Cryptocurrencies as Hedges and Safe-havens: A Flexible Semi-parametric Approach

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Abstract

The outbreak of the COVID-19 pandemic led to a considerable increase in financial market volatility. This study employs linear and time-varying regression models to examine the role of cryptocurrencies as potential hedges and safe-havens for various financial assets, including stocks, bonds, and gold. In the linear regression models, cryptocurrencies do not exhibit hedging properties against stocks. However, they demonstrate hedging capabilities against bonds. When employing a time-varying regression model, our findings indicate that the hedging characteristics of cryptocurrencies vary across periods for stocks and gold. During the COVID-19 pandemic, when stock and gold market volatilities experienced significant increases, cryptocurrencies did not exhibit hedging properties against either asset. These periods are identified as the period between the end of 2020 and the end of 2022 for stocks and between early 2019 and the end of 2021 for gold. In contrast, the estimated results suggest that cryptocurrencies act as bond hedge assets.

JEL code: G10; G11; G14; G15

Keywords: Cryptocurrency; Hedge; Safe-haven; Functional coefficient

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1 Introduction

Since the emergence of Bitcoins, numerous cryptocurrencies have been created, leading to significant growth in their market capitalization and transaction volume. The recognition of Bitcoin as a legitimate financial entity was reinforced in December 2017, by the introduction of futures contracts for Bitcoin by the Chicago Mercantile Exchange (CME) Group and the Chicago Board Options Exchange (CBOE). This development profoundly impacted trading volumes, solidifying its status as a credible financial instrument. The price of Bitcoin experienced substantial fluctuations, characterized by hyper-exponential growth from March 2020 ($5,000) to December 2020 ($20,000), followed by two peaks in April ($63,000) and November 2021 ($67,000) and a subsequent decline in November 2022. These fluctuations in price and extreme volatility, along with the inherent value of cryptocurrencies, have generated significant interest among investors and the general public, leading to active research in this field (Ciaian, Rajcaniova, and Kancs, 2016). Prior studies primarily focused on examining the financial characteristics, returns, and volatility patterns of Bitcoins (Balcilar, Bouri, Gupta, and Roubaud, 2017; Catania, Grassi, and Ravazzola, 2019; Bouri, Gupta, and Roubaud, 2019; Cross, Hou, and Trinh, 2021). More recent research has explored the relationship between Bitcoin and other financial assets, energy markets, and commodities (Yermack, 2015; Ciaian, Rajcaniova, and Kancs, 2016; Li and Lucey, 2017; Shahzad, Bouri, Roubaud, Kristoufek, and Lucey, 2019; Bouri, Lucey, and Roubaud, 2020; Akhtaruzzaman, Boubaker, Lucey, and Sensoy, 2021; Wen, Tong, and Ren, 2022).

The growing interest in cryptocurrencies as a hedge against other assets has gained traction in the field of portfolio construction and risk management, particularly among professional investors. Hedge assets act as financial safeguards, offsetting losses resulting from a decline in the price of the target asset and exhibiting either no correlation or a negative correlation with another asset. Owing to their unique price formation dynamics, cryptocurrencies are presumed to be minimally affected by macroeconomic variables and display weak or no correlation with traditional assets. Consequently,, cryptocurrencies are recognized as valuable diversifiers or hedging tools (Bouri, Jalkh, Molnár, and Roubaud, 2017; Luther and Salter, 2017; Corbet, Meegan, Larkin, Lucey, and Yarovaya, 2018; Das and Kannadhasan, 2018; Charfeddine, Benlagha, and Maouchi, 2020). For instance, during the 2013 European debt crisis, it was visually observed that cryptocurrency prices moved in the opposite direction to traditional assets in response to global uncertainty.

Previous studies have primarily focused on hedge and safe-haven assets such as gold, other financial assets (stocks, bonds), energy, and commodities. Gold has traditionally been considered a hedge and safe-haven asset during times of economic instability (Baur and Lucey, 2010; Ciner, Gurdgiev, and Lucey, 2013; Beckmann, Berger, and Czudaj, 2015; Cross, Hou, and Trinh, 2021). However, the safe-haven and hedging capabilities of gold have been scrutinized in several studies, including those by Lucey and Li (2015) and Shahzad, Raza, Roubaud, Hernandez, and Bekiros (2019). Additionally, Akhtaruzzaman, Boubaker, Lucey, and Sensoy (2021) discovered that gold lost its safe-haven status during the second phase of the COVID-19 pandemic (March 17, 2020–April 24, 2020) when investors turned to gold as a "flight to safety," resulting in a substantial increase in its portfolio weight. Consequently, cryptocurrencies have gained prominence in the past decade as financial safeguards against market turmoil, replacing gold as the preferred asset for certain individuals (Bouoiyour, Selmi, and Wohar, 2019).

Bouri, Gupta, Lau, Roubaud, and Wang (2018) found that Bitcoin acts as a hedge against the global financial stress index at both tails of the distribution. From a medium-term perspective, it is also found that Bitcoin can serve as a safe-haven against the global financial stress index. Similarly, Bouri, Gupta, Tiwari, and Roubaud (2017) demonstrated that Bitcoin reacts positively to global uncertainty and can hedge against lower and upper ends of Bitcoin returns and global uncertainty. Selmi, Mensi, Hammoudeh, and Bouoiyour (2018) explored the relationship between oil and Bitcoin and found that Bitcoin and gold tend to behave similarly during times of financial stress, serving as a hedge, safe-haven, or diversification against oil, depending on market conditions. Charfeddine, Benlagha, and Maouchi (2020) analyzed the spillovers between Bitcoin and other financial assets, revealing Bitcoin's potential to hedge stocks and the crude oil market. Post the COVID-19 pandemic, studies have examined how the relationship between cryptocurrencies and other assets has changed within the cryptocurrency market. Notably, Mariana, Ekaputra, and Husodo (2021) found that Bitcoin and Ethereum served as safe-havens for stocks during the COVID-19 crisis.

