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# DO POLICY REGIMES MATTER? THE INTERDEPENDENCE OF BITCOIN WITH EQUITIES, GOLD, AND USD/INR IN INDIA

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## Abstract

This study investigates state-contingent linkages. This is done using the multivariate quantile-on-quantile framework. The dataset employed is daily data. The span of the data is from 1 January 2018 to 13 July 2023. The linkages examined are between Bitcoin (BTC/USD) and three domestic risk factors. These factors include Indian equities (NIFTY-100), gold (XAU/USD), and the rupee-dollar exchange rate (USD/INR). The analysis maps dependence surfaces $\beta(\theta,\Phi)$ or the analysis examines BTC with respect to each predictor. It also evaluates how the linkages adjust across five specific Indian policy windows. These periods are defined by key events. The windows investigated are: the RBI banking restriction, the post-Supreme Court/pre-tax interval, the VDA tax, the TDS phase, and the post-FTX period. Full-sample results indicate modest comovement near the joint median but pronounced tail effects: BTC-equity linkages strengthen during equity drawdowns; BTC-gold dependence turns positive in gold's upper quantiles; and BTC's association with USD/INR intensifies under rupee depreciation. Regime-difference panels show selective reweighting across transitions, dampening center-region links while preserving or amplifying tail sensitivities. Findings remain robust under reasonable tuning choices. The evidence supports state-contingent portfolio management and motivates macroprudential monitoring of crypto-FX channels.

**Keywords:** Bitcoin, Quantile-on-Quantile Regression, State-Contingent Dependence, Tail Risk, Regime Shifts

**JEL Codes:** C21, C22, G11, G12, F31, E44

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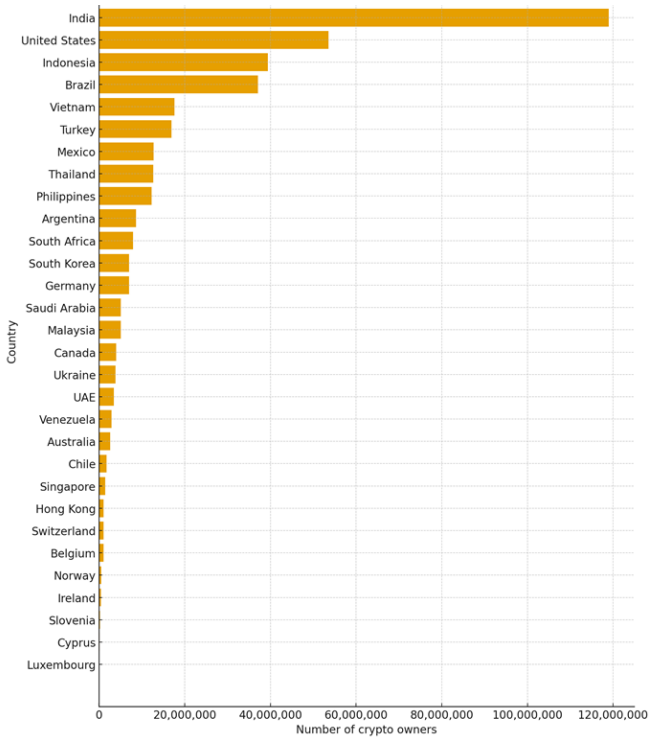
## INTRODUCTION

Bitcoin is a new form of cryptocurrency based on blockchain technology. It was introduced as a peer-to-peer digital cash system, and it appeared only 45 days after the global financial crisis of 2008. Trading on exchanges started a few years later, and many researchers use data beginning in 2011. For this reason, the academic literature on Bitcoin is still quite recent (Baur et al., 2019).

The use of cryptocurrencies continues to grow in many countries. As a major company working in cryptocurrency payments, we aim to provide important statistics that help businesses understand this market and identify new opportunities for expansion. In 2023, global crypto ownership was estimated at around 4.2%, which corresponds to more than 420 million users worldwide. Between 2015 and 2025, the price of Bitcoin increased by more than 173,000% (https://coinledger.io/research/top-10-countries-that-use-bitcoin Access:11/09/2025).

As of May 2025, the countries with the most crypto are as follows:

**Graph 1.** Number of crypto ownerships by country




**Source:** https://coinledger.io/research/top-10-countries-that-use-bitcoin (2025, May 30)

The Graph 1 indicates that India hosts the largest absolute number of crypto owners worldwide (≈119 million). The selection of India as the focus of this study is based on several critical reasons. First, India is

home to the largest absolute number of crypto asset owners worldwide, with approximately 119 million people. This massive user scale makes India a natural and significant focal case for examining the interaction of crypto assets with the local financial ecosystem. More importantly, between 2018 and 2023, India witnessed very distinct and sharp regime shifts in the institutional approach toward crypto assets. This period, ranging from the RBI (Reserve Bank of India) banking restriction in 2018 to the Supreme Court's reversal of this decision in 2020, and subsequently to the 30% Virtual Digital Asset (VDA) tax and 1% tax-deducted-at-source (TDS) regulations that came into effect in 2022, provides a unique research ground for measuring the impact of "policy regimes" on market dependencies.

The study's timeframe, covering January 1, 2018, to July 13, 2023, was also meticulously determined to reflect this dynamic structure. This period represents a phase where the Bitcoin market structure evolved into a more advanced stage following the post-futures period. The selected window includes not only the domestic policy shifts mentioned above but also many globally decisive macroeconomic and sectoral events, such as the COVID-19 financial turmoil, the 2020 halving, the 2021 bull market, the 2022–2023 monetary tightening cycle, and the collapse of the FTX exchange. This broad and event-oriented perspective provides sufficient observations for joint-tail analyses while aiming to maintain the consistency of results by avoiding potential structural breaks after mid-2023. Accordingly, subsequent sections analyze linkages in the BTC-NIFTY100-XAU/USD-USD/INR setting.

This study is motivated by the need to understand how radical shifts in domestic regulatory environments influence the behavior of emerging asset classes. Specifically, the research seeks to answer how distinct policy regimes, ranging from banking restrictions to explicit taxation frameworks, reconfigure the state-contingent linkages between Bitcoin and traditional Indian financial pillars such as equities, gold, and the national currency. By addressing this question, the analysis moves beyond static correlation to explore whether institutional interventions dampen or amplify the transmission of risks across the crypto-fiat interface. The originality of this research lies in its multi-dimensional approach to the Indian crypto-ecosystem, which represents the world's largest absolute base of digital asset owners with approximately 119 million users. While existing literature often focuses on developed markets or assumes a uniform market structure, this study provides a unique contribution by explicitly segmenting the analysis into five critical policy windows, including the RBI restrictions and the implementation of VDA and TDS regulations. Furthermore, by employing a Multivariate Quantile-on-Quantile Regression (M-QQR) framework, the study captures the complexity of the full joint distribution of returns, allowing for the identification of tail-risk symmetries, such as the strengthening of linkages during equity drawdowns or rupee depreciation, that remain invisible to standard mean-based models. Ultimately, this research provides a comprehensive

macroprudential view of how Bitcoin interacts with the primary pillars of the Indian financial market under different policy regimes.

In recent years, many studies have investigated whether Bitcoin can be viewed as a safe investment tool. Some research finds that Bitcoin shows safe-asset characteristics (Fang et al., 2019; Kajtazi & Moro, 2019; Matkovskyy et al., 2020; Rehman et al., 2020; Rubbaniy et al., 2021, 2022; Yan et al., 2022). However, other studies present the opposite conclusion and argue that Bitcoin does not behave as a safe asset (Bianchi et al., 2022; Bouri et al., 2017; Long et al., 2021; Shehzad et al., 2021).

Bitcoin is often described as a new form of gold (Baur & Hoang, 2021; Jia et al., 2023; Klein et al., 2018). Several studies compare Bitcoin and gold by looking at their common points and their differences (Al-Khazali et al., 2018; Dyhrberg, 2016a; Dyhrberg, 2016b). Gold is traditionally seen as a safe haven asset (Baur & McDermott, 2016). This is typically true during periods of economic or political stress. The role is especially important when inflation rates are high. However, recent evidence indicates a different result. This traditional assumption does not always hold true.

Gold typically gains value when global inflation rises. This also occurs when interest rates fall. This situation usually happens during economic downturns. For this reason, Gold is viewed as a hedge against uncertainty. It is particularly useful when large political events create instability. The upward trend in Gold prices mainly results from investors turning to safer assets. This action increases the demand for Gold. Gold is also used for portfolio diversification and as collateral (Fabris & Ješić, 2023).

