflected in pronounced skewness and excess kurtosis across all assets (Table 1). Jarque–Bera statistics are large in every case, confirming the presence of heavy tails. Cryptocurrencies and some tokenized assets display the strongest departures from normality, with extreme kurtosis and substantial dispersion.

Differences across asset classes are evident. Cryptocurrencies exhibit the highest volatility, with substantially larger standard deviations and wider return ranges. By contrast, gold-backed digital assets such as PAXG and XAUT display much lower dispersion, with values close to those of gold, indicating more stable return dynamics. An exception is DGX, which exhibits higher volatility and kurtosis than the other gold-backed cryptocurrencies. A possible explanation relates to differences in market liquidity, trading activity, and market depth. Compared with PAXG and XAUT, DGX has historically attracted a smaller investor base and lower trading volumes, making prices more sensitive to individual transactions and temporary market imbalances. Such characteristics may amplify price adjustments during periods of market stress and contribute to the extreme return observations reported in Table 1. Stablecoins show low average returns and, in some cases, extreme kurtosis, reflecting occasional large deviations. Traditional assets and commodities display intermediate volatility levels. Detailed summary statistics are provided in Table A1 (Appendix A).

Figure 1 illustrates the behavior of gold and silver returns, volatility proxies, and rolling correlations. Both return series exhibit volatility clustering, with periods of low variability followed by sharp spikes that intensify in 2025–2026. Volatility proxies confirm large and persistent fluctuations, with noticeable increases over the same period. This visual evidence is further supported by ARCH-LM and Ljung–Box tests on squared returns, reported in Appendix B, which reject the null hypotheses of no ARCH effects and no serial dependence in volatility for both gold and silver. Rolling correlations vary over time, with both the strength and sign of dependence changing across the sample and no stable pattern emerging. The results highlight substantial variation in dependence patterns and support the use of a framework that accommodates evolving correlations across asset groups.

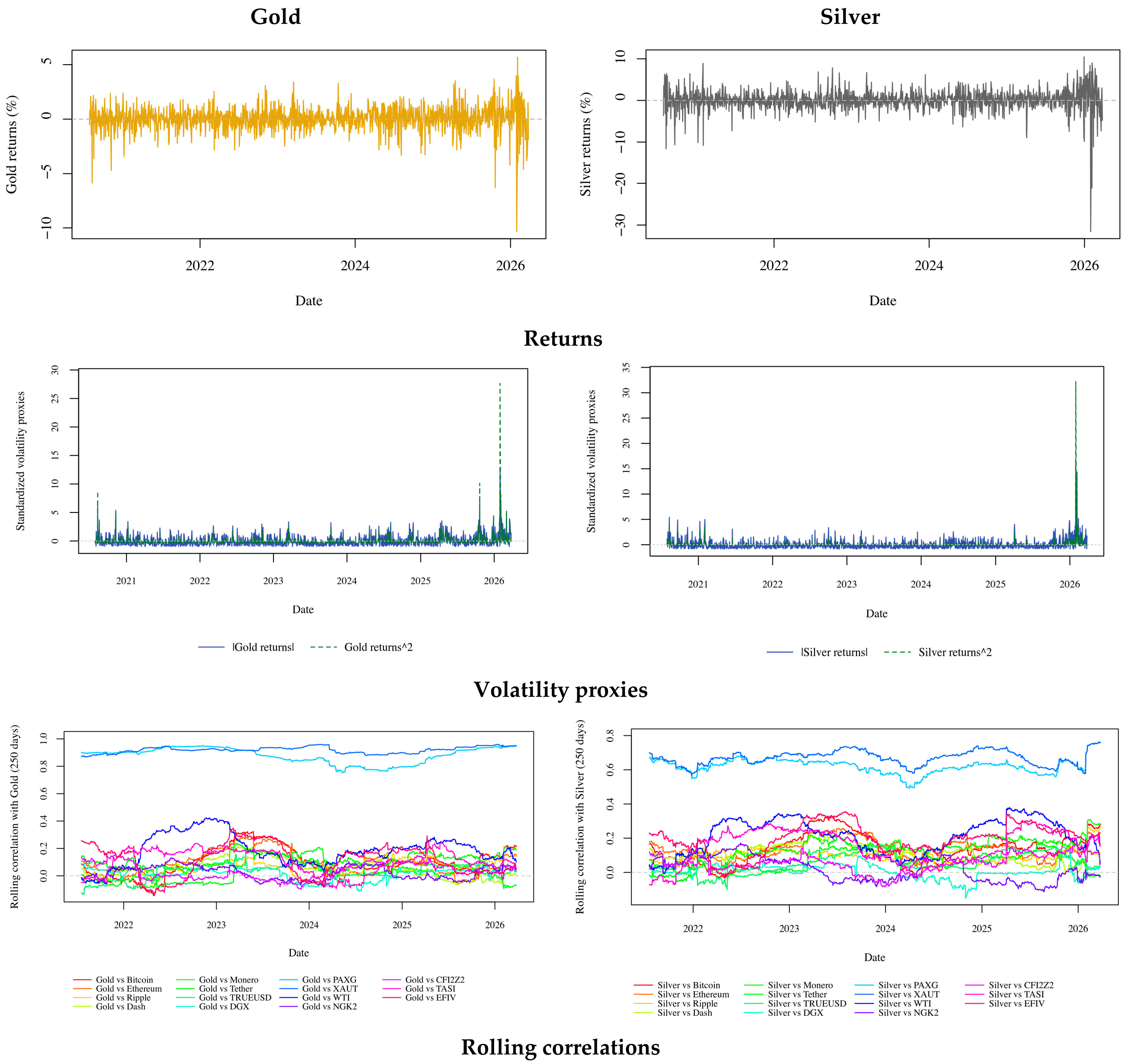


Figure 1. Returns, volatility proxies, and rolling correlations for gold and silver. Note: The horizontal dotted line indicates the zero level. The vertical dashed line marks the beginning of the estimation period.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max	JB
Bitcoin	0.126	3.675	−0.306	8.300	−28.683	19.367	1738.6
Ethereum	0.130	5.294	−1.151	16.948	−47.697	34.994	12,206.6
Ripple	0.119	6.594	0.617	21.814	−54.017	61.417	21,715.1
Dash	−0.060	6.660	1.189	23.353	−45.550	80.756	25,649.6
Monero	0.098	5.122	−1.238	19.502	−51.948	34.360	17,008.7
Tether	0.000	0.041	−0.569	17.463	−0.441	0.310	12,855.6
TRUEUSD	0.000	0.164	9.179	290.673	−1.900	4.083	5,075,594.0
DGX	−0.081	9.839	2.434	141.294	−151.260	186.727	1,169,672.1
PAXG	0.055	1.111	−0.820	13.042	−10.818	6.560	6323.5
XAUT	0.056	1.067	−0.976	14.130	−10.811	6.531	7799.3
WTI	0.056	2.330	−0.478	6.115	−13.458	11.519	648.5
NGK2	0.031	5.336	−0.945	20.904	−64.397	35.568	19,798.8
CFI2Z2	0.066	2.446	−0.277	7.246	−16.984	15.874	1120.1
TASI	0.027	0.828	−0.771	9.851	−7.019	4.933	3012.2
EFIV	0.050	1.040	−0.028	9.270	−6.071	9.099	2401.9
Silver	0.070	2.432	−2.145	28.334	−31.572	10.454	40,329.3
Gold	0.055	1.093	−0.988	11.464	−10.350	5.687	4614.1

Note: Descriptive statistics are reported for daily logarithmic returns (%), computed as first differences of logarithmic prices.

4. Econometric Framework

4.1. Model Estimation

The empirical analysis is conducted using a multivariate stochastic volatility model with grouped latent factors (MSV-GFT). The framework incorporates one global factor and group factors to capture common and heterogeneous sources of dependence across conventional cryptocurrencies, stablecoins, gold-backed cryptocurrencies, commodity indicators, financial market variables, and precious metals. The structure allows correlations and volatilities to evolve over time while accounting for differences in economic function, market behavior, and sources of risk across asset groups (Taylor, 1994; Asai et al., 2006).