However, some studies argue that Bitcoin is more suited to serve as a diversifier rather than an adequate hedge or safe-haven against other assets (Briere, Oosterlinck, and Szafarz, 2015; Dyhrberg, 2016; Bouri, Molnár, Azzi, Roubaud, and Hagfors, 2017; Bouri, Jalkh, Molnár, and Roubaud, 2017; Baur, Hong, and Lee, 2018; Corbet, Meegan, Larkin, Lucey, and Yarovaya, 2018; Ji, Bouri, Gupta, and Roubaud, 2018). Specifically, Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017) suggest that Bitcoin is inadequate as a hedge for other assets, with the exception of Asian stocks, but it can be suitable for diversification purposes. Similarly, Bouri, Jalkh, Molnár, and Roubaud (2017) revealed that Bitcoin's hedging and safe-haven properties against commodities were only observed prior to the 2013 stock market crash, after which it primarily served as a diversifier. Interestingly, Shahzad, Bouri, Roubaud, and Kristoufek (2020) demonstrated that gold outperforms Bitcoin as a hedge, offering higher and more stable hedging benefits for the G7 stock index, particularly when the stock and gold markets are in a bearish state, whereas Bitcoin only exhibits hedging capabilities for the Canadian stock index. Kajtazi and Moro (2019) demonstrate that Bitcoin positively influences the performance of portfolios containing various assets; however, most of the portfolio's performance enhancement stems from increased returns rather than reduced volatility. Furthermore, some argue that cryptocurrencies remain highly volatile and unstable, driven by irrational bubbles, suggesting that the market is still far from efficient and mature (Cheah and Fry, 2015; Cheung, Roca, and Su, 2015; Fry and Cheah, 2016; Bouoiyour, Selmi, Tiwari, and

Olayeni, 2016; Corbet, Lucey, and Yarovaya, 2018; Corbet, Lucey, Urquhart, and Yarovaya, 2019; Hafner, 2020).

Furthermore, with the rapid evolution of the cryptocurrency market in terms of returns and excess volatility over the past decade, the role of time has emerged as a crucial factor. Therefore, the primary objective of this study is to examine the dynamic nature of the relationship between cryptocurrencies and other assets, including stocks, bonds, and gold, by analyzing changes in their performance during major market shocks across different time periods. Prior research has highlighted the dynamic association between the cryptocurrency market and other assets, attributed to the increased returns and volatility of cryptocurrencies (Ji, Bouri, Gupta, and Roubaud, 2018; Shahzad, Bouri, Roubaud, Kristoufek, and Lucey, 2019; Urom, Abid, Guesmi, and Chevallier, 2020; Abakah, Alana, Madigu, and Rojo, 2020). Additionally, cryptocurrencies exhibit varying responsiveness to uncertainty across periods (Qin, Su, and Tao, 2021). Notably, recent research has focused on the contagion effect of the COVID-19 pandemic on financial markets, highlighting the structural changes in the cryptocurrency market as a response to the downturn caused by COVID-19 (Huang, Duan, and Mishra, 2021; Chemkha, BenSaïda, Ghorbel, and Tayachi, 2021; Wen, Tong, and Ren, 2022).

The main contributions of this study are as follows. First, we account for a rich set of cryptocurrencies, including the well-known eight cryptocurrencies, and test whether they can provide risk coverage for stocks, bonds, and gold, thus providing more general guidance for risk managers. The dataset covers April 2014 to December 2022 and encompasses significant events and volatile periods in the cryptocurrency market. By considering a relatively extended period that includes major events such as the cryptocurrency market crash in 2018, the COVID-19 pandemic, and the Russia-Ukraine conflict, we observe the dynamic relationship between cryptocurrencies and other assets in response to market shocks more clearly. Importantly, our study is particularly interesting as it covers the pre, during-, and post-COVID-19 periods, in contrast to existing studies that primarily focus on the temporary impact of COVID-19 (Conlon and McGee, 2020; Chan, Le, and Wu, 2019; Corbet, Larkin, and Lucey, 2020; Corbet, Hou, Hu, Larkin, and Oxley, 2020; Mariana, Ekaputra, and Husodo, 2021).

Second, to address the time-varying behavior, we investigate the property of hedging using a novel approach, a type of semi-parametric method known as the partial linear model proposed by Fan and Huang (2005) and Zhang, Lee, and Song (2002). The semi-parametric approach is quite useful compared to the parametric and nonparametric approaches in several ways, as it offers a compromise between them (Robinson, 1988; Fan and Huang, 2005). The time-varying and asymmetric behavior of financial markets has been discussed using different approaches in prior studies (Khalfaoui, Boutahar, and Boubaker, 2015; Li and Lucey, 2017; Antonakakis, Chatziantoniou and Gabauer, 2019; Shahzad, Bouri, Roubaud, Kristoufek, and Lucey, 2019; Bouri, Lucey, and Roubaud, 2020). However, these studies mostly employed parametric approaches, which run the risk of mis-specifying the model due to the strict assumption that the distribution of the model must be specified with parameters for estimation. In contrast, one of the notable advantages of the partial linear model is its robustness to model misspecification, allowing more reliable estimates to be obtained. As the time-varying hedging behavior is described by an unknown function, the partial linear model provides greater flexibility compared to parametric models, overcoming the limitations of non-parametric models that often face challenges related to the "dimensional curse" when estimating the unknown function.