Bitcoin and Gold share some common features. These include decentralized mining, ownership structure, and supply control. Still, they also differ in important ways. Gold is an old and established physical asset. Bitcoin is a digital asset and is much younger. Gold cannot be reproduced. Bitcoin, in contrast, can be copied by creating new coins with different names (Baur & Hoang, 2021).

The discussion on whether Bitcoin should be treated as a financial asset is still ongoing. However, the existing literature includes studies that analyze its relationship with other financial assets (Baur & Hoang, 2021; Fabris & Ješić, 2023; Hu et al., 2020; Hussain Shahzad et al., 2020; Jareño et al., 2020; Ozturk, 2020; Uzonwanne, 2021; Zeng et al., 2023). The literature review reveals studies that find a strong correlation between Bitcoin and Gold (Bouoiyour et al., 2019; Panagiotidis et al., 2019; Selmi et al., 2018; Shahzad et al., 2019). In contrast, other studies find a weaker relationship between Bitcoin and Gold (Baur & Hoang, 2021; Dyhrberg, 2016a; Gajardo et al., 2018; Henriques & Sadorsky, 2018; Pal & Mitra, 2019; Panagiotidis et al., 2019; Wu et al., 2019). Studies analyzing the relationship between Bitcoin and the stock market also exist (Baur et al., 2018b; Christoffersen et al., 2018; Hu et al., 2020; Hussain Shahzad et al.,

2020; Kwon, 2020; Kyriazis, 2020; Ma & Tanizaki, 2019; Omri, 2023; Pham et al., 2022; Salisu et al., 2019; Uzonwanne, 2021; Wang et al., 2019; Zeng et al., 2023). Additionally, the literature includes studies analyzing the relationship between Bitcoin and exchange rates (Atik et al., 2015; Georgoula et al., 2015; Szetela et al., 2016; Bouri et al., 2017; Erdas & Caglar, 2018; Ji et al., 2018; Baur et al., 2018a; Kristjanpoller & Bouri, 2019; Khaled, 2020; Palazzi et al., 2021; BenSaïda, 2023; Dumitrescu et al., 2023).

This paper performs an analysis of return comovement. This movement together is studied across different market states. The research examines four distinct assets. These assets include Bitcoin (BTC), Indian equities (NIFTY-100), gold (XAU/USD), and the rupee-dollar exchange rate (USD/INR). For this purpose, it uses a multivariate quantile-on-quantile approach. Instead of focusing on the mean or simple pairwise correlations, this method examines the full joint distribution of market conditions. In this way, we can observe whether BTC works as a diversifier, hedge, or safe haven when equities fall, the rupee comes under pressure, or gold prices increase.

The study follows Jia et al. (2023), who apply the QQR method to BTC-gold-equity returns. Our contribution is to include the exchange rate, estimate multivariate dependence surfaces, extend the sample period to 1 January 2018-13 July 2023, and test the results across several policy-related periods in India, such as the banking restriction, the Supreme Court's reversal, the VDA tax and the 1% TDS, and the post-FTX period.

The remainder of this study is organized as follows: Section 2 provides a detailed literature review on the relationship between Bitcoin, Gold, Stock Market and Exchange Rate; Section 3 describes the data and the methodology; Section 4 presents the findings of the study and Section 5 provides the results and discussion.

## LITERATURE REVIEW

The academic literature on Bitcoin is still relatively recent, as trading on exchanges only gained significant momentum after 2011 (Baur et al., 2019). The central debate in the existing discourse revolves around Bitcoin's role within the financial ecosystem, primarily focusing on its properties as a hedge, diversifier, or safe haven. Some research finds that Bitcoin exhibits safe-asset characteristics (Fang et al., 2019; Kajtazi & Moro, 2019; Matkovskyy et al., 2020; Rehman et al., 2020; Rubbaniy et al., 2021, 2022; Yan et al., 2022). However, other studies present the opposite conclusion, arguing that Bitcoin does not behave as a safe asset (Bianchi et al., 2022; Bouri et al., 2017; Long et al., 2021; Shehzad et al., 2021). A significant portion of the literature frames Bitcoin as "new gold" or "digital gold" due to shared features like

decentralized mining and limited supply (Baur & Hoang, 2021; Jia et al., 2023; Klein et al., 2018). Comparative studies often contrast these two assets during periods of economic or political stress (Al-Khazali et al., 2018; Dyhrberg, 2016a; Dyhrberg, 2016b). While gold is traditionally viewed as a safe haven during high inflation (Fabris & Ješić, 2023), empirical findings on its relationship with Bitcoin are mixed. Some studies report a strong correlation between Bitcoin and gold returns (Bouoiyour et al., 2019; Panagiotidis et al., 2019; Selmi et al., 2018; Shahzad et al., 2019). In contrast, others find a weaker or near-zero relationship (Baur & Hoang, 2021; Dyhrberg, 2016a; Gajardo et al., 2018; Henriques & Sadorsky, 2018; Pal & Mitra, 2019; Panagiotidis et al., 2019; Wu et al., 2019). Methodological approaches also reveal fundamental differences; for instance, Bitcoin returns display persistent multifractal behavior and higher degrees of multifractality compared to gold (Telli & Chen, 2020). Furthermore, the connectedness among Bitcoin, gold, and other commodities like crude oil tends to increase during periods of high volatility (Ozturk, 2020).

Regarding equity markets, Bitcoin's sensitivity to stock returns has been extensively analyzed across various market states (Baur et al., 2018b; Christoffersen et al., 2018; Hu et al., 2020; Hussain Shahzad et al., 2020; Kwon, 2020; Kyriazis, 2020; Ma & Tanizaki, 2019; Omri, 2023; Pham et al., 2022; Salisu et al., 2019; Uzonwanne, 2021; Wang et al., 2019; Zeng et al., 2023). Research indicates that U.S. stock market returns can have a significant and positive effect on Bitcoin returns, particularly in higher quantiles (Jareño et al., 2020). While Bitcoin may function as a hedge or safe haven against certain stock indices (Baur et al., 2018a; Kyriazis, 2020), its performance is often found to be weaker than that of gold, particularly across G7 or developed markets (Shahzad et al., 2019; Christoffersen et al., 2018). Studies also identify one-way volatility spillovers from emerging markets to Bitcoin and suggest that Bitcoin price fluctuations can improve the predictability of stock returns in G7 countries (Omri, 2023; Salisu et al., 2019). Similar to its relationship with other assets, Bitcoin exhibits tail behavior comparable to the stock market index in terms of contemporaneous correlation (Kwon, 2020) and serves as a source of net return spillovers in South Asian and Chinese markets (Zeng et al., 2023).

The interaction between Bitcoin and foreign exchange (FX) markets represents a third critical pillar of the research (Atik et al., 2015; Georgoula et al., 2015; Szetela et al., 2016; Bouri et al., 2017; Erdas & Caglar, 2018; Ji et al., 2018; Baur et al., 2018a; Kristjanpoller & Bouri, 2019; Khaled, 2020; Palazzi et al., 2021; BenSaïda, 2023; Dumitrescu et al., 2023). Cointegration analyses have detected causal relationships between Bitcoin and major global currencies like the Japanese yen (Atik et al., 2015), while time-series evidence shows strong negative correlations with the USD and EUR (Georgoula et al., 2015). Short-term movements in Bitcoin prices are often influenced by global financial indicators, including exchange rates and the Dow Jones Index (Ciaian et al., 2016). Conditional variance linkages have been identified across

major currencies like the yuan and euro (Szetela et al., 2016; Palazzi et al., 2021), with cross-market relationships becoming particularly strong during Bitcoin crashes or the 2021-2022 pandemic period (BenSaïda, 2023). However, the strength of these linkages varies geographically; for instance, while significant relationships exist in European non-euro countries (Dumitrescu et al., 2023), almost no significant relationship is found between cryptocurrency returns and many Arab currencies (Khaled, 2020).