Let r_t denote the vector of asset returns at time t. The return process is specified as:

$$r_t = \mu + \varepsilon_t \tag{1}$$

where μ is the vector of unconditional mean returns and ε_t is a vector of innovations with conditional covariance matrix Σ_t. Conditional on Σ_t, the innovations follow:

$$\varepsilon_t \mid \Sigma_t \sim N(0, \Sigma_t) \tag{2}$$

The covariance matrix evolves according to a stochastic specification, allowing volatilities and correlations to vary over time (Harvey et al., 1994; Kim et al., 1998). The feature is important in the setting because periods of financial and geopolitical uncertainty are often associated with changes in volatility and dependence across assets.

Dependence across assets is modeled through one global latent factor and three latent factors linked to the asset groups considered in the analysis. The global factor captures comovement across all markets, and the remaining factors capture similarities among assets with comparable economic characteristics. This structure separates patterns of dependence from relationships associated with segments of the market.

The conditional covariance matrix is decomposed as:

$$\Sigma_t = D_t R_t D_t \tag{3}$$

where D_t is a diagonal matrix of time-varying standard deviations and R_t is the conditional correlation matrix (Engle, 2002). The diagonal elements of D_t follow stochastic volatility processes, and R_t captures the dynamic dependence implied by the grouped factor structure.

The diagonal elements of D_t are generated from latent log-volatility processes. For asset i, the volatility dynamics follow a first-order autoregressive stochastic volatility specification:

$$\begin{gathered} h_{i,t} = \mu_{h_i} + \phi_{h_i}(h_{i,t-1} - \mu_{h_i}) + \phi_{h_i}\eta_{i,t},\ \eta_{i,t} \sim N(0,1) \\ D_t = diag\left(exp\left(\frac{h_{1,t}}{2}\right), \cdots, exp\left(\frac{h_{p,t}}{2}\right)\right) \end{gathered} \tag{4}$$

The conditional correlation matrix is generated through latent dependence factors. Let q_t denote the vector of latent dependence states. Each element follows an autoregressive process:

$$\begin{gathered} q_{k,t} = \mu_{k_k} + \phi_{q_k}(q_{k,t-1} - \mu_{q_k}) + \sigma_{q_k}\zeta_{k,t},\ \zeta_{k,t} \sim N(0,1) \\ d = \frac{p(p-1)}{2} \end{gathered} \tag{5}$$

where d is the size of q_t.

The latent dependence vector is mapped into a valid correlation matrix through the Generalized Fisher Transformation. First, the latent states are arranged into a symmetric matrix:

$$\begin{gathered} H_t = invech(q_t) \\ A_t = exp(H_t) \\ R_t = (A_t - I)(A_t + I)^{-1} \end{gathered} \tag{6}$$

This transformation guarantees that R_t remains a valid correlation matrix at each point in time.

The MSV-GFT framework provides a unified representation of comovement, volatility transmission, and risk propagation across traditional and digital asset markets. It captures both common and group specific sources of dependence and allows correlations to evolve over time.

Model parameters, latent volatilities, and dependence factors are estimated within a Bayesian framework using Particle Gibbs with Ancestor Sampling (PGAS). The PGAS algorithm is implemented with 50 particles. Posterior inference is based on 5000 Markov Chain Monte Carlo (MCMC) iterations, with the first 1000 iterations discarded as burn-in. Thinning is performed by retaining every tenth draw from the posterior sample. Convergence is assessed using both graphical and quantitative diagnostics, including trace plots, autocorrelation functions, effective sample sizes, and Geweke statistics reported in Appendix C, which indicate stable posterior distributions and satisfactory mixing of the Markov chains. All estimations are implemented in R version 4.5.1 (13 June 2025). The latent volatility and dependence paths were sampled conditional on fixed transition parameters. The volatility process used μ_h = log(0.01), φ_h = 0.98, and σ_h = 0.10, while the latent dependence process used μ_q = 0, φ_q = 0.98, and σ_q = 0.05. We treared these parameters as fixed calibration values throughout estimation and were not sampled within the PGAS procedure. The leverage coefficients were assigned independent Gaussian priors, γ_i ~ N(0, 1). The estimation was implemented in R 4.5.1 using developed code for the MSV-GFT model, the GFT mapping, and the PGAS sampler, together with the packages coda, Matrix, openxlsx, dplyr, tidyr, ggplot2, zoo, and rmgarch.

4.2. Portfolio and Hedging Measures

The time-varying covariance matrices estimated from the MSV-GFT model are used to evaluate portfolio allocation and hedging strategies involving gold and silver as benchmark assets. The analysis considers interactions between precious metals and three groups of assets. Conditional covariance estimates provide the basis for portfolio construction because optimal hedge ratios and portfolio weights depend directly on time-varying variances and covariances (Kroner & Ng, 1998).

To examine whether hedging effectiveness changes across market conditions, the sample was divided into low-, medium-, and high-volatility periods. For both gold and silver, the 33rd and 67th percentiles of the distribution of absolute returns were used to define the three volatility groups. The volatility regimes are defined using observed market volatility, without using realized volatility measures or estimates obtained from statistical models. Hedge ratios and hedge effectiveness were estimated separately for each volatility group. As a result, the estimates may differ from those obtained for the full sample. Differences may arise in both magnitude and sign. The results reflect hedging performance under different market conditions and should not be viewed as a decomposition of the full-sample out-of-sample results.

Time-varying correlations describe the degree of comovement between precious metals and the assets included in each group. Changes in correlation patterns provide information regarding diversification opportunities and the potential transmission of risk across markets.

The optimal hedge ratio between asset i and asset j is computed as:

$$h_{ij,t} = \frac{\mathrm{Cov}_{ij,t}}{\mathrm{Var}_{j,t}} \tag{7}$$

where $\mathrm{Cov}_{ij,t}$ denotes the conditional covariance between the two assets and $\mathrm{Var}_{j,t}$ represents the conditional variance of the hedging instrument. The hedge ratio determines the position required in the hedging asset to minimize portfolio risk.

Minimum variance portfolio weights are derived from the conditional covariance matrix following Kroner and Ng (1998). Portfolio composition adjusts over time in response to changes in dependence and volatility across asset groups.

Hedging performance is evaluated using hedge effectiveness (*HE*), defined as:

$$HE = 1 - \frac{\sigma_h^2}{\sigma_u^2} \tag{8}$$

where σ_h^2 and σ_u^2 denote the variances of the hedged and unhedged positions, respectively (Ku et al., 2007). The hedge ratio varies over time according to the estimated conditional covariance matrix. The hedge effectiveness values reported in Table 2 summarize the performance of the hedging strategy over the entire out-of-sample period. Consequently, the hedge effectiveness values represent the overall variance reduction achieved during the out-of-sample evaluation period.

Table 2. OOS summary MSV-GFT leverage.

Group	Base	H	Mean Log-Likelihood	Total Log-Likelihood
G1	Silver	750	−256.8	−192,563.0
G1	Gold	750	−224.9	−168,646.2
G2	Silver	750	−28.4	−21,280.0
G2	Gold	750	−23.5	−17,603.8
G3	Silver	750	−88.9	−66,663.4
G3	Gold	750	−66.8	−50,111.5

Note: H denotes the out-of-sample forecasting horizon. Higher log-likelihood values indicate better predictive performance.

Portfolio performance is assessed using annualized returns, annualized volatility, Sharpe ratios, and maximum drawdown. Minimum variance portfolios are compared with equally weighted portfolios. The evaluation is conducted out of sample. Portfolio weights are estimated using information available at time t, and portfolio returns are realized in the subsequent period. The full sample covers the period from 30 July 2020 to March 2026 and contains 1466 daily observations. The first 716 observations, spanning 30 July 2020 to 3 May 2023, form the initial in-sample estimation period. The remaining 750 observations, beginning on 4 May 2023, are used for out-of-sample evaluation. Thus, H = 750 denotes the length of the out-of-sample evaluation period. Forecasts are generated using an expanding-window scheme in which the model is recursively re-estimated as new observations become available.

5. Empirical Results

5.1. Dynamic Correlations

Figure 2 presents the dynamic conditional correlations between gold, silver, and the three asset groups. Correlation patterns differ substantially across asset classes and provide initial evidence of heterogeneous dependence structures. Gold and silver display similar dynamics, although relationships involving silver exhibit greater variability over time.