This study examines not only the behavior of cryptocurrencies during normal market conditions but also their role as safe-haven assets during market turmoil. We adopt the definitions of hedge and safe-haven assets from Baur and Lucey (2010) and Baur and McDermott (2010), who analyze correlations during normal market periods and market crashes. Following this approach, we explore the characteristics of safe-haven assets by considering periods of market downturn as those with returns below the 0.05 and 0.01 quantile levels of the target asset. This methodology has been commonly employed in prior studies to investigate the downside risk coverage of various assets (Conlon and McGee, 2020; Goodell and Goutte, 2021; Mariana, Ekaputra, and Husodo, 2021).

This study proceeds as follows. Section 2 introduces the time-varying parameter model. Section 3 describes the data used in our empirical analysis. Sections 4 and 5 present the empirical results and discussion, respectively. Finally, Section 6 concludes the study.

2 Econometric Models

To test whether cryptocurrency can be a hedge and safe-haven for stocks, bonds, and gold, we consider the following regression model:

$$R_{c,t} = \alpha + \beta_1 R_{s,t} + \delta_1 R_{b,t} + \gamma_1 R_{g,t} + \beta_2 R_{s,t(\tau)} + \delta_2 R_{b,t(\tau)} + \gamma_2 R_{g,t(\tau)} + \epsilon_t, \tag{2.1}$$

where $R_{c,t}$, $R_{s,t}$, $R_{b,t}$ and $R_{g,t}$ denote returns on a cryptocurrency, stock, bond, and gold prices, respectively, and $R_{s,t(\tau)}$, $R_{b,t(\tau)}$ and $R_{g,t(\tau)}$ account for crashes in the stock, bond, and gold markets, respectively. The latter can be defined as returns less than τ quantile ($\tau = 0.05$ and 0.01). For example, $R_{s,t(\tau)} = R_{s,t}$ if $R_{s,t} \leq \tau$-quantile of $\{R_{s,t}\}_{t=1}^T$, and $R_{s,t(\tau)} = 0$; otherwise. If β_1 (δ_1, γ_1) is zero or negative, the cryptocurrency is a hedge for stocks (bonds, gold) because on average the assets are uncorrelated or negatively correlated with each other. If β_2 (δ_2, γ_2) is nonpositive, then the cryptocurrency serves as a safe-haven for stocks (bonds, gold). The error term ϵ_t is a random disturbance with mean zero and finite variance σ^2. The above model (2.1) is a benchmark model and it can be extended to other well-known flexible models.

The parameters in (2.1) can be readily estimated by the least squares method, and the corresponding interpretation is quite clear. However, in reality, it is unclear whether marginal effects are indeed fixed. To incorporate time-varying parameters, (2.1) can be extended as

$$R_{c,t} = \alpha + \beta_1(t/T) R_{s,t} + \delta_1(t/T) R_{b,t} + \gamma_1(t/T) R_{g,t} + \beta_2 R_{s,t(\tau)} + \delta_2 R_{b,t(\tau)} + \gamma_2 R_{g,t(\tau)} + \epsilon_t, \tag{2.2}$$

where $\beta_1(t/T)$, $\delta_1(t/T)$, and $\gamma_1(t/T)$ denote smooth time-varying functional coefficients. Note that the coefficients in (2.2) are functions of the ratio t/T rather than of time t, which guarantees the consistency of the non-parametric estimators for the coefficients under some regularity conditions. Furthermore, $\beta_1(t/T)$, $\delta_1(t/T)$, and $\gamma_1(t/T)$ can detect investors' time-varying hedging behavior if the estimated coefficients over certain time periods are uncorrelated and negatively correlated. Safe-haven behavior can be captured by nonpositive estimates of the fixed coefficients β_2, δ_2, and γ_2.

The functional coefficients in (2.2) can be estimated by the local linear semi-parametric estimation method. The model in (2.2) belongs to a general class of semi-parametric models, as discussed in Zhang, Lee, and Song (2002) and Fan and Huang (2005). In general, (2.2) can be represented in the following form:

$$R_{c,t} = \sum_{j=1}^{3} g_j\Big(\frac{t}{T}\Big)X_{tj} + \sum_{i=1}^{4} \eta_i Z_{ti} + \epsilon_t, \tag{2.3}$$

where $X_t = (R_{s,t}, R_{b,t}, R_{g,t})'$, $g(\cdot) = (\beta_1(\cdot), \delta_1(\cdot), \gamma_1(\cdot))'$, $Z_t = (1, R_{s,\tau(t)}, R_{b,\tau(t)}, R_{g,\tau(t)})'$, and $\eta = (\alpha, \beta_2, \delta_2, \gamma_2)'$. By fixing the effects of Z_{ti}, (2.3) allows us to understand how the effects of X_t vary across time periods. Under the assumption that $g_j(\cdot)$ is continuous and has a second derivative, $g_j(\cdot)$ can be approximated by its first-order Taylor expansion $g_j(u) \approx g_j(u_0) + g_j'(u_0)(u - u_0) \equiv a_j + b_j(u - u_0)$ locally around a small neighborhood of u_0. To estimate the model, we considered the following local linear estimator: Using matrix notation, $\mathbf{R_c} = (R_{c,1}, \ldots, R_{c,T})'$, $\mathbf{Z} = (\mathbf{Z}_1, \ldots, \mathbf{Z}_T)'$, $\mathbf{X} = (\mathbf{X}_1, \ldots, \mathbf{X}_T)'$, and $U = (1/T, 2/T, \cdots, 1)$, then (2.3) can be written as follows:

$$\mathbf{R} = \mathbf{g}'(U)\mathbf{X} + \boldsymbol{\eta}'\mathbf{Z} + \epsilon,$$

where $\boldsymbol{g}(\cdot) = (g_1(\cdot), g_2(\cdot), g_3(\cdot))'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3, \eta_4)'$.