Despite the depth of these individual areas, a significant gap remains in the literature. Most existing studies utilize mean-based models or standard pairwise correlations that fail to capture the full complexity of joint market distributions. Furthermore, there is a lack of research that simultaneously integrates equity, gold, and currency risks within a single multivariate framework, particularly in the context of a major emerging market like India. While India hosts the world's largest absolute number of crypto owners (Kemmerer, 2025), the impact of its unique and rapid policy transitions, such as the RBI banking restrictions, the Supreme Court's reversal, and the subsequent implementation of VDA and TDS tax regimes, on market dependencies remains largely unexplored. This study fills this gap by employing the Multivariate Quantile-on-Quantile Regression (M-QQR) approach (Alola et al., 2023; Ozkan et al., 2023) to provide a state-contingent analysis of Bitcoin's interdependence under shifting institutional frameworks.

## DATA AND METHODOLOGY

This section presents the data and the empirical design. This paper first outlines the sample and markets utilized. The construction of the return series is also described. Basic conventions are presented for comparability across assets. Next, the multivariate quantile-on-quantile framework is sketched. This framework traces state-dependent linkages. The linkages are among Bitcoin, equities, gold, and the exchange rate. The high-level approach to estimation and inference is presented as well.

### Data

This study uses daily data. The period runs from 1 January 2018 to 13 July 2023. The starting point reflects the post-futures period. At this time, the market structure of Bitcoin became more developed. The period also covers key policy events specific to India. These events include the banking restriction in April 2018. It also covers the restriction's reversal by the Supreme Court in March 2020. Later, the virtual digital asset tax of 30 percent (effective April 2022) was introduced. The 1 percent tax-deducted-at-source rule (effective July 2022) was also introduced. The sample period further includes several important global episodes. Examples are the COVID-19 turmoil, the May 2020 halving, the 2021 bull market, and the

monetary-tightening cycle during 2022-2023. This specific window provides enough observations in the joint tails. It also avoids structural breaks that occur after mid-2023.

To study whether dependence changes across different regimes, the sample is divided into event-based windows. These windows reflect institutional shifts in India and one major global shock. The RBI circular of 6 April 2018 restricted banking access for crypto-related firms. This action likely influenced domestic liquidity and price discovery. This restriction ended when the Supreme Court reversed the decision on 4 March 2020.

In 2022, the policy stance changed from permissive to explicitly taxed. The 30% virtual digital asset tax started on 1 April 2022, and the 1% tax-deducted-at-source on crypto transfers began on 1 July 2022. Both measures affect trading frictions and market turnover. In addition, the collapse of FTX on 11 November 2022 represents an external shock to market structure and investor confidence.

For these reasons, we estimate the M-QQR surfaces separately for five non-overlapping windows: the RBI restriction period, the post-SC/pre-tax period, the tax period, the TDS period, and the post-FTX period. We use the same quantile grid and bandwidth in all subsamples to ensure comparability. Since the tax and TDS windows are naturally short, we interpret their results in a qualitative way and avoid overfitting.

The analysis utilizes four primary return series: Bitcoin priced in U.S. dollars (BTC/USD), Indian equities represented by the NIFTY-100 index (denominated in INR), gold spot prices in U.S. dollars (XAU/USD), and the USD/INR exchange rate. The selection of these specific variables is grounded in established financial literature and tailored to the unique economic context of India, which hosts the world's largest absolute number of crypto owners, totaling approximately 119 million. Bitcoin (BTC/USD) is designated as the dependent variable, following the ongoing academic discourse regarding its role as either a "digital gold" or a speculative asset. Among the independent variables, the NIFTY-100 index serves as a proxy for domestic equity market risk, a choice consistent with Jia et al. (2023), who emphasize the importance of equity-crypto linkages in portfolio diversification. Gold (XAU/USD) is included as a traditional safe-haven benchmark to compare its hedging properties with Bitcoin, as established by Baur and Hoang (2021) and Jia et al. (2023), providing essential insights given India's cultural and economic affinity for the metal. Furthermore, the USD/INR exchange rate is incorporated to capture currency-related risks and crypto-FX channels; these are particularly salient for emerging markets like India, where currency stress often coincides with shifts in domestic liquidity and capital-flow pressures, as highlighted by BenSaïda (2023) and Dumitrescu et al. (2023). By integrating these variables, the model aims to provide a comprehensive view of how Bitcoin interacts with the primary pillars of the Indian financial market under

shifting policy regimes. Consistently throughout the study, a positive return in USD/INR is taken to mean a depreciation of the rupee.

Price data come from widely used academic and commercial sources. All series use closing quotes. Because Bitcoin and gold trade almost continuously, we apply a fixed daily cut-off at 00:00 UTC to make the timestamps consistent across assets. Trading calendars are matched by taking the common intersection of available dates, and any day with missing observations in any market is removed to maintain a balanced dataset. Returns are calculated as continuously compounded log differences,

$$r_t = 100[\ln(P_t) - (\ln(P_{t-1})] \quad (1)$$

expressed in percentage points. No filtering or winsorization is applied in the baseline analysis. Robustness checks show that using a two-sided 1 percent winsorization does not change the main results.

To justify the application of the Multivariate Quantile-on-Quantile Regression (M-QQR) framework, a series of preliminary assumption tests were conducted. These include the Jarque-Bera test to evaluate normality, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for stationarity, and the Broock-Dechert-Scheinkman (BDS) test to detect structural non-linearity within the return series. The comprehensive empirical results, along with the detailed interpretations of these preliminary tests, are presented and discussed at the Findings Section to provide a robust foundation for the subsequent M-QQR analysis. For robustness, we also analyze event-based sub-samples that capture changes in the institutional and market environment. These include the period of the banking restriction, the post-reversal but pre-tax interval, the tax and TDS phases, and the post-FTX period.

**Methodology**

This study uses the recently developed multivariate quantile-on-quantile regression (M-QQR) method introduced by Alola et al. (2023) and Ozkan et al. (2023). The M-QQR approach is a non-parametric modeling technique.

The research applies this model to examine how Bitcoin affects the Indian economy. To do this, we study the relationship between Bitcoin and the NIFTY100 index, which is the most liquid stock index in India. We also investigate the link between Bitcoin and the Indian Rupee, as well as the ounce price of gold.

As a first step, the analysis identifies the functional relationship between the variables using the following approach:

$$lnBTC = f(lnNIFTY, lnRUPEE, lnGOLD) \quad (2)$$

The natural logarithm, indicated as $ln$, is applied to represent the logarithm with base e. In this study, the variable $f$ is used to indicate a function, while *BTC* is used to represent the dependent variable, which corresponds to the price of Bitcoin. The independent variables include $NIFTY$ (NIFTY-100 Index), $RUPEE$ (India's domestic currency), and $GOLD$ (price of one ounce of gold in U.S. dollars) .

The econometric model describes the relationship shown in Equation (3) (Jia et al., 2023). This model can be written as follows:

$$lnBTC_t = \rho_0 + \theta_1 lnNIFTY_t + \theta_2 lnRUPEE_t + \theta_3 lnGOLD_t + \varepsilon_t \quad (3)$$

In this context, $\rho_0$ indicates the constant, $t$ symbolizes the time period, and $\varepsilon_t$ symbolizes the error term. The error term is defined by a mean value approaching zero and a variance symbolized by $\sigma^2$ and $\varepsilon_t / u_t \sim iid(0, \sigma^2)$.

The next part of the study employs the multivariate quantile-over-quantile regression (QQR) method. This approach helps to examine how relationship complexity influences prices. The prices examined are for four assets. The assets are Bitcoin, the NIFTY100 index, the Indian Rupee, and the ounce value of gold. For comparison, we also apply a standard quantile-on-quantile analysis at this stage.

Sim and Zhou (2015) introduce a nonparametric method. This method is based on quantile-over-quantile analysis. Their approach makes it possible to study the relationship between two variables. Specifically, it examines how this relationship changes across different points of their distributions. The study also investigates changes in the relationship over time. To analyze the complex interdependence between Bitcoin and Indian financial assets, we first define the standard bivariate Quantile-on-Quantile Regression (QQR) as our foundational model. This approach allows us to examine how a specific quantile of a predictor ($x$) affects a specific quantile of Bitcoin returns ($y$) . The local-linear QQR model is specified as follows:

$$BTC_t = \beta_0(\theta, \Phi) + \beta_1(\theta, \Phi)(x_t - x^{\Phi}) + \propto^{\theta} BTC_{t-1} + \varepsilon_t^{\theta}\rangle \quad (4)$$

The variables $\theta$ and $\Phi$ indicate quantiles ranging from 0.05 to 0.95 for the dependent and independent variables, respectively. The term $\varepsilon_t^{\theta}$ is frequently referred to as the residual term, and it is assumed to have a quantile of zero for the variable $\theta$. Furthermore, the relationship between $x$ and $y$ can be potentially explained by part $(\beta_1(\theta,\Phi)(x_t - x^{\Phi}))$ of Equation (4), which accounts for the interdependence between their respective distributions.