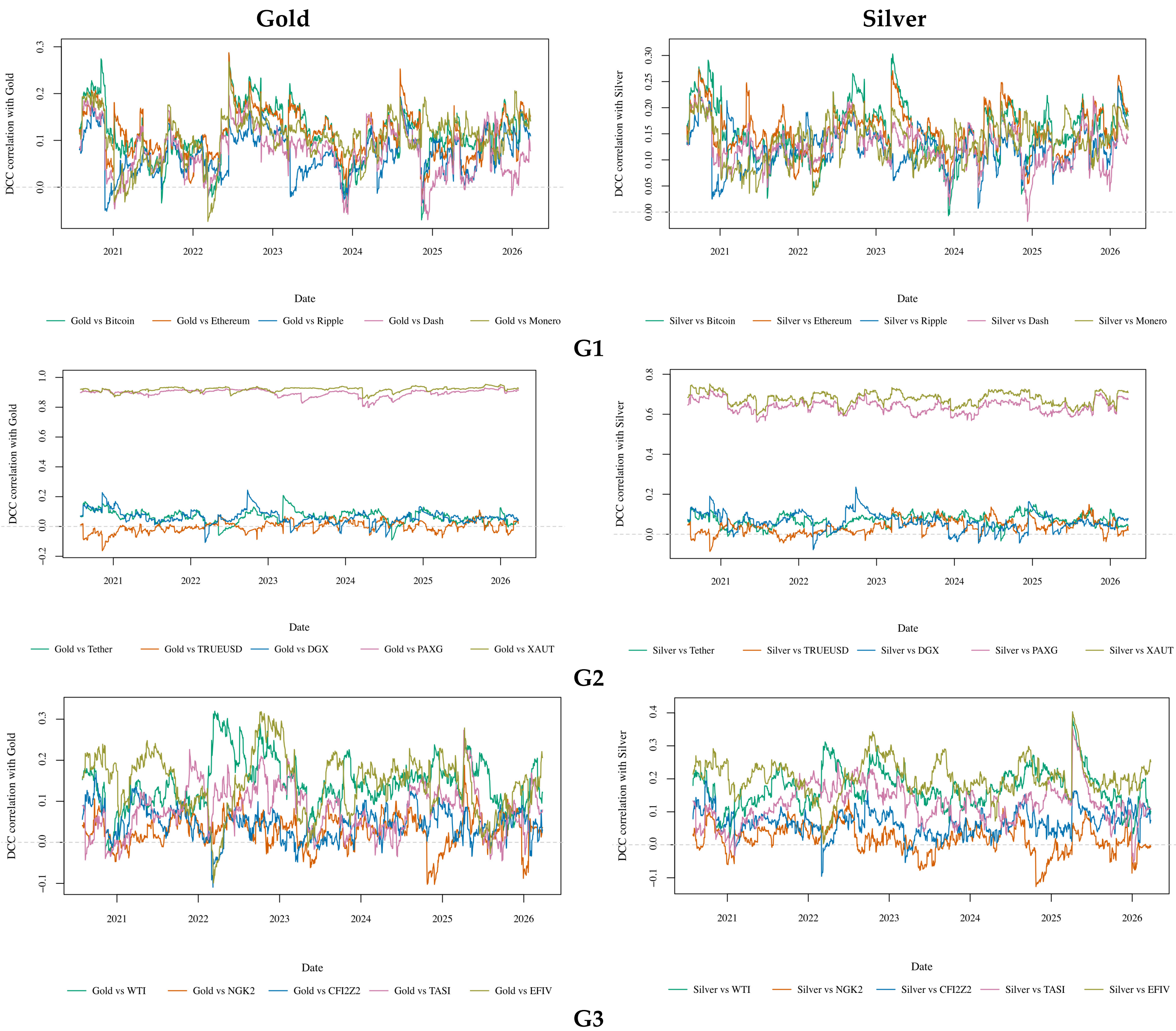


Figure 2. DCC between gold, silver, and asset groups (G1–G3). Note: The horizontal dashed line indicates zero correlation.

Conventional cryptocurrencies (G1) are characterized by weak and unstable correlations with both precious metals. Most correlations remain close to zero and fluctuate over time, indicating limited integration between cryptocurrency markets and precious metals. Dependence patterns are particularly sensitive to market conditions and do not reveal persistent comovement.

Stablecoins and gold-backed cryptocurrencies (G2) exhibit a markedly different pattern. Gold-backed assets, particularly PAXG, XAUT, and DGX, display positive correlations with gold and silver throughout the sample period. Correlations remain relatively stable and substantially exceed those observed for conventional cryptocurrencies. Fiat-backed stablecoins exhibit weaker relationships, suggesting that the dependence structure is linked to physical gold and cannot be explained solely by price stability.

Commodity and financial market indicators (G3) exhibit moderate and time-varying correlations with precious metals. Dependence patterns vary across assets and market conditions, reflecting the influence of developments in commodity and financial markets. Correlations are generally lower and less persistent than those observed for gold-backed cryptocurrencies.

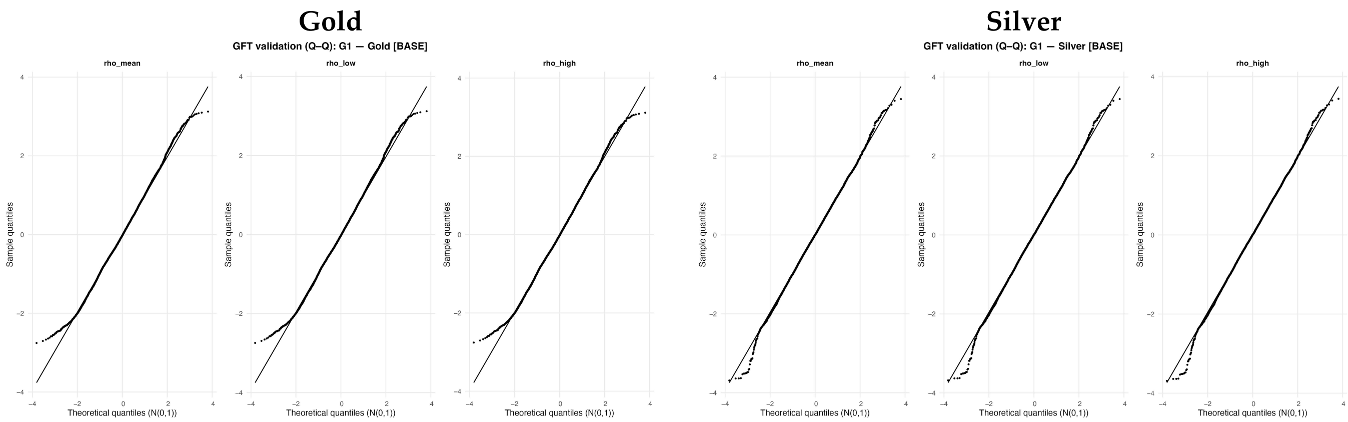
Several conclusions emerge from Figure 2. Gold-backed cryptocurrencies display the strongest and most stable relationships with precious metals. Conventional cryptocurrencies exhibit weak and unstable dependence patterns. The Dynamic Conditional Correlation (DCC) estimates in Table A2 indicate that commodity and financial market indicators are characterized by moderate correlations with precious metals, generally stronger than those of conventional cryptocurrencies but substantially weaker than those of gold-backed cryptocurrencies.

5.2. Model Validation

Figure 3 presents Quantile–Quantile (Q–Q) plots for the correlations estimated under the MSV-GFT framework. Empirical quantiles follow theoretical quantiles across all asset groups and for both precious metals. Most observations remain close to the reference line, indicating that the model provides a good fit to the correlation structure.