There are several ways proposed in literature to estimate $\boldsymbol{g}(\cdot)$ and $\boldsymbol{\eta}$ (Zhang, Lee, and Song (2002) and Fan and Huang (2005), among others): In this study, we used the least-squares profile estimation approach proposed by Fan and Huang (2005). Since the dimension of U_t is equal to 1.

(2.3) does not suffer from dimensionality problem, which is a typical concern in non-parametric and semi-parametric models when the dimensions of U_t are greater than 1. Following Fan and Huang (2005), a consistent estimator for parameter η can be obtained by

$$\hat{\boldsymbol{\eta}} = \{\mathbf{Z}'(\mathbf{I} - \mathbf{S})'(\mathbf{I} - \mathbf{S})\mathbf{Z}\}^{-1}\mathbf{Z}'(\mathbf{I} - \mathbf{S})'(\mathbf{I} - \mathbf{S})\mathbf{Y},$$

where $\mathbf{S}$ is the smoothing matrix,

$$\mathbf{S} = \begin{pmatrix} \{\mathbf{X}_1' \quad 0\}\{\mathbf{D}_{u_1}'\mathbf{W}_{u_1}\mathbf{D}_{u_1}\}^{-1}\mathbf{W}_{u_1} \\ \vdots \\ \{\mathbf{X}_1' \quad 0\}\{\mathbf{D}_{u_T}'\mathbf{W}_{u_T}\mathbf{D}_{u_T}\}^{-1}\mathbf{W}_{u_T} \end{pmatrix}$$

with

$$\mathbf{D}_u = \begin{pmatrix} \mathbf{X}_1' & \left(\frac{U_1 - u}{w}\right)\mathbf{X}_1' \\ \vdots & \vdots \\ \mathbf{X}_T' & \left(\frac{U_T - u}{w}\right)\mathbf{X}_T' \end{pmatrix}, \quad \text{and} \quad \mathbf{W}_u = \operatorname{diag}(K_w(U_1 - u), \ldots, K_w(U_T - u)).$$

Therefore, using the above estimator $\boldsymbol{\eta}$, the smooth time-varying parameters $g\left(\frac{t}{T}\right)$ can be estimated using the local linear estimation method using the following transformed regression:

$$\check{R}_{c,t} = R_{c,t} - \sum_{i=1}^{4} \hat{\eta}_i Z_{ti} = \sum_{j=1}^{3} g_j\Big(\frac{t}{T}\Big)X_{tj} + \epsilon_t, \tag{2.4}$$

which can be viewed as the non-parametric varying-coefficient model. To estimate the model, we considered the following local linear estimator:

$$\min_{\{a_j,b_j\}_{j=1}^3} \sum_{s=1}^{T} \left[\check{R}_{c,t} - \sum_{j=1}^{3} \left\{a_j + b_j\left(\frac{s-t}{T}\right)\right\} X_{jt}\right]^2 K_h\left(\frac{s-t}{T}\right),$$

where $K_h(\cdot) = K(\cdot/h)/h$, $K(\cdot)$ is a kernel function, and h is a bandwidth parameter satisfying $h \to 0$ and $hT \to \infty$ as $T \to \infty$. By solving the minimization problem, we obtain the estimators $\{(\hat{a}_j, \hat{b}_j), j = 1, 2, 3\}$. Following Fan and Gijbels (1996), we obtain:

$$\hat{g}_j\left(\frac{t}{T}\right) = \sum_{s=1}^{T} W_{n,j}\left(\frac{s-t}{T}, \mathbf{X}_k\right)\check{R}_{c,t}, \tag{2.5}$$

where $W_{n,j}((s-t)/T, \mathbf{X}_k) = e'_{j,2p}(\tilde{\mathbf{X}}'\mathbf{W}\tilde{\mathbf{X}})^{-1}(\mathbf{X}_k, ((s-t)/T)\mathbf{X}_k)' K_h((s-T)/T)$ is the effective kernel defined in Fan and Gijbels (1996), $e_{j,2p}$ is a $2p\times 1$ unit vector with 1 at the jth position, $\tilde{\mathbf{X}}$ denotes a $T\times 2p$ matrix with $(\mathbf{X}'_i, \mathbf{X}'_i((i-t)/T))$ as its ith row, and $\mathbf{W} = \text{diag}\{K_h((1-t)/T), \cdots, K_h((T-t)/T)\}$, $\mathbf{X}_t = (X_{1t}, \cdots, X_{pt})'$. To obtain the estimators of the time-varying coefficients, we have to select the kernel function $k(\cdot)$ and the bandwidth parameter h. Similar to the traditional non-parametric method, the bandwidth selection is much more important than that of the kernel function. In the empirical analysis, we use cross-validation, which is the usual data-driven bandwidth selection approach for selecting h.