We implement a local–linear quantile-on-quantile estimator following Sim and Zhou (2015). For each predictor quantile $\Phi$ and response quantile $\theta$, the coefficients $\beta_0(\theta,\Phi),\ \beta_1(\theta,\Phi)(x_t - x^{\Phi}) + \propto^{\theta}$ solve:

$$\min_{\beta_0,\beta_1,\alpha} \sum_t \omega_t(\Phi)\, \rho_\theta(y_t - \beta_0 - \beta_1(x_t - x^{\Phi}) - \alpha y_{t-1}) \tag{5}$$

Where $\rho_\theta(u) = u(\theta - 1\{u < 0\})$ is the check loss, and the kernel weights are:

$$\omega_t(\Phi) = \frac{K\left(\frac{\hat{F}(x_t) - \Phi}{h}\right)}{\sum_s K\left(\frac{\hat{F}_x(x_s) - \Phi}{h}\right)} \tag{6}$$

with $\hat{F}$ the empirical CDF of $x_t$ and $K(.)$ a Gaussian kernel, $K(u) = (2\pi)^{-1/2}\exp\left(-\frac{u^2}{2}\right)$. We trim $\theta, \Phi \in [0.05, 0.95]$ to mitigate boundary effects and set the baseline bandwidth to $h = 0.05$. or the short Tax and TDS windows used in the regime-difference panels, we adopt compact settings to avoid empty cells (0.10 quantile steps; $h = 0.15$ with adaptive expansion up to $\pm 0.45$; minimum effective local ($N = 30$). When we use an Epanechnikov kernel or a local-constant specification, the results do not change in any meaningful way. This shows that the main findings remain the same.

Similarly, Equation 4 introduces the quantile-on-quantile regression (QQR) method, which relies on only one explanatory variable. However, this approach does not include other important variables that may affect the dependent variable. To address this limitation and make the analysis more complete, we propose an extension of the QQR approach. This extension places the method in a multivariate framework, which we refer to as Multivariate QQR.

To address the limitations of bivariate models and provide a comprehensive view of the Indian market, we extend this into the Multivariate QQR (M-QQR) framework. The multivariate version allows us

to study the relationship between the quantiles of the dependent variable and the quantiles of several independent variables at the same time. This model can be mathematically represented as:

$$BTC_t = \beta_0(\theta, \Phi_1, \Phi_2, \Phi_3) + \beta_1(\theta, \Phi_1)(NIFTY_t - NIFTY^{\Phi_1}) + \beta_2(\theta, \Phi_2)(RUPEE_t - RUPEE^{\Phi_2}) + \beta_3(\theta, \Phi_3)(GOLD_t - GOLD^{\Phi_3}) + \propto^{\theta} BTC_{t-1} + \varepsilon_t^{\theta} \quad (7)$$

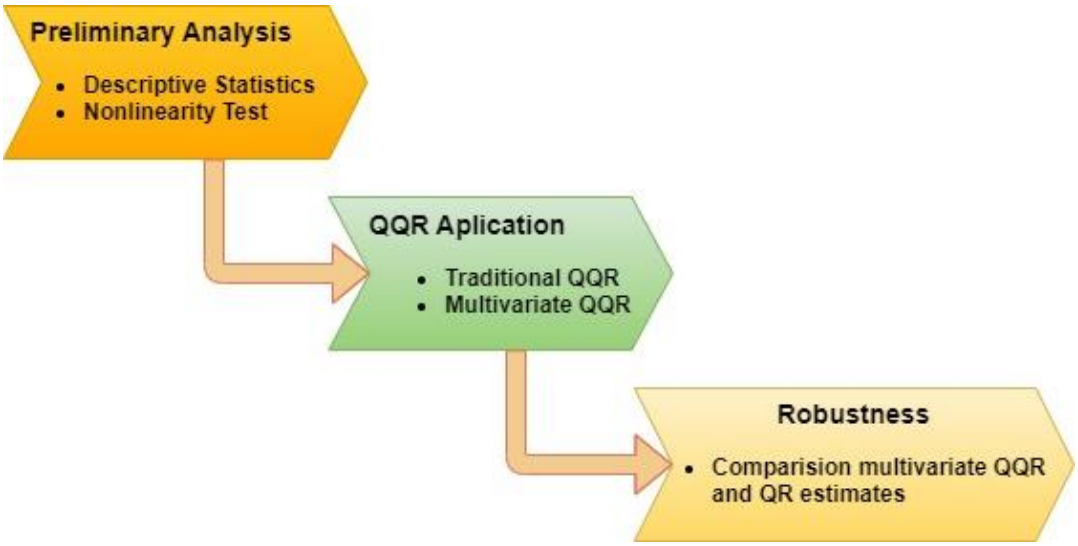
In this multivariate specification NIFTY, RUPEE, and GOLD represent the three domestic risk factors. $\Phi_1, \Phi_2, \Phi_3$ indicate the quantiles of independent variables and $\theta$ represent the quantile of dependent variable. Furthermore, $\beta_1, \beta_2, \beta_3$ document the slope coefficients that represent the sensitivity of Bitcoin returns to each factor across various joint market states. The QQR method requires a careful selection of the optimal bandwidth. For this reason, the study uses a bandwidth size of 0.05. This specific choice is consistent with the earlier work of Sim and Zhou (2015).

To ensure reliable cell-wise estimation in short windows (Tax and TDS), we employ a coarser quantile grid (0.10 steps), a wider bandwidth ($h = 0.15$) with adaptive expansion up to ±0.45, and a minimum local sample size of 30 for the regime-specific difference surfaces. These compact settings prevent empty cells in the difference surfaces. They also preserve comparability across transitions. The results are qualitatively consistent with the baseline.

The final step involves testing the robustness of the results. Specifically, it tests the multivariate quantile regression (QR) results. For this purpose, the multivariate QR method is utilized. This method was developed by Koenker and Bassett Jr. (1978). This approach is selected because QR has been widely used in earlier studies. Importantly, it provides a reliable way to check the consistency of the QQR results (Yasmeen et al., 2022; Sharma et al., 2023).

Figure 1 shows the flowchart for the analysis process. This process begins with a preliminary analysis. In this part of the study, the statistical characteristics of the examined series are first analyzed. These characteristics include the mean, maximum, minimum, standard deviation, skewness, kurtosis, normality, and stationarity.

**Figure 1.** Analysis flow




Moreover, it is very important to check if the data series is linear or nonlinear. This step ensures that the chosen econometric techniques are appropriate. Using linear data in nonlinear models, or using nonlinear data in linear models, can lead to incorrect results. To achieve this, the Broock-Dechert-Scheinkman (BDS) nonlinearity test is utilized. Broock et al. (1996) developed this test. This test is based on chaos theory. It is currently very popular in the literature for checking (non)linearity. Researchers such as Syed et al. (2021), Ramzan et al. (2022), and Khan et al. (2023) have also used this test in their studies.

## FINDINGS

The multivariate quantile-on-quantile regressions are estimated using the full sample. The sample period spans from 1 January 2018 to 13 July 2023. This approach helps to study how daily returns move together across different market states. The returns examined include Bitcoin (BTC/USD), Indian equities (NIFTY-100), gold (XAU/USD), and the rupee–dollar exchange rate (USD/INR).

The dependence surfaces for Bitcoin are presented next. These surfaces show the linkages of BTC with equities, gold, and the exchange rate. It is important to note that a positive return in USD/INR reflects a depreciation of the rupee. The discussion begins with an overview of the median relationships. It then moves to the joint tails. The joint tails are especially important for risk management and safe-haven behavior. Finally, the robustness of the results is assessed using sub-samples based on specific events.

The descriptive statistics for the 1,366 daily observations are presented in Table 1. All return series exhibit negative skewness and high kurtosis coefficients, ranging from 4.87 for USD/INR to as high as

16.41 for NIFTY-100, well exceeding the threshold for a normal distribution. The Jarque–Bera test statistics (1371.45 for BTC, 10344.55 for NIFTY-100, 201.87 for USD/INR, and 553.70 for XAU/USD) significantly reject the null hypothesis of a normal distribution with p-values of 0.0000 across all variables. These findings indicate that the data possess "fat tails" and non-Gaussian behavior, which justifies the use of a quantile-based approach over standard mean-based regressions.