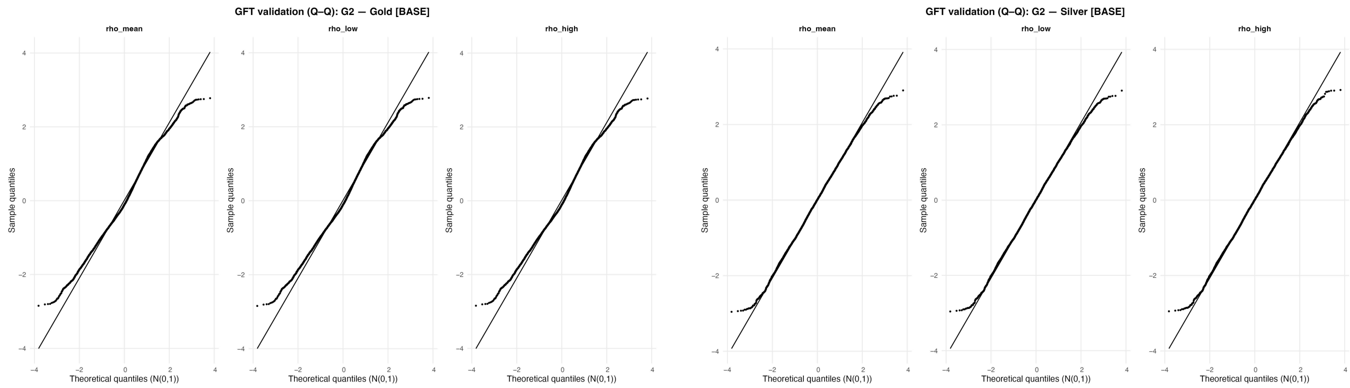
Small deviations appear in the lower and upper tails of the distributions. Such departures are common in financial data because extreme market conditions often produce observations that deviate from theoretical distributions. The departures remain limited and do not alter the overall fit of the model.

Similar patterns are observed across the three asset groups. Gold and silver exhibit comparable Q–Q profiles, suggesting that the estimated dependence structure remains stable across benchmark assets and asset groups. The grouped factor framework provides a reliable representation of dependence dynamics and supports the subsequent analysis of correlations, portfolio allocation, and hedging performance.

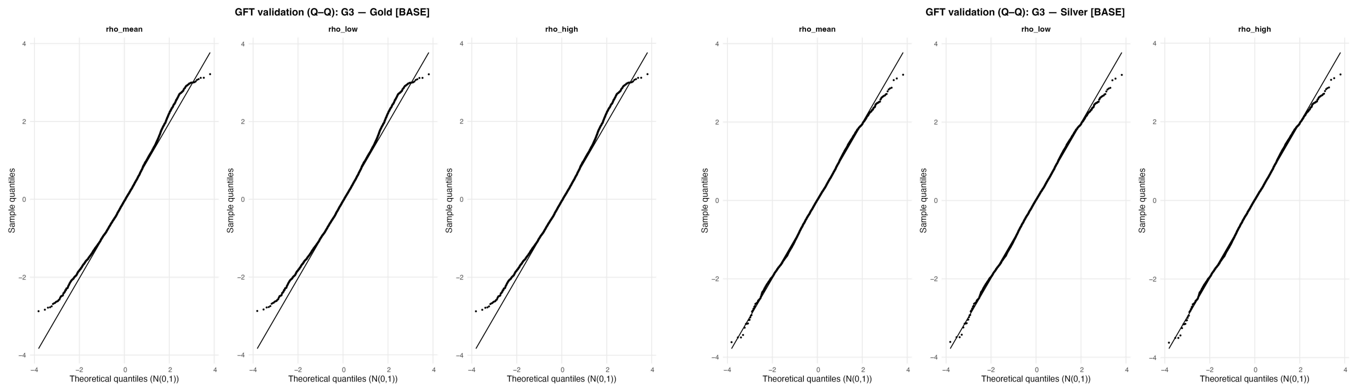


G1

Figure 3. *Cont.*



G2



G3

Figure 3. Q–Q plots of latent correlations for gold and silver across asset groups (G1–G3). Note: Black dots represent the sample quantiles, and the solid black line represents the theoretical normal reference line.

5.3. Out-of-Sample Performance

Out-of-sample performance is evaluated over a forecasting horizon of 750 observations. For each period, portfolio decisions are based exclusively on information available up to time t. Performance measures are computed using returns realized at time $t + 1$. The exercise assesses the ability of the model to forecast the conditional covariance matrix accurately and evaluates the economic value of the forecasts for portfolio allocation and hedging.

Table 2 reports the out-of-sample predictive performance of the MSV-GFT model across the three asset groups. The results reveal substantial differences in forecasting accuracy. The strongest performance is observed for stablecoins and gold-backed cryptocurrencies (G2), followed by commodity and financial market indicators (G3), while conventional cryptocurrencies (G1) exhibit the weakest predictive performance.

For both gold and silver, G2 produces the highest mean and total log-likelihood values, indicating more stable and predictable dependence structures. In contrast, G1 records lower log-likelihood values, suggesting greater instability and challenging forecasting conditions. G3 occupies an intermediate position, with predictive performance that exceeds G1 but remains below G2.

The ranking is identical for both precious metals. Gold consistently generates higher log-likelihood values than silver across all groups, suggesting a modest advantage in predictive performance.

Figure 4 illustrates the evolution of latent correlations for representative assets from each group relative to gold and silver. Correlation patterns differ substantially across asset classes. Conventional cryptocurrencies exhibit pronounced fluctuations and frequent changes in correlation magnitude. Stablecoins and gold-backed cryptocurrencies display persistent dependence patterns, particularly for PAXG and XAUT. Commodity and financial market indicators occupy an intermediate position, with relationships that vary over time but remain less volatile than those observed for conventional cryptocurrencies.

Figure 4. Evolution of latent correlations for selected assets in G1–G3 relative to gold and silver.

The OOS results reveal substantial differences in economic performance across asset groups. Global minimum variance portfolios constructed from G2 assets deliver the strongest performance. Sharpe ratios reach 0.6443 for gold and 0.1396 for silver, the highest values among all portfolio groups.

Hedging effectiveness, reported in Table 3, is strongest for gold-backed cryptocurrencies. XAUT achieves hedge effectiveness values of 0.3851 for gold and 0.1510 for silver. Corresponding values for PAXG are 0.2261 and 0.1537. The results indicate reductions in portfolio risk and highlight the potential of gold-backed cryptocurrencies as hedging instruments.

Table 3. OOS Hedge effectiveness summary.

Group	Base	Asset	Hedge Effectiveness
G1	Silver	Bitcoin	−0.0058
G1	Silver	Ethereum	−0.0248
G1	Silver	Ripple	−0.0065
G1	Silver	Dash	−0.0172
G1	Silver	Monero	−0.0021
G1	Gold	Bitcoin	−0.0096
G1	Gold	Ethereum	−0.0065
G1	Gold	Ripple	−0.0528
G1	Gold	Dash	−0.0298
G1	Gold	Monero	−0.0123
G2	Silver	Tether	−0.0009
G2	Silver	TRUEUSD	0.0001
G2	Silver	DGX	−0.0149
G2	Silver	PAXG	0.1537
G2	Silver	XAUT	0.1510
G2	Gold	Tether	−0.0006
G2	Gold	TRUEUSD	0.0004
G2	Gold	DGX	−0.0150
G2	Gold	PAXG	0.2261
G2	Gold	XAUT	0.3851
G3	Silver	WTI	−0.0004
G3	Silver	NGK2	−0.0242
G3	Silver	CFI2Z2	−0.0263
G3	Silver	TASI	0.0094
G3	Silver	EFIV	0.0093
G3	Gold	WTI	−0.0040
G3	Gold	NGK2	−0.0127
G3	Gold	CFI2Z2	−0.0040
G3	Gold	TASI	−0.0125
G3	Gold	EFIV	0.0084

Conventional cryptocurrencies generate negative hedge effectiveness values. Portfolio risk increases after hedging, indicating that cryptocurrency positions do not provide reliable protection against fluctuations in precious metals. Commodity and financial market indicators produce weaker and less consistent hedging outcomes. Risk reduction remains limited for most assets in G3. Additional MCMC convergence diagnostics, including representative trace plots, autocorrelation functions, effective sample sizes (ESS), and Geweke statistics, are reported in Appendix C.

An additional robustness analysis was conducted using SPDR Gold Shares (GLD), one of the most widely traded gold ETFs, as an alternative benchmark. The results, reported in Table A6 (Appendix D), confirm the stability of the main findings. Gold-backed cryptocurrencies continue to exhibit substantially stronger hedging effectiveness than conventional cryptocurrencies, stablecoins, and financial market indicators. XAUT and PAXG remain the best assets, indicating that the main conclusions are not sensitive to the choice of gold benchmark.