However, as the cryptocurrency's return, $R_{c,t}$, is given by the dependent variable in (2.2), the error terms are highly likely to have a volatility clustering effect. This is confirmed by Li, Kim, and Park (2015) when the dependent variable is crude oil futures returns. In the empirical analysis, we find that the error term follows a GARCH-type process. Neglecting the GARCH effect in the error term process may lead to an inefficient estimator. To avoid this inefficiency problem, the GARCH-type specification is included in (2.2)–(2.4).

$$\begin{aligned} \epsilon_t|\mathcal{F}_{t-1} &\sim G(0, h_t), \\ h_t &= c_0 + c_1\epsilon_{t-1}^2 + c_2 h_{t-1}, \end{aligned} \tag{2.6}$$

where $G(0, h_t)$ denotes a distribution with mean 0 and variance h_t. Distribution G can be any well-known distribution, such as normal, Student's t, or skewed t-distributions. In our empirical analysis, we used a normal distribution, which is the most frequently used distribution in empirical analyses. As (2.4) is expressed in a non-parametric specification, the usual maximum likelihood estimation (MLE) for (2.4) and (2.6) is not available. Thus, in this study, we use a weighted local linear estimation method in which the weights are given by the estimated $1/\sqrt{h_t}$. However, h_t is unobservable. To obtain a feasible estimator, we need to estimate h_t first. This can be achieved by estimating the GARCH-type model using $\hat{\epsilon}$ in (2.3), which we can obtain using the usual local linear estimation method with an appropriate choice of bandwidth h. Additionally, h_t can be estimated using the conventional MLE method. Along with the estimated $\hat{h}_t$, (2.4) can be rewritten by

$$\tilde{\check{R}}_c, t = \sum_{j=1}^{3} g_j(t/T)\tilde{X}_{jt} + \tilde{\epsilon}_t, \tag{2.7}$$

where $\tilde{\check{R}}_{c,t} = \check{R}_{c,t}/\sqrt{\hat{h}_t}$, $\tilde{X}_{jt} = X_{jt}/\sqrt{\hat{h}_t}$ and $\tilde{\epsilon}_t = \epsilon_t/\sqrt{\hat{h}_t}$. By this transformation, $\tilde{\epsilon}_t$ in (2.6) does not follow the GARCH process: The efficient non-parametric estimators for $g_j(\cdot)$, $j = 1, 2, 3$, are then estimated using the local linear estimation method. These steps are repeated until convergence of the non-parametric estimator is achieved.[1] This estimation procedure is referred to as the profile least squares method in Fan and Huang (2005). They derived asymptotic Properties of the semi-parametric estimator.

3 Data and Descriptive Statistics

The daily closing prices (in USD) are utilized for the period ranging from April 29, 2014, to December 31, 2022. The time series of cryptocurrency prices were acquired from CoinMarketGap.[2] The analysis focuses on the eight most well-known cryptocurrency assets, namely Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Litecoin (LTC), Chainlink (LINK), Bitcoin Cash (BCH), Monero (XMR), and EOS (EOS). The daily prices of the S&P 500 index are used as a proxy for stock prices, the United States Treasury 10-year bond prices represent bond prices, and the Gold Fixing Price at 3 P.M. (London time) in the London Bullion Market is used for gold prices.[3]

Figures 1-3 depict time series graphs illustrating the level and return of prices. The cryptocurrency market experienced a significant downturn in March 2020, which was likely influenced by

[1] When the models are estimated in our empirical analysis, the non-parametric estimates are almost the same after the fourth iteration in most cases. All the models are estimated by using the R software; and the codes are available upon request.

[2] Cryptocurrency trading occurs 24 hours a day. The closing price represents the latest data within the specified range based on coordinated universal time (CUT). The time series of cryptocurrency prices can be accessed at https://www.coinmarketcap.com.

[3] The gold price is obtained from Federal Reserve Economic Data. The stock and bond prices are obtained from Datastream.

a sharp decline in the stock market. However, prices subsequently rebound, following a recovery pattern similar to that observed for stock prices. Notably, cryptocurrency prices displayed a substantial upward trend from November 2020, peaking in April 2021. Subsequently, prices declined sharply until June 2021, followed by a sharp increase in October 2021. By contrast, stock prices have a consistent upward trajectory since the significant price drop in March 2020, which was attributed to the impact of the COVID-19 pandemic. On the contrary, as one can see in Figure 3, bond prices have continuously declined since 2019, with a sharp fall observed until April 2020 due to the influence of COVID-19. However, bond prices experienced a noteworthy surge until April 2021. Interestingly, gold prices have an inverse relationship with bond prices. They consistently increased from the end of 2018, continuing their upward trend until August 2021, after which it gradually declined.

[Figures 1-3]

Table 1 provides an overview of the descriptive statistics for the return series. The return series exhibits skewed and fat-tailed behavior, indicating deviations from a normal distribution. This is further supported by the results of the Jarque-Bera normality test, which indicate that none of the return series conforms to a normal distribution. Furthermore, the Ljung-Box Q-test statistics reveal the presence of serial correlations in most return series, except for ETH and gold. This finding suggests a significant relationship between the past and current returns in these series. To investigate the presence of ARCH effects, Engle's (1982) LM test statistics were employed. The results, which are significant at the 1% level, reject the null hypothesis of no ARCH effect. This finding supports the presence of volatility clustering characteristics, as illustrated by Figures 1-3 .