**Table 1.** Descriptive statistics

| | | BTC | NIFTY100 | USD/INR | XAU/USD |
|---|---|---|---|---|---|
| Observations | | 1366 | 1366 | 1366 | 1366 |
| Mean | | 0.001720 | 0.000488 | 0.000189 | 0.000340 |
| Median | | 0.000422 | 0.000898 | 0.000173 | 0.000445 |
| Minimum | | -0.346847 | -0.111672 | -0.016622 | -0.057150 |
| Maximum | | 0.274623 | 0.088866 | 0.016059 | 0.037865 |
| Std. Dev. | | 0.046104 | 0.012016 | 0.003557 | 0.009121 |
| Skewness | | -0.055692 | -0.655196 | -0.094256 | -0.207954 |
| Kurtosis | | 7.907487 | 16.41759 | 4.873864 | 6.091176 |
| Jarque-Bera | Test Statistics | 1371.455 | 10344.55 | 201.8779 | 553.7051 |
| | p Value | 0.000000 | 0.000000 | 0.000000 | 0.000000 |

Table 2 reports the results of the Augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) stationarity tests. The ADF test statistics (-37.36 for BTC, -39.16 for NIFTY-100, -37.76 for USD/INR, and -36.30 for XAU/USD) and PP statistics (-37.36 for BTC, -39.09 for NIFTY-100, -37.78 for USD/INR, and -36.44 for XAU/USD) are all well below the critical values at the 1% significance level. These results satisfy the stationarity condition, confirming that the return series are appropriate for the subsequent econometric analysis.

**Table 2.** Unit root tests

| | ADF | | | | PP | | | |
|---|---|---|---|---|---|---|---|---|
| | **Test Statistics** | **Confidence Interval** | | **p-value** | **Test Statistics** | **Confidence Interval** | | **p-value** |
| **BTC** | -37.3626 | **%1** | -3.43 | 0.00 | -37.36231 | **%1** | -3.44 | 0.00 |
| | | **%5** | -2.86 | | | **%5** | -2.86 | |
| | | **%10** | -2.57 | | | **%10** | -2.57 | |
| **NIFTY100** | -39.16328 | **%1** | -3.43 | 0.00 | -39.09715 | **%1** | -3.44 | 0.00 |
| | | **%5** | -2.86 | | | **%5** | -2.86 | |
| | | **%10** | -2.57 | | | **%10** | -2.57 | |
| **USD/INR** | -37.76971 | **%1** | -3.43 | 0.00 | -37.78771 | **%1** | -3.44 | 0.00 |
| | | **%5** | -2.86 | | | **%5** | -2.86 | |
| | | **%10** | -2.57 | | | **%10** | -2.57 | |
| **XAU/USD** | -36.30244 | **%1** | -3.43 | 0.00 | -36.44048 | **%1** | -3.44 | 0.00 |
| | | **%5** | -2.86 | | | **%5** | -2.86 | |
| | | **%10** | -2.57 | | | **%10** | -2.57 | |

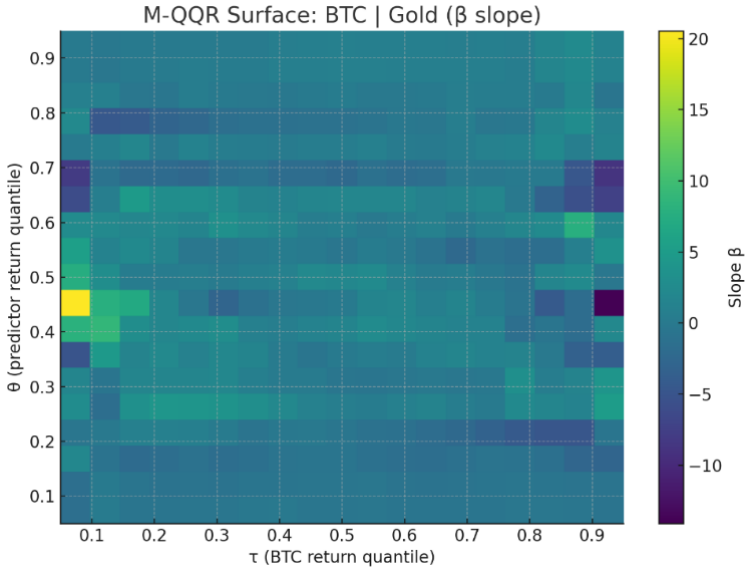
The results of the Broock-Dechert-Scheinkman (BDS) nonlinearity test are provided in Table 3. The z-statistics across dimensions 2-6 (reaching as high as 14.42 for NIFTY-100) strongly reject the null hypothesis of independent and identically distributed variables. This confirmed presence of structural non-linearity necessitates the application of the Multivariate Quantile-on-Quantile (M-QQR) method, as it is uniquely suited to capture the asymmetric and state-contingent market dependencies identified in the preliminary analysis.

**Table 3.** BDS tests

| | Dimension | BDS Statistic | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|---|
| **BTC** | 2 | 0.010492 | 0.002741 | 3.828088 | 0.0001 |
| | 3 | 0.021017 | 0.004359 | 4.821071 | 0.0000 |
| | 4 | 0.030379 | 0.005197 | 5.845445 | 0.0000 |
| | 5 | 0.035498 | 0.005423 | 6.545343 | 0.0000 |
| | 6 | 0.038706 | 0.005237 | 7.390621 | 0.0000 |
| **NIFTY100** | 2 | 0.024970 | 0.002439 | 10.23935 | 0.0000 |
| | 3 | 0.048582 | 0.003881 | 12.51858 | 0.0000 |
| | 4 | 0.061129 | 0.004628 | 13.20831 | 0.0000 |
| | 5 | 0.066999 | 0.004831 | 13.86877 | 0.0000 |
| | 6 | 0.067306 | 0.004666 | 14.42519 | 0.0000 |
| **USD/INR** | 2 | 0.012244 | 0.002301 | 5.321874 | 0.0000 |
| | 3 | 0.025212 | 0.003653 | 6.902441 | 0.0000 |
| | 4 | 0.036802 | 0.004345 | 8.469566 | 0.0000 |
| | 5 | 0.043680 | 0.004524 | 9.654590 | 0.0000 |
| | 6 | 0.045730 | 0.004359 | 10.49162 | 0.0000 |
| **XAU/USD** | 2 | 0.006336 | 0.002466 | 2.569818 | 0.0102 |
| | 3 | 0.018013 | 0.003912 | 4.603900 | 0.0000 |
| | 4 | 0.026498 | 0.004653 | 5.695171 | 0.0000 |
| | 5 | 0.029772 | 0.004843 | 6.147584 | 0.0000 |
| | 6 | 0.029679 | 0.004664 | 6.362943 | 0.0000 |

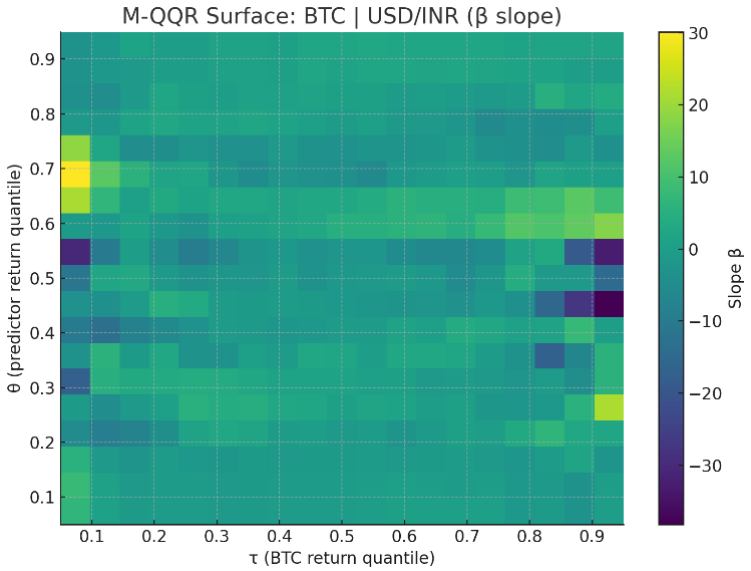
Building on the evidence of nonlinearity from the BDS tests (Table 3), we now turn to the multivariate quantile-on-quantile (M-QQR) results. Figures 2-4 display the estimated dependence surfaces $\beta(\theta, \tau)$ for Bitcoin with respect to equities (NIFTY-100), gold (XAU/USD), and the USD/INR exchange rate, where $\tau$ ndexes BTC return quantiles and $\theta$ indexes predictor quantiles; the bandwidth is set to $h = 0.05$ throughout, a positive USD/INR return denotes rupee depreciation. We will first give a summary of the patterns seen around the median values. After this, we will look at the joint tails. The joint tails are the areas where the implications for portfolio strategies and risk-management are most important.