Additional evidence is provided in Tables A7 and A8 (Appendix E), which reports hedge effectiveness across volatility regimes. Results reveal substantial heterogeneity across market conditions. Hedge effectiveness increases markedly during high-volatility periods, particularly for gold-backed cryptocurrencies. For gold, hedge effectiveness rises from

0.1917 to 0.8970 for PAXG and from 0.2513 to 0.9129 for XAUT when moving from low- to high-volatility regimes. Similar patterns emerge for silver, where hedge effectiveness increases from 0.0140 to 0.6364 for PAXG and from 0.0255 to 0.6723 for XAUT. The findings indicate that the hedging benefits of gold-backed cryptocurrencies become considerably stronger during periods of elevated market uncertainty and financial stress.

6. Discussion

Our results indicate that relationships between digital assets and precious metals are unstable and sensitive to market conditions and shock characteristics. Gold and silver do not behave as interchangeable assets, and treating precious metals as a homogeneous group may lead to misleading conclusions regarding hedging properties. The regime-dependent correlations identified in our study are consistent with previous findings that dependence structures and hedging effectiveness vary across market states and crisis episodes (Gökgöz et al., 2024).

The findings suggest a more cautious interpretation of the hedging role of cryptocurrencies. Previous studies report that Bitcoin and other digital assets may provide diversification, hedging, or safe-haven benefits under specific conditions (Shahzad et al., 2020; Thampanya et al., 2020). Similar evidence indicates that gold provides stronger safe-haven protection than Bitcoin during periods of extreme market turbulence (Q. Wang et al., 2022). Out-of-sample results suggest that such benefits are not sufficiently persistent to support a reliable hedging function. Hedging effectiveness depends on market conditions and dependence patterns across assets (Echaust et al., 2024). Correlation instability reduces the effectiveness of cryptocurrencies as risk instruments and limits their usefulness during periods of uncertainty.

The results also contribute to the interpretation of dynamic interdependence and spillovers. Time-varying and asymmetric dependence between cryptocurrencies and precious metals has been widely documented (Elsayed et al., 2022; Fasanya et al., 2022; Mensi et al., 2023). Cryptocurrency uncertainty has also been shown to influence volatility dynamics in precious-metal markets, indicating the existence of transmission channels between digital assets and traditional safe-haven assets (Wei et al., 2023). The analysis confirms the presence of changing dependence patterns but indicates substantial differences in strength and persistence across asset classes. Dependence structures are shaped by asset characteristics and vary across digital asset categories. Gold-backed cryptocurrencies maintain persistent comovement with precious metals. Conventional cryptocurrencies and market indicators exhibit weaker and less stable relationships. As a result, conclusions drawn from one asset category should not be extended directly to other digital asset groups.

A central finding concerns the distinction between gold and silver. Several studies examine precious metals jointly or treat them as a homogeneous asset class (Yousaf et al., 2023). The results suggest that such an approach may obscure important differences. Gold retains a more stable hedging role across market conditions. Silver displays greater variability in dependence patterns and portfolio performance. The contrast is consistent with the dual financial and industrial role of silver and highlights the importance of analyzing precious metals separately when evaluating diversification and risk strategies.

The analysis provides new evidence on gold-backed digital assets, where existing findings remain inconclusive. Jalan et al. (2021) report that gold-backed cryptocurrencies did not exhibit safe-haven properties during the COVID-19 period and displayed volatility patterns similar to Bitcoin. The results reported here offer a different perspective. Gold-backed assets exhibit persistent comovement with precious metals and generate positive OOS hedging performance. The findings suggest that exposure to physical gold remains the dominant driver of dependence patterns. Effectiveness appears to depend on market conditions, shock characteristics, and the empirical framework used to evaluate performance. The inclusion of recent episodes of geopolitical stress, including the 2026 U.S.–Iran conflict, provides additional evidence of resilience under heightened uncertainty. Additional evidence from the volatility analysis suggests that the hedging performance of gold-backed cryptocurrencies is not constant across market conditions. Hedge effectiveness increases substantially during high-volatility periods for both gold and silver, with the strongest improvements observed for PAXG and XAUT (see Appendix E, Tables A7 and A8).

The analysis also informs the debate on the hedging role of cryptocurrencies. Previous studies show that cryptocurrencies may provide diversification benefits and reduce downside risk under specific conditions (Bouri et al., 2020; Bossman et al., 2024). Out-of-sample results indicate that such benefits are not sufficiently stable to support a reliable hedging function. Correlation instability translates into weak or negative hedging effectiveness, particularly during periods of market stress. Our findings suggest that cryptocurrencies may serve as speculative diversification instruments but cannot be regarded as dependable substitutes for traditional hedging assets.

From a methodological perspective, the findings highlight the importance of models that accommodate regime changes, asymmetries, and heterogeneous dependence structures (González et al., 2021). Dependence patterns differ not only across time but also across asset classes. Ignoring this heterogeneity may lead to misleading conclusions regarding connectedness, diversification, and hedging effectiveness. Conventional cryptocurrencies offer limited protection during adverse market conditions. The distinction between gold and silver remains equally important, as portfolio outcomes differ substantially across the two precious metals.

7. Conclusions

This study examines the dynamic relationships among precious metals, conventional cryptocurrencies, stablecoins, gold-backed cryptocurrencies, and market indicators from commodity and financial markets using a multivariate stochastic volatility model with grouped factor structure. The results reveal substantial heterogeneity in dependence patterns across asset classes and underscore the importance of accounting for time-varying correlations and group dynamics.

A central finding is that gold-backed cryptocurrencies occupy a distinct position within digital asset markets. Dependence structures involving gold-backed assets are considerably more stable than those observed for conventional cryptocurrencies and generate positive OOS hedging performance. The results suggest that exposure to physical gold remains the dominant driver of dependence patterns associated with these assets. Conventional cryptocurrencies exhibit weak and unstable relationships with precious metals and provide limited protection during periods of market stress.

The analysis also highlights important differences between gold and silver. Gold maintains a more stable hedging role across market conditions. Silver exhibits greater variability in dependence patterns and portfolio outcomes. Treating precious metals as a homogeneous asset class may therefore obscure economically relevant differences and lead to misleading conclusions regarding diversification and risk management.

From a practical perspective, the findings indicate that gold-backed cryptocurrencies provide the most effective hedging performance among the digital assets considered in the analysis. Conventional cryptocurrencies are more suitable for portfolio diversification.

Diversification benefits vary across market regimes. Portfolio allocation decisions should account for changing dependence structures and differences across asset classes.

Several limitations should be acknowledged. The results are conditioned by the selected asset groups and by a sample period characterized by substantial financial and geopolitical uncertainty. Future research may examine alternative classifications of digital assets, additional gold-backed instruments, and longer sample periods encompassing different market conditions. Comparisons with gold exchange-traded funds (ETFs), other commodity-backed tokenized assets, and financial instruments linked to underlying physical commodities may also help evaluate the generalizability of the patterns documented in this study.

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Abbreviations

The following abbreviations are used in this manuscript:

U.S.	United States
USDT	Tether
TUSD	TrueUSD
DGX	Digix Gold Token
PAXG	PAX Gold
XAUT	Tether Gold
WTI	West Texas Intermediate crude oil
NGK2	Natural gas futures
CFI2Z2	The commodity futures index
TASI	Tadawul All Share Index
EFIV	The S&P 500 ESG Index
MSV-GFT	Multivariate stochastic volatility framework with grouped factor structure
DCC	Dynamic Conditional Correlation
Q–Q	Quantile–Quantile
OOS	Out-of-sample

Appendix A

Table A1. Summary statistics of dynamic correlations estimated with the MSV-GFT model.