[Table 1]

4 Empirical Results

To investigate the hedging behavior of cryptocurrencies, we consider three models for comparison: two fixed coefficient models (linear regression and GARCH regression models) and a semi-parametric model with time-varying coefficients. A linear regression model is favored because of its simplicity and clear interpretation. However, given the evidence of volatility clustering in the cryptocurrency market (Selmi, Tiwari, and Hammoude, 2018; Bouri, Gupta, and Roubaud, 2019) and price clustering observed across all three markets (Figures 1-3), a GARCH regression model was also employed. Note that failing to account for autoregressive conditional heteroscedasticity in the data leads to inefficient estimates. Finally, we employ a semi-parametric model to examine the time-varying hedging behavior described by (2.3)-(2.6). The estimated coefficients provide evidence of whether cryptocurrencies act as hedges or safe-havens in these three markets. Specifically, $\hat{\beta}_1$, $\hat{\delta}_1$, and $\hat{\gamma}_1$ represent the simultaneous effects of stocks, bonds, and gold, respectively, on each cryptocurrency under average market conditions, whereas $\hat{\beta}_2$, $\hat{\delta}_2$, and $\hat{\gamma}_2$ capture the effects during extremely negative market conditions, which are referred to as safe-haven effects. A negative or zero coefficient value of $\hat{\beta}_1$, $\hat{\delta}_1$, and $\hat{\gamma}_1$ supports the hypothesis that cryptocurrencies act as hedges, whereas a positive coefficient value does not.

Table 2 presents the estimation results for the linear regression model. The coefficient estimates ($\hat{\beta}_1$) for all cryptocurrencies corresponding to stocks are positive and statistically significant, suggesting that, on average, cryptocurrencies do not serve as effective hedges against stocks. Conversely, the estimated coefficients for bonds ($\hat{\delta}_1$) and gold ($\hat{\gamma}_1$) indicate that cryptocurrencies exhibit no significant correlation with these assets. This implies that cryptocurrencies have the potential to serve as hedges, with the exception of EOS in relation to gold. Moreover, the coefficient estimates representing safe-haven effects ($\hat{\beta}_2$, $\hat{\delta}_2$, and $\hat{\gamma}_2$) reveal that for bonds and gold, all cryptocurrencies are not significantly different from zero, except for LTC in relation to gold. Additionally, LTC and

EOS demonstrate no significant correlations with stocks.

[Table 2]

Table 3 presents the results of the GARCH (1,1) regression model. The estimates ($\hat{c}_1$ and $\hat{c}_2$) for the GARCH effect are found to be statistically significant, indicating the presence of persistent conditional heteroscedasticity. The results for the stock and bond markets ($\hat{\beta}_1$ and $\hat{\delta}_1$) are similar to those of the linear regression analysis. Specifically, all cryptocurrencies are effective hedging tools against bonds but do not serve as hedges against stocks. However, for gold, the GARCH regression estimates demonstrate that six out of eight cryptocurrencies lack hedging capabilities, whereas the linear model indicates that only EOS lacks hedging capabilities. Regarding the coefficients related to safe-haven effects ($\hat{\delta}_2$ and $\hat{\gamma}_2$), the results imply that we cannot reject the existence of safe-havens for bonds and gold at the 0.05 and 0.01 quantile levels. The exceptions to this observation are LTC and EOS at the 0.01 quantile level of the gold market. However, LINK, BCH, and EOS are potentially safe-havens for extreme stock returns.

[Table 3]

Figures 4-6 summarize estimation results for the time-varying coefficients. The solid line represents the estimated coefficients, and the dashed lines represent the corresponding 95% confidence bands. These figures comprehensively depict how the coefficient estimates develop over time. Additionally, Table 4 concisely summarizes the estimated coefficients representing the safe-haven characteristics.

Figure 4 demonstrates the results of the estimated time-varying coefficients for stocks. The estimated coefficient was nonpositive before early 2020. However, between mid-2020 and the end of 2022, the correlation is statistically significant and positive. Following the peak value in early 2022, the degree of comovement between the two variables gradually diminished. Our findings suggest that before early 2020, cryptocurrencies effectively served as hedging instruments against downside risks in equity markets, indicating their potential as hedging assets during periods of market stability. However, their hedging effectiveness in turbulent markets is contingent upon the timing and prevailing market conditions, which lack robustness across different market states (bullish or bearish). For instance, during calm market phases, such as from 2019 to early 2020, cryptocurrencies have demonstrated reliability as hedging vehicles. By contrast, during periods of market turbulence, although cryptocurrencies retained their hedging status during the bull and bust phases from 2017 to 2018, they lost their hedging efficacy during the COVID-19 downturn (after mid-2020). Notably, during both phases, cryptocurrencies' prices and trading volumes exhibited significant increases, accompanied by high returns and excessive volatility. Simultaneously, stock markets experienced an upward trend. In the first phase, the limited correlation between stocks and cryptocurrencies indicates that quantitative easing measures partly influence the moderate uptrend in the stock market, whereas the exponential growth of cryptocurrencies is primarily driven by speculative factors (Chowdhury, 2016; Klein, Thu and Walther, 2018). However, the sharp decline in cryptocurrencies in 2018 was attributed to government regulations in emerging countries such as China, which did not have a similar impact on the stock market.

[Figure 4]

Figure 5 illustrates the relationship between bonds and cryptocurrencies throughout the sample period. The results indicate estimates that do not significantly differ from zero, indicating that cryptocurrencies can serve as reliable hedges against bond market losses over the entire sample period. Only BTC and BNB have positive and statistically significant values between early 2019 and before mid-2019. Our findings that cryptocurrency returns are uncorrelated with bond returns in both normal and stressed market conditions aligns with the understanding that different price influencers operate in these two markets. While bond returns are contingent upon interest rates, which are linked to the business cycle (Hamilton, 2005), exposing them to systemic economic risk, cryptocurrencies are governed by a different mechanism. Notably, market confidence plays a decisive role in shaping returns and risks associated with cryptocurrencies, and this aspect deserves attention as price formation driven by market sentiment diverges significantly from that of bonds.