**Figure 2.** Multivariate quantile-on-quantile dependence surface $\beta(\theta, \Phi)$ for BTC with respect to XAU/USD returns.



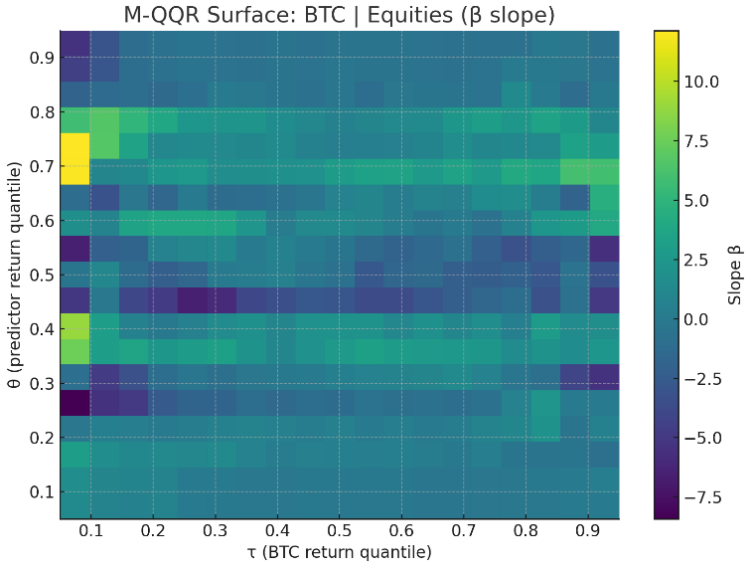

**Notes:** $\Phi$ indexes BTC return quantiles; $\theta$ indexes predictor quantiles; bandwidth $h = 0.05$. Common color scale across figures.

**Figure 3.** Multivariate quantile-on-quantile dependence surface $\beta(\theta, \Phi)$ for BTC with respect to USD/INR returns




**Notes:** $\Phi$ indexes BTC return quantiles; $\theta$ indexes predictor quantiles; bandwidth $h = 0.05$. Common color scale across figures.

**Figure 4.** Multivariate quantile-on-quantile dependence surface $\beta(\theta, \Phi)$ for BTC with respect to NIFTY-100 returns




**Notes:** $\Phi$ indexes BTC return quantiles; $\theta$ indexes predictor quantiles; bandwidth $h = 0.05$. Common color scale across figures.

When the analysis focuses on the region around the median, the BTC–equity surface appears small. This indicates that the average comovement between the two is weak. The study then examines the joint lower tail. In this area, the slope becomes much steeper when equity sell-offs occur together with negative BTC quantiles. This pattern supports the presence of a state-dependent relationship. The linkage becomes noticeably stronger when market conditions are stressed. By contrast, in equity rallies (upper $\theta$) the association attenuates around the BTC median. To sum up, Figure 2 shows a limited dependence around the median. However, it suggests a much stronger sensitivity in the tails. This means that any benefits from diversification are conditional on the current market state. They are not the same across all conditions.

Figure 3 presents the BTC-gold surface. Near the center of the distribution, the linkages appear weak. However, the slope becomes strongly positive when gold is in its upper quantiles and BTC is at or above its median. This pattern matches market periods in which rising demand for safe-haven assets increases the price of gold, while BTC also performs better. In the opposite corner, where gold is in its lower quantiles and BTC is in its lower tails, the relationship becomes weaker. This indicates an asymmetric interaction that is economically meaningful mainly during episodes of strong gold rallies.

Linkages intensify when the rupee depreciates (upper $\theta$ for USD/INR), especially for median-to-upper BTC quantiles, indicating that currency stress aligns with stronger positive BTC comovement. The

slope is small near the center of the joint distribution. However, the association is either weaker or mixed in the lower BTC tail. We view a positive USD/INR return as a rupee depreciation. With this understanding, Figure 4 suggests something important. It shows that currency stress regimes are the main place where BTC's co-movement becomes stronger.

When we consider all three M-QQR surfaces together, they show that Bitcoin's dependence on domestic risk factors is small near the center of the joint distribution. However, this dependence is clearly state-dependent in the tails. With equities (Figure 2), the comovement is limited around the median. Yet, it gets much stronger during joint downturns. This finding means that the benefits of diversification are lost when stress in equities happens at the same time as bad states for BTC. With gold (Figure 3), the surface is asymmetric. Linkages are weak during normal market times. But they become strongly positive when gold is in its upper quantiles. This matches the periods of safe-haven demand. The linkage weakens when both assets fall together. For the currency (Figure 4), Rupee depreciation (positive USD/INR returns) is linked to stronger positive BTC slopes. This is especially true for BTC quantiles from the median to the upper levels. The association remains small around the center.

Overall, the evidence points to a regime-sensitive dependence that occurs in episodes. The median relationships are not enough to show the true strength and direction of the linkages. These linkages become visible during equity drawdowns, gold rallies, and currency stress. Therefore, portfolio hedging strategies should be planned on a state-contingent basis, not a static one.

Using the full-sample results (Figures 2-4) as a benchmark, we first note that the qualitative patterns are robust to reasonable implementation choices. Specifically, they are unchanged when the bandwidth varies over $h \in [0.03, 0.07]$ and when returns are two-sided winsorized at 1 percent. To keep the focus on economic interpretation, cell-wise bootstrap overlays are not shown in the main text; if required, block-wild bootstrap p-value masks can be provided in an online appendix.

We use a common baseline quantile grid and bandwidth across subsamples. For the short Tax and TDS windows, we adopt compact settings (0.10 quantile steps, $h = 0.15$ with adaptive expansion up to $\pm 0.45$, minimum local $N = 30$) to avoid empty cells. The subsamples are: the RBI banking restriction (6 April 2018–3 March 2020), the post-Supreme Court/pre-tax interval (4 March 2020–31 March 2022), the initial VDA tax window (1 April 2022–30 June 2022), the TDS phase (1 July 2022–10 November 2022), and the post-FTX segment (11 November 2022–13 July 2023). All figures are rendered on a common color scale for comparability, and, consistent with our sign convention, positive USD/INR returns denote rupee depreciation.

The study examines the period of the banking restriction, when domestic liquidity was limited. During this time, the dependence surfaces appear noisier around the center. However, they show a much clearer strengthening in the joint lower tails for both BTC-equities and BTC-USD/INR. This pattern indicates a tighter comovement during equity sell-offs and periods of currency stress. The linkage between BTC and gold remains generally weak in this window. Only a few isolated areas display a positive slope, and these cases occur mainly when gold is in its upper quantiles.

After the Supreme Court reversal, the surfaces look smoother. The linkages around the median area remain small. Tail sensitivity starts to appear again when equities are falling (in drawdown) or the rupee is under pressure. Specifically, rupee depreciation (upper USD/INR quantiles) is linked to more positive BTC slopes. At the same time, BTC-gold interactions mostly strengthen during gold rallies.