Group	Base	Asset	Number of Aligned Dates	Mean ρ	SD of ρ	Min ρ	Max ρ	Freq. CI > 0	Freq. CI < 0	Freq. of CI Crossing 0
G1	Silver	Bitcoin	1466	0.0116	0.1070	−0.3352	0.2574	0.5628	0.4352	0.0020
G1	Gold	Bitcoin	1466	−0.0115	0.1121	−0.2904	0.3110	0.4482	0.5477	0.0041
G1	Silver	Ethereum	1466	0.0095	0.0913	−0.2534	0.2458	0.5907	0.4086	0.0007
G1	Gold	Ethereum	1466	0.0215	0.0793	−0.2041	0.2543	0.5955	0.4018	0.0027
G1	Silver	Ripple	1466	0.0029	0.0793	−0.2267	0.2181	0.5389	0.4591	0.0020
G1	Gold	Ripple	1466	0.0124	0.0833	−0.2871	0.2647	0.5621	0.4379	0.0000
G1	Silver	Dash	1466	−0.0048	0.0849	−0.2104	0.2469	0.4611	0.5382	0.0007
G1	Gold	Dash	1466	0.0216	0.1032	−0.2781	0.3121	0.5614	0.4352	0.0034
G1	Silver	Monero	1466	0.0235	0.0965	−0.2131	0.3264	0.5389	0.4604	0.0007
G1	Gold	Monero	1466	0.0062	0.1046	−0.3025	0.2684	0.5218	0.4748	0.0034
G2	Silver	Tether	1466	−0.0081	0.0896	−0.2826	0.2281	0.4823	0.5136	0.0041
G2	Gold	Tether	1466	0.0109	0.0954	−0.2318	0.2624	0.5314	0.4652	0.0034
G2	Silver	TRUEUSD	1466	0.0201	0.0988	−0.2363	0.3000	0.5846	0.4120	0.0034
G2	Gold	TRUEUSD	1466	0.0067	0.1191	−0.3968	0.2819	0.5355	0.4645	0.0000
G2	Silver	DGX	1466	0.0286	0.0892	−0.2002	0.3057	0.6098	0.3902	0.0000
G2	Gold	DGX	1466	0.0050	0.0947	−0.2531	0.2704	0.5157	0.4809	0.0034
G2	Silver	PAXG	1466	0.1104	0.0970	−0.1669	0.4078	0.8738	0.1262	0.0000
G2	Gold	PAXG	1466	0.1514	0.1038	−0.1351	0.4385	0.9134	0.0866	0.0000
G2	Silver	XAUT	1466	0.1156	0.0902	−0.1305	0.3515	0.8888	0.1112	0.0000
G2	Gold	XAUT	1466	0.1822	0.1034	−0.1230	0.4573	0.9516	0.0484	0.0000
G3	Silver	WTI	1466	−0.0056	0.0748	−0.2308	0.2087	0.4802	0.5177	0.0020
G3	Gold	WTI	1466	0.0165	0.0858	−0.1977	0.2422	0.5587	0.4393	0.0020
G3	Silver	NGK2	1466	−0.0155	0.0900	−0.2511	0.2478	0.4509	0.5484	0.0007
G3	Gold	NGK2	1466	−0.0067	0.1014	−0.2792	0.2596	0.4836	0.5143	0.0020
G3	Silver	CFI2Z2	1466	0.0053	0.0919	−0.2067	0.2704	0.4966	0.5020	0.0014
G3	Gold	CFI2Z2	1466	−0.0220	0.0961	−0.2833	0.2629	0.3874	0.6105	0.0020
G3	Silver	TASI	1466	−0.0189	0.0933	−0.2866	0.2424	0.4195	0.5784	0.0020
G3	Gold	TASI	1466	−0.0328	0.0953	−0.2418	0.2476	0.3588	0.6392	0.0020
G3	Silver	EFIV	1466	0.0237	0.0913	−0.2310	0.3575	0.6207	0.3772	0.0020
G3	Gold	EFIV	1466	0.0352	0.0917	−0.2509	0.2468	0.6671	0.3315	0.0014

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Table A2. Summary statistics of dynamic correlations for Gold and Silver.

Group	Base	Asset	Mean ρ	SD of ρ	Min ρ	Max ρ	Freq. CI > 0	Freq. CI < 0	Freq. of CI Crossing 0	Mean ρ DCC	SD of ρ DCC	Min ρ DCC	Max ρ DCC
G1	Gold	Bitcoin	−0.0115	0.1121	−0.2904	0.3110	0.4482	0.5477	0.0041	0.1133	0.0576	−0.0699	0.2862
G1	Gold	Dash	0.0216	0.1032	−0.2781	0.3121	0.5614	0.4352	0.0034	0.0745	0.0525	−0.0695	0.1979
G1	Gold	Ethereum	0.0215	0.0793	−0.2041	0.2543	0.5955	0.4018	0.0027	0.1130	0.0481	−0.0263	0.2873
G1	Gold	Monero	0.0062	0.1046	−0.3025	0.2684	0.5218	0.4748	0.0034	0.1051	0.0505	−0.0732	0.2677
G1	Gold	Ripple	0.0124	0.0833	−0.2871	0.2647	0.5621	0.4379	0.0000	0.0708	0.0450	−0.0513	0.1926
G1	Silver	Bitcoin	0.0116	0.1070	−0.3352	0.2574	0.5628	0.4352	0.0020	0.1544	0.0535	−0.0071	0.3030
G1	Silver	Dash	−0.0048	0.0849	−0.2104	0.2469	0.4611	0.5382	0.0007	0.1250	0.0394	−0.0179	0.2394
G1	Silver	Ethereum	0.0095	0.0913	−0.2534	0.2458	0.5907	0.4086	0.0007	0.1541	0.0431	0.0420	0.2741
G1	Silver	Monero	0.0235	0.0965	−0.2131	0.3264	0.5389	0.4604	0.0007	0.1363	0.0392	0.0321	0.2317
G1	Silver	Ripple	0.0029	0.0793	−0.2267	0.2181	0.5389	0.4591	0.0020	0.1230	0.0386	0.0073	0.2418
G2	Gold	DGX	0.0050	0.0947	−0.2531	0.2704	0.5157	0.4809	0.0034	0.0621	0.0454	−0.1075	0.2439
G2	Gold	PAXG	0.1514	0.1038	−0.1351	0.4385	0.9134	0.0866	0.0000	0.8963	0.0235	0.7977	0.9363
G2	Gold	TRUEUSD	0.0067	0.1191	−0.3968	0.2819	0.5355	0.4645	0.0000	−0.0008	0.0365	−0.1627	0.1100
G2	Gold	Tether	0.0109	0.0954	−0.2318	0.2624	0.5314	0.4652	0.0034	0.0650	0.0417	−0.0908	0.2081
G2	Gold	XAUT	0.1822	0.1034	−0.1230	0.4573	0.9516	0.0484	0.0000	0.9195	0.0161	0.8583	0.9539
G2	Silver	DGX	0.0286	0.0892	−0.2002	0.3057	0.6098	0.3902	0.0000	0.0625	0.0441	−0.0775	0.2357
G2	Silver	PAXG	0.1104	0.0970	−0.1669	0.4078	0.8738	0.1262	0.0000	0.6396	0.0317	0.5606	0.7302
G2	Silver	TRUEUSD	0.0201	0.0988	−0.2363	0.3000	0.5846	0.4120	0.0034	0.0375	0.0359	−0.0862	0.1486
G2	Silver	Tether	−0.0081	0.0896	−0.2826	0.2281	0.4823	0.5136	0.0041	0.0702	0.0313	−0.0338	0.1494
G2	Silver	XAUT	0.1156	0.0902	−0.1305	0.3515	0.8888	0.1112	0.0000	0.6794	0.0322	0.5950	0.7516
G3	Gold	CFI2Z2	−0.0220	0.0961	−0.2833	0.2629	0.3874	0.6105	0.0020	0.0455	0.0382	−0.1093	0.1662
G3	Gold	EFIV	0.0352	0.0917	−0.2509	0.2468	0.6671	0.3315	0.0014	0.1433	0.0717	−0.0991	0.3184
G3	Gold	NGK2	−0.0067	0.1014	−0.2792	0.2596	0.4836	0.5143	0.0020	0.0286	0.0397	−0.1024	0.1876
G3	Gold	TASI	−0.0328	0.0953	−0.2418	0.2476	0.3588	0.6392	0.0020	0.0785	0.0581	−0.0452	0.2732
G3	Gold	WTI	0.0165	0.0858	−0.1977	0.2422	0.5587	0.4393	0.0020	0.1429	0.0602	−0.0276	0.3195
G3	Silver	CFI2Z2	0.0053	0.0919	−0.2067	0.2704	0.4966	0.5020	0.0014	0.0674	0.0381	−0.0955	0.1939
G3	Silver	EFIV	0.0237	0.0913	−0.2310	0.3575	0.6207	0.3772	0.0020	0.2033	0.0538	0.0028	0.4034
G3	Silver	NGK2	−0.0155	0.0900	−0.2511	0.2478	0.4509	0.5484	0.0007	0.0180	0.0432	−0.1267	0.1413
G3	Silver	TASI	−0.0189	0.0933	−0.2866	0.2424	0.4195	0.5784	0.0020	0.1227	0.0580	−0.0544	0.3527
G3	Silver	WTI	−0.0056	0.0748	−0.2308	0.2087	0.4802	0.5177	0.0020	0.1719	0.0566	0.0178	0.3836

Table A3. OOS Portfolio summary.