[Figure 5]

Figure 6 summarizes the results of estimated varying coefficients for gold. BTC, LTC, BCH, and XMR exhibited similar patterns, with a positive estimated coefficient observed between 2019 and 2021. However, the estimates are not significantly different from zero before 2019 and after 2021. Our findings suggest that from 2019 to 2021, BTC, LTC, BCH, and XMR did not effectively serve as hedges in the gold market. However, they provide some level of protection for gold under normal and stressful market conditions before 2019 and after 2022. In contrast, the estimated coefficients for ETH, BNB, LINK, and EOS are not significant over the whole time-horizon. This implies they have hedging capability against gold.

Our findings reveal significant heterogeneity in investors' reactions to shocks in the gold market across different cryptocurrencies. Specifically, cryptocurrencies that have existed for longer periods, such as BTC, XMR, and LTC (released before 2014), do not provide adequate financial protection against gold price losses. These cryptocurrencies demonstrate hedging capabilities when the gold market is calm, but this hedging effect diminishes during significant upturns in the gold market. That is, the relationship between these cryptocurrencies and the gold market is time-dependent and contingent upon the state of the gold market. In addition to the three cases mentioned above, cryptocurrencies served as effective hedges against gold price fluctuations before 2019. They began to correlate positively after that, and the linkage continued to grow on average until mid-2020 when gold prices continued their steep uptrend. The moderate rise in gold prices was driven by developments in emerging markets before 2020, after which gold prices rose steeply driven by the COVID-19 pandemic. Subsequently, when gold prices fell and returned to a calm market (after mid-2020), the linkage vanished, and cryptocurrencies regained their role as hedges against gold when gold was in a stable state.

[Figure 6]

Table 4 presents the estimation results of the semi-parametric model, which investigates the role of cryptocurrencies as safe-haven assets for stocks, bonds, and gold. These findings differ from those obtained from the linear and GARCH regression models, revealing distinct patterns. A closer examination of the results demonstrates the following key insights. First, focusing on stocks, most cryptocurrencies, except for EOS, exhibit significant positive values at the 0.05 quantile level, indicating that most cryptocurrencies do not act as safe-haven assets for stocks. However, under extremely severe market conditions (at the 0.01 quantile level), all cryptocurrencies except XMR demonstrate the characteristics of safe havens for stocks. Regarding bonds, only LINK and BCH are identified as safe-haven assets at the 0.05 quantile level. However, under severe market conditions (at the 0.01 quantile level), five of the eight cryptocurrencies (BTC, LTC, BCH, XMR, and EOS) tended to act as safe havens for bonds. For gold, all cryptocurrencies display the characteristics of safe-haven assets at the 0.05 quantile level. Moreover, under extreme market conditions (at the 0.01 quantile level), only four cryptocurrencies serve as safe-havens for gold (ETH, BNB, LINK, and EOS). In summary, the number of identified safe-haven assets increases for stocks and bonds during severe market conditions. Conversely, in the case of gold, the number of cryptocurrencies demonstrating safe-haven properties has decreased. These findings differ from the results of the linear and GARCH regression models that identify cryptocurrencies as safe-haven assets for bonds and gold. Moreover, these findings support prior research indicating that cryptocurrencies can serve as safe-havens during periods of extreme market volatility (Ji, Bouri, Gupta, and Roubaud, 2018; Jiang, Wu, Tian, and Nie, 2021).

[Table 4]

5 Discussion

From the estimated results of linear and time-varying coefficient models, it is evident that the relationship between cryptocurrencies and other assets can change over time, particularly in response to market conditions. The focus should not be on whether cryptocurrencies are hedge assets at a particular point but rather on how the movements of these assets have changed due to market shocks, which specific shocks have altered their relationship, and the nature of this change. During the turbulent period of COVID-19 (mid-2020 to the end of 2021), cryptocurrencies lost their hedging capability against stocks. During this period, they exhibited a positive correlation, which can be attributed to the bullish state of both markets. Cryptocurrencies experienced hyper-exponential growth accompanied by excessive volatility, while stock prices exhibited a steep upward trend. Both the stock and cryptocurrency markets were affected by the same shock, namely, the increased uncertainty driven by COVID-19. The rise in cryptocurrency prices can be attributed to speculative factors stemming from the panic surrounding COVID-19, as confirmed by Goodell and Goutte (2021), who found a strong connection between increased Bitcoin prices and COVID-19-related deaths. Starting in early 2022, when both markets entered a simultaneous bearish phase, the strength of their association weakened as the impact of the COVID-19 shock dissipated. Consequently, cryptocurrencies appear to have regained their roles as hedging instruments. These findings can be attributed to the fact that market shocks to stock prices and cryptocurrencies are driven by various factors related to uncertainty (Bouri, Gupta, Tiwari, and Roubaud, 2017). Wen, Tong, and Ren (2022) utilize time-varying parameter vector autoregression (TVP-VAR) to explore hedging ability by examining changes in impulse response during the COVID-19 downturn between stocks and cryptocurrencies. They claim a consistent positive spillover without hedging capabilities throughout the sample period (mid-2019 to mid-2021), which contradicts the reality that cryptocurrencies, particularly Bitcoin, have experienced super-exponential growth since mid-2020, in contrast to the relatively stable market prior to mid-2020.