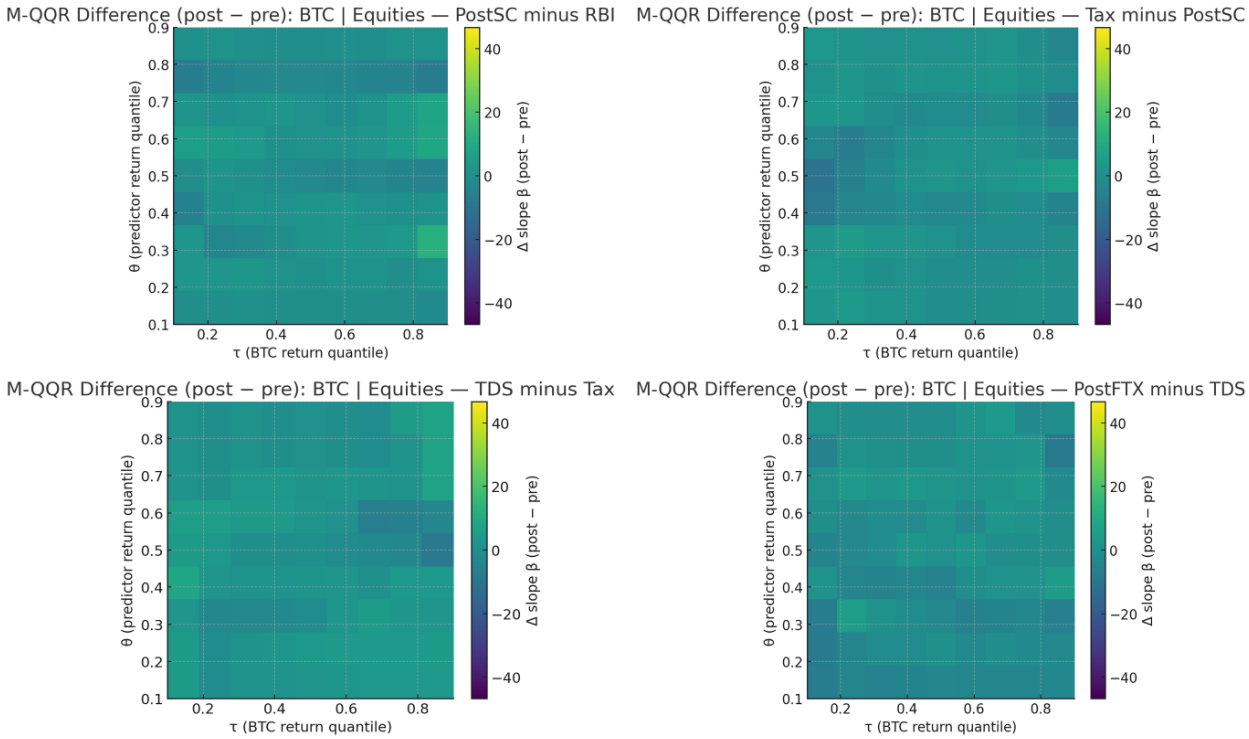
The introduction of the 30% VDA tax and later the 1% TDS created frictions in local trading. These frictions seem to reduce the associations near the center of the distribution. However, the episodic strengthening still happens in the tails. This is most visible during rupee depreciation and, to a smaller degree, during high gold upper-quantile episodes. The dependence between BTC and equities still shows a clear state-contingent nature in these short periods. Therefore, we focus on qualitative findings instead of detailed statistical differences across the cells.

After the post-FTX period, the asymmetries are more clearly seen. The comovement between BTC and equities becomes stronger in the joint lower tails. The BTC-gold linkages show a positive tilt when gold is in its upper quantiles. Also, the BTC-USD/INR slopes stay positive when the rupee depreciates. At the same time, the slopes in the center region remain small.

Overall, these sub-sample findings support the main message from the full sample analysis. The dependence near the median region is small. However, economically important linkages appear in the tails. These linkages happen during equity drawdowns, gold rallies, and currency stress. Therefore, a state-contingent approach is needed for diversification and hedging. Simple, mean-based summaries often fail to show the true comovement that occurs exactly when it is most critical.

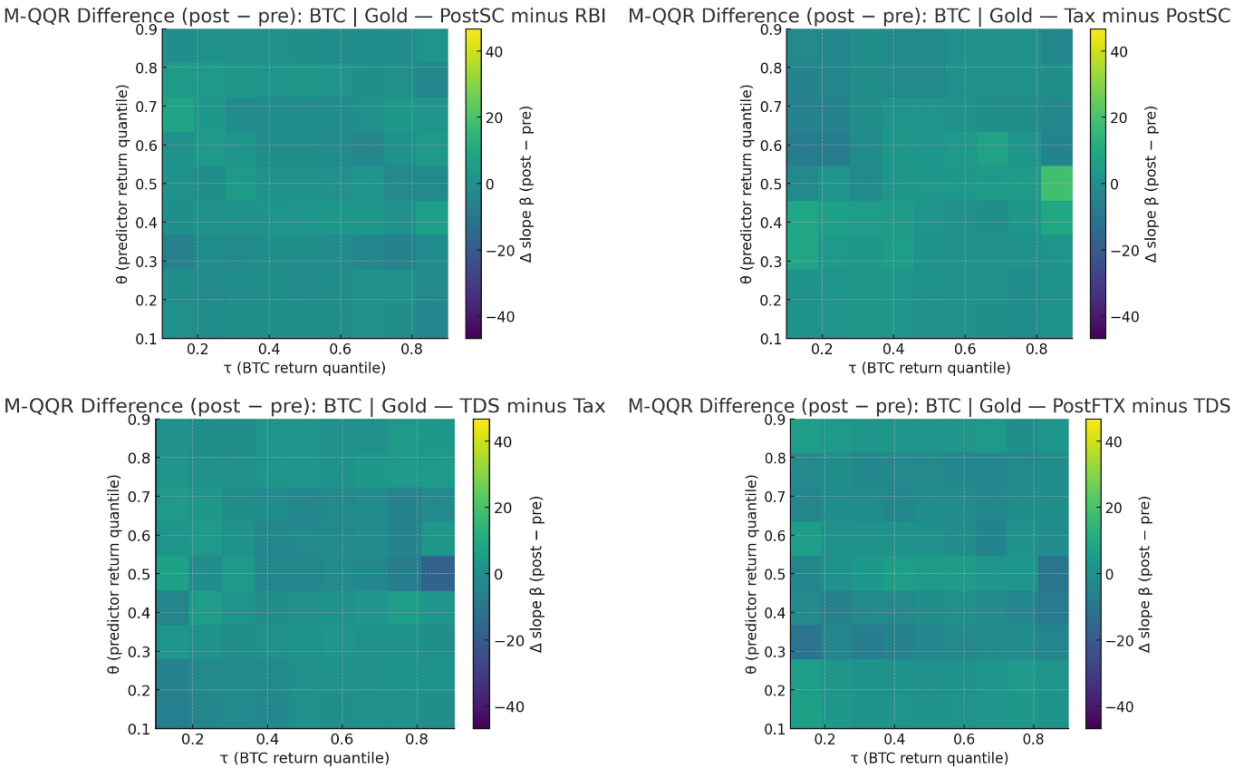
The difference surfaces document how the local slopes $\beta(\theta,\tau)$ change across adjacent policy windows. Because the colors are symmetric around zero, the positive areas indicate stronger comovement after the transition. The analysis first turns to equities, where any noticeable changes would be expected to appear mainly in stressed market conditions.