Group	Base	H	*p*	Mean GMV Turnover	GMV Mean Daily Return	GMV Ann. Volatility	GMV Ann. Return	GMV Sharpe Ratio	GMV Max. Drawdown	EW Mean Daily Return	EW Ann. Volatility	EW Ann. Return	EW Sharpe Ratio	EW Max. Drawdown
G1	Silver	750	6	0.0501	−0.0119	39.6144	−0.9508	−0.0756	−5136.7600	−0.0034	47.8030	−0.5740	−0.0178	−1,034,957.1
G1	Gold	750	6	0.0440	0.0152	28.7513	43.6443	0.1331	−18.1051	−0.0052	46.3513	−0.7343	−0.0285	−1,553,222.2
G2	Silver	750	6	0.0308	0.0012	2.1290	0.3458	0.1396	−1.0415	0.0202	17.7347	155.1719	0.2877	−1.0630
G2	Gold	750	6	0.0340	0.0053	2.0879	2.8253	0.6443	−0.9997	0.0184	15.7003	97.4794	0.2950	−1.0000
G3	Silver	750	6	0.0402	−0.0223	10.7621	−0.9966	−0.5212	−1.0000	−0.0087	20.2641	−0.8891	−0.1081	−1.3526
G3	Gold	750	6	0.0398	−0.0086	9.2433	−0.8863	−0.2342	−1.0037	−0.0106	19.0376	−0.9310	−0.1397	−1.6212

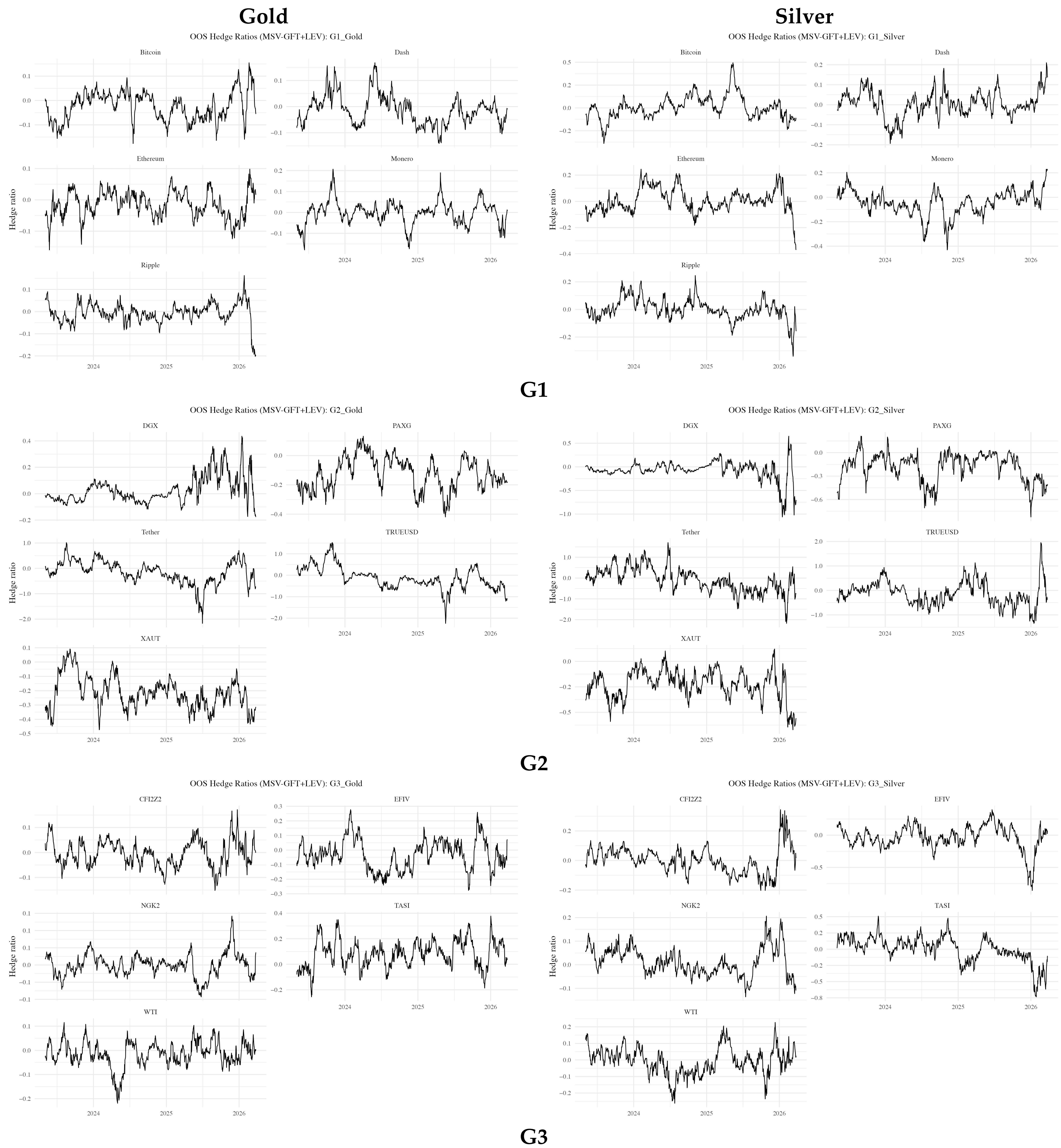


Figure A1. OOS Hedge ratio.