**Figure 5.** BTC-Equities (NIFTY-100): M-QQR difference surfaces (post-pre) across regime transitions (2×2 panels).



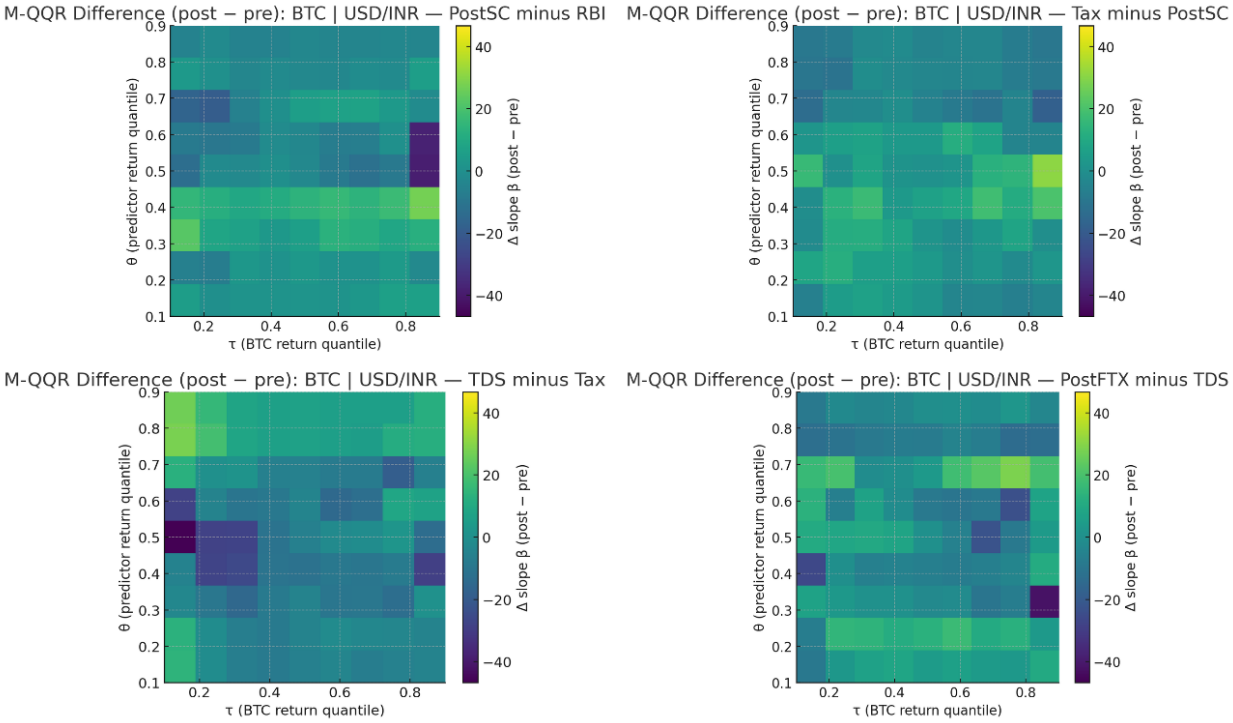

When compared with equities, the equity-BTC adjustments remain small. These adjustments appear mainly in the joint lower tails, with only minor changes near the center of the distribution. Shorter analysis windows, such as the Tax and TDS periods, naturally produce less clear patterns. Even so, the direction of change is consistent across all panels. The discussion then moves to gold, which reflects safe-haven dynamics more closely than domestic sources of risk.

**Figure 6.** BTC-Gold (XAU/USD): M-QQR difference surfaces (post-pre) across regime transitions (2×2 panels).




The observed differences for Gold are minimal. These small divergences mostly occur in the metal's upper price quantiles. This phenomenon suggests that market regime shifts become important only when safe-haven demand is elevated. In all other situations, the market surface remains broadly stable. Currency conditions show a contrast. They affect domestic liquidity and capital-flow pressures more directly. As a result, larger adjustments may emerge when the rupee is in depreciation bands.

**Figure 7.** BTC-USD/INR: M-QQR difference surfaces (post-pre) across regime transitions (2×2 panels).




The currency panel presents the most apparent changes. Positive movement (deltas) is concentrated when the USD/INR value is high. This movement is also observed when the BTC value is at or above the median. Meanwhile, movement in the center region remains limited. All three composites together suggest a key finding. This finding is that regime transitions reweight the dependencies selectively. This pattern is most visible during periods of equity drawdowns, gold price rallies, and rupee weakness. This outcome supports a state-contingent perspective on both diversification and hedging strategies.

## RESULTS AND DISCUSSION

This section of the paper reports the dependence structures. We study the relationship between Bitcoin and three domestic risk factors. These factors are equities (NIFTY-100), gold (XAU/USD), and the exchange rate (USD/INR). The multivariate quantile-on-quantile (M-QQR) framework is the method utilized. First, we summarize the full-sample surfaces (Figures 2-4). Subsequently, we examine the regime-difference composites. These composites trace adjustments across policy windows in India (Figures 5-7). Throughout, $\tau$ indexes BTC return quantiles and $\theta$ indexes predictor quantiles; positive USD/INR returns denote rupee depreciation.

The multivariate quantile-on-quantile (M-QQR) results, estimated across the full sample from 1 January 2018 to 13 July 2023, provide a nuanced view of Bitcoin's interdependence with Indian financial pillars, revealing that these linkages are highly state-contingent rather than static. When the analysis focuses on the region around the joint median, the comovement between Bitcoin and the NIFTY-100 appears limited, indicating that under normal market conditions, the average comovement is weak and Bitcoin may function as an effective diversifier. However, a critical tail amplification effect is observed in the joint lower tails, where the slope becomes significantly steeper during equity sell-offs that coincide with negative Bitcoin quantiles. From an economic perspective, this state-dependent relationship suggests that diversification benefits against domestic equities erode exactly during stress periods, a finding consistent with the view that correlations are conditional and increase during market drawdowns. Similarly, the BTC-gold dependence surface exhibits a pronounced asymmetry where linkages remain muted near the center but turn strongly positive when gold is in its upper quantiles and Bitcoin is at or above its median. This pattern matches market episodes where rising demand for safe-haven assets increases the price of gold while Bitcoin also performs better, suggesting that Bitcoin's hedging properties are episodic and primarily active during specific safe-haven rallies. The most robust structure is observed in the currency dimension, where rupee depreciation (positive USD/INR returns) is consistently linked to stronger positive Bitcoin slopes, particularly for median-to-upper Bitcoin quantiles. This intensification indicates a channel where currency stress coincides with tighter Bitcoin comovement, potentially reflecting shifts in domestic liquidity, capital-flow conditions, or flight-to-quality narratives within the Indian market. Collectively, these findings underscore that median relationships are insufficient to capture the true strength of these linkages, which only become visible during equity drawdowns, gold rallies, and currency stress. Consequently, the evidence points toward a regime-sensitive dependence that necessitates state-contingent portfolio management and risk limits calibrated to the joint market state rather than static diversification strategies.

Several checks support the stability of these conclusions. Qualitative patterns are unchanged when the bandwidth varies over $h \in [0.03, 0.07]$ and under two-sided 1% winsorization of returns. For the short Tax and TDS windows, we adopt compact settings (0.10 quantile steps, $h = 0.15$ with adaptive expansion up to $\pm 45$ minimum local $N = 30$) to avoid empty cells in the difference surfaces; results remain consistent with the baseline interpretation.

The analysis remains descriptive and non-causal. The short regime windows limit the opportunity for fine-grained inference. Our design also does not include additional controls, such as global risk factors or order-flow data. These limitations notwithstanding, the patterns are coherent across assets and regimes. They are also robust to reasonable tuning choices. Future work could add structural identification. It could

also analyze the intraday microstructure. This would clarify the mechanisms causing the state-dependence documented in this paper.

## CONCLUSION

This study provides a comprehensive analysis of how Bitcoin co-moves with Indian equities (NIFTY-100), gold (XAU/USD), and the USD/INR exchange rate using a multivariate quantile-on-quantile framework over the 2018 and 2023 period. The findings successfully answer the central research question by revealing that distinct policy regimes in India, ranging from banking restrictions to explicit taxation, do not affect market dependencies uniformly but instead reweight them selectively across the joint distribution. The original contribution of this research lies in its application of the M-QQR methodology to the world's largest absolute crypto-user base (approximately 119 million), documenting for the first time how institutional transitions amplify tail sensitivities while often dampening median-region links. Unlike standard mean-based models, this approach captures the pronounced, state-contingent linkages where comovement strengthens significantly during equity drawdowns, gold price rallies, and rupee depreciation.

In comparison with existing literature, these results support the view that Bitcoin's hedging properties are conditional and episodic, mirroring gold's safe-haven role only in specific high-demand states while behaving as a speculative asset during broader market stress. From a regulatory perspective, the significantly stronger Bitcoin-USD/INR linkage observed during periods of rupee weakness underscores the necessity for Indian policymakers to monitor crypto-FX channels within macroprudential dashboards, as spillovers through these channels can amplify overall financial stress. While the current tax and TDS regime appears to moderate linkages near the median, the persistence of tail sensitivities suggests that predictable and integrity-focused rules are preferable to measures that might fragment liquidity or push trading to offshore platforms.

These findings argue for state-contingent risk management rather than static diversification; investors should calibrate risk budgets to joint market states, particularly dialing down exposure when domestic equities enter lower quantiles or the rupee moves into depreciation bands. Despite these insights, the analysis remains descriptive and non-causal, and the short policy windows utilized here limit the opportunity for fine-grained inference. Furthermore, the study does not include additional global risk controls or order-flow data. Future research should incorporate global risk factors, explore high-frequency intraday data, and deploy structural identification strategies to clarify the specific mechanisms driving the state-dependence documented in this work.

## AUTHOR STATEMENT

The author declares that all contributions to this manuscript were made solely by the author. The author also declares that there are no conflicts of interest.

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