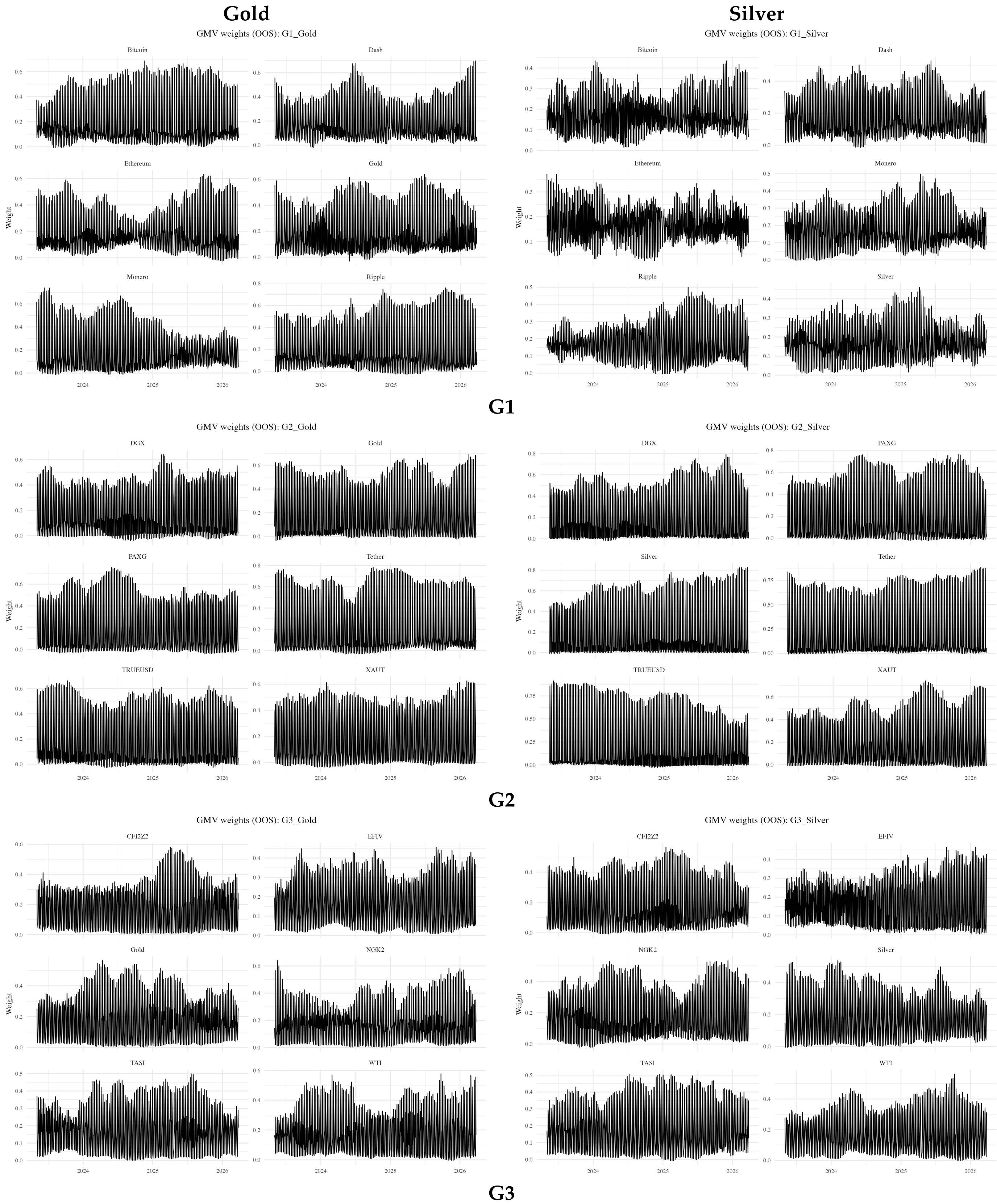


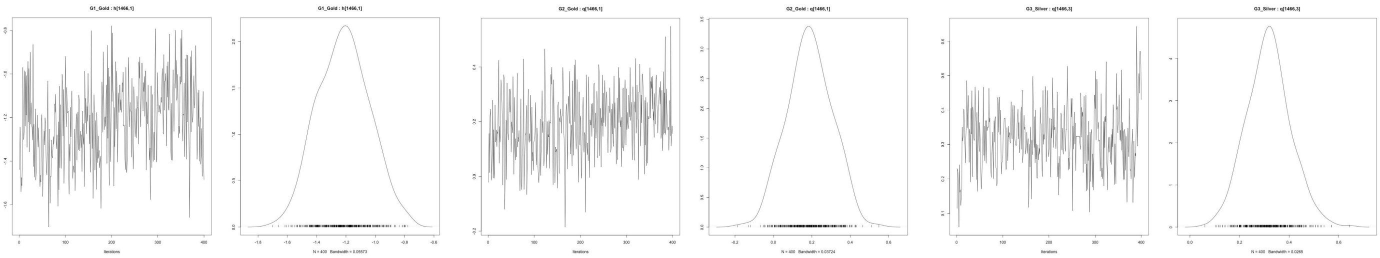
Figure A2. OOS Weights.

Appendix B

Table A4. Results of ARCH-LM and Ljung–Box tests on squared returns.

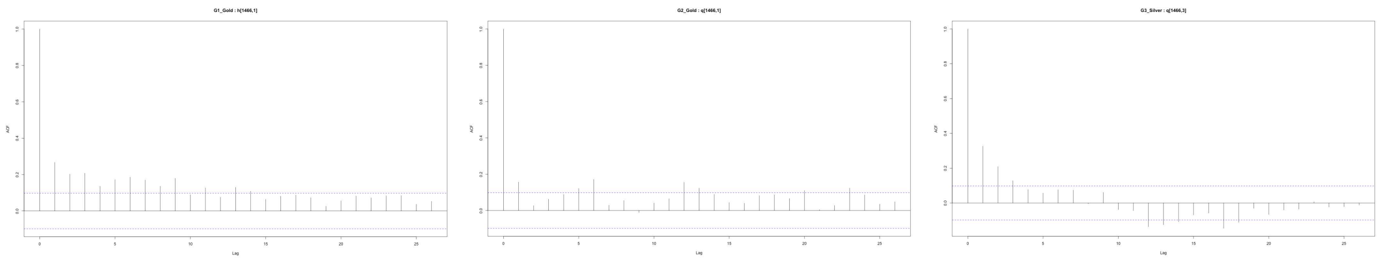
Asset	Statistic ARCH-LM	*p* Value ARCH-LM	Statistic LB	*p* Value LB
Gold	181.45	<0.001	312.46	<0.001
Silver	228.99	<0.001	295.48	<0.001

Appendix C



G1—Gold h [1466,1] G2—Gold q [1466,1] G3—Silver q [1466,3]

Figure A3. Trace plots.



G1—Gold h [1466,1] G2—Gold q [1466,1] G3—Silver q [1466,3]

Figure A4. Autocorrelation functions. Note: The blue dashed lines represent the 95% confidence intervals.

Table A5. Quantitative convergence diagnostics.

Group	Variable	ESS	Geweke Z
G1 Gold	h [1466,3]	168.25	4.03
G1 Gold	q [1466,2]	42.51	6.34
G2 Gold	h [1466,1]	153.79	−3.32
G2 Gold	q [1466,3]	249.83	0.15
G3 Gold	h [1466,1]	252.68	−2.65
G3 Silver	q [1466,3]	160.35	−0.54

Appendix D

Table A6. Robustness analysis using SPDR Gold Shares (GLD) as an alternative benchmark.

Group	Asset	HE_Gold	HE_GLD	Difference
G1	Bitcoin	0.0123	0.0109	−0.0014
G1	Ethereum	0.0126	0.0125	−0.0001
G1	Ripple	0.0050	0.0035	−0.0015

Table A6. *Cont.*

Group	Asset	HE_Gold	HE_GLD	Difference
G1	Dash	0.0022	0.0016	−0.0006
G1	Monero	0.0095	0.0080	−0.0015
G2	Tether	0.0025	0.0041	0.0016
G2	TRUEUSD	0.0003	0.0007	0.0004
G2	DGX	0.0008	0.0004	−0.0004
G2	PAXG	0.8230	0.7849	−0.0381
G2	XAUT	0.8546	0.8264	−0.0282
G3	WTI	0.0223	0.0184	−0.0039
G3	NGK2	0.0009	0.0001	−0.0008
G3	CFI2Z2	0.0017	0.0013	−0.0004
G3	TASI	0.0073	0.0055	−0.0018
G3	EFIV	0.0165	0.0202	0.0037

Appendix E

Table A7. Hedge effectiveness across volatility regimes for gold.

Group	Asset	Low Vol	Medium Vol	High Vol
G1	Bitcoin	0.0011	0.0032	0.0271
G1	Dash	0.0001	0.0008	0.0066
G1	Ethereum	0.0103	0.0013	0.0300
G1	Monero	0.0002	0.0021	0.0233
G1	Ripple	0.0046	0.0000	0.0161
G2	DGX	0.0063	0.0007	0.0021
G2	PAXG	0.1917	0.5851	0.8970
G2	TRUEUSD	0.0008	0.0026	0.0001
G2	Tether	0.0013	0.0002	0.0083
G2	XAUT	0.2513	0.6629	0.9129
G3	CFI2Z2	0.0088	0.0011	0.0053
G3	EFIV	0.0031	0.0068	0.0301
G3	NGK2	0.0007	0.0046	0.0010
G3	TASI	0.0001	0.0031	0.0145
G3	WTI	0.0007	0.0445	0.0331

Table A8. Hedge effectiveness across volatility regimes for silver.

Group	Asset	Low Vol	Medium Vol	High Vol
G1	Bitcoin	0.0003	0.0305	0.0419
G1	Dash	0.0001	0.0097	0.0320
G1	Ethereum	0.0029	0.0195	0.0471
G1	Monero	0.0003	0.0132	0.0550

Table A8. *Cont.*

Group	Asset	Low Vol	Medium Vol	High Vol
G1	Ripple	0.0023	0.0060	0.0264
G2	DGX	0.0005	0.0018	0.0005
G2	PAXG	0.0140	0.2487	0.6364
G2	TRUEUSD	0.0004	0.0002	0.0061
G2	Tether	0.0004	0.0046	0.0030
G2	XAUT	0.0255	0.2722	0.6723
G3	CFI2Z2	0.0006	0.0009	0.0147
G3	EFIV	0.0126	0.0049	0.0783
G3	NGK2	0.0003	0.0003	0.0000
G3	TASI	0.0000	0.0125	0.0210
G3	WTI	0.0000	0.0023	0.0524

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