However, the COVID-19 pandemic has triggered a surge in gold purchases and prices due to its widely recognized function as a store of value (Akhtaruzzaman, Boubaker, Lucey, and Sensoy, 2021). The popularity of gold as an investment contributed to this increase. However, the estimated time-varying coefficients for the gold market indicate significant variations in the relationships between stocks, cryptocurrencies, and gold. For instance, from mid-2020 to mid-2021, when the stock and cryptocurrency markets exhibited a positive correlation, cryptocurrencies such as ETH, BNB, LINK, and EOS had either no or negative relationships with gold. This suggests that the correlation between cryptocurrencies and stocks may have the opposite effect on the relationship between gold and stocks. Consequently, the hedging behavior for specific coins varies significantly during the sampling period, which can destabilize the financial market.

Our study complements the work of Conlon and McGee (2020), who consider a structural break by artificially determining the duration of the COVID-19 period to test dynamic hedging behavior. In contrast, we capture smoothly changing parameters using semi-parametric methods, enabling us to investigate smooth changes over the entire sample period and provide reliable information for long-term investors while considering a rich data period. This approach is particularly advantageous for cryptocurrencies, which often exhibit high transaction costs and illiquidity. Furthermore, our study expands on the work of Shahzad, Bouri, Roubaud, and Kristoufek (2020), who solely focus on changes in the hedge ratio over time through conditional variance without allowing for time-varying behavior in the return equation and considering the constancy of hedging ability. They argue that Bitcoin is a poor hedging instrument against US stocks, whereas our findings indicate that the potential hedging power of Bitcoin is likely to change over periods. These findings have practical implications for policymakers and risk managers.

6 Conclusion

This study provides valuable insights into the hedging behavior of cryptocurrencies in relation to traditional assets such as stocks, bonds, and gold. By applying various econometric models, including linear regression, GARCH regression, and a semi-parametric model with time-varying coefficients, we examine the dynamic nature of the relationship between cryptocurrencies and these assets. Our findings highlight that the relationship between cryptocurrencies and stocks can vary over time, particularly during market shocks, such as the COVID-19 pandemic. While cryptocurrencies initially lost their hedging capability for stocks during the pandemic's turbulent period, they regained their role as hedging instruments as market conditions stabilized. This suggests that the impact of market shocks and the factors driving uncertainty play crucial roles in shaping the correlation between cryptocurrencies and stocks.

Furthermore, our analysis reveals intriguing patterns in the relationship between cryptocurrencies and gold. The correlation between cryptocurrencies and stocks influences the correlation between cryptocurrencies and gold. During certain periods, cryptocurrencies exhibit no relationship with gold, indicating a potential diversification benefit. However, the hedging behavior of specific cryptocurrencies can vary significantly, underscoring the need for careful consideration of market conditions and individual characteristics of different coins. Our study contributes to the existing literature by employing semi-parametric methods that capture smoothly changing parameters over an entire sample period. This approach enables us to provide more reliable information for long-term investors and policymakers, particularly when considering the unique characteristics of cryptocurrencies, such as transaction costs and illiquidity.

The practical implications of our findings extend to risk managers and policymakers who seek to understand the role of cryptocurrencies in portfolio diversification and risk management strategies. Our results demonstrate that the hedging power of cryptocurrencies is not constant but develops with the dynamic market conditions. Therefore, a dynamic approach to incorporating cryptocurrencies into investment portfolios is necessary to fully leverage their potential benefits. Although our study sheds light on the hedging behavior of cryptocurrencies, it is important to acknowledge its limitations. Future research could explore additional factors influencing the relationship between cryptocurrencies and traditional assets, such as macroeconomic indicators or regulatory changes. Additionally, a deeper investigation into the implications of transaction costs and illiquidity in cryptocurrency markets would further enhance our understanding of their roles as hedging instruments.

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Table 1: DESCRIPTIVE STATISTICS

	BTC	ETH	BNB	LTC	LINK	BCH	XMR	EOS	STOCK	BOND	GOLD
Mean	0.002	0.003	0.005	0.001	0.002	-0.001	0.002	-0.001	0.000	0.000	0.000
Std. Dev.	0.049	0.077	0.084	0.071	0.083	0.079	0.077	0.079	0.011	0.031	0.009
Skewness	-0.116	-2.611	1.765	1.096	-0.086	0.059	0.520	-0.133	-0.845	0.280	-0.271
Kurtosis	15.198	57.828	43.678	21.085	8.611	11.187	13.303	9.844	20.169	33.931	6.322
JB test	15654.7	243931.6	98503.7	34900.2	1808.0	3963.6	10040.4	2802.7	31299.2	100650.5	1191.4
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(5)	16.322	8.4598	41.899	13.582	10.58	10.716	20.365	12.776	73.925	68.049	5.398
(p-value)	(0.006)	(0.133)	(0.000)	(0.018	(0.032)	(0.057)	(0.001)	(0.026)	(0.000)	(0.000)	(0.249)
ARCH(5)	18.919	41.455	9.915	23.874	15.336	22.636	50.079	14.066	282.201	500.392	18.023
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	2524	1930	1418	2524	1377	1419	2247	1434	2524	2524	2524

Notes: This table provides descriptive statistics for the data. The table, denotes the Jarque–Bera normality test, $Q(p)$ is the Ljung-Box test for white noise with lag order p, and ARCH (p) is Engle's (1982) LM test for the ARCH effects with lag order p. The numbers in parentheses are the p-values for the test statistics.

Table 2: Estimation results of the linear regression model

	BTC	ETH	BNB	LTC	LINK	BCH	XMR	EOS
α	**0.0026****	**0.0037****	**0.0058****	0.0015	0.0036	-0.0006	0.0026	-0.0012
	(0.0011)	(0.0018)	(0.0030)	(0.0017)	(0.0025)	(0.0024)	(0.0017)	(0.0023)
β_1	**0.3788*****	**0.6704*****	**1.0886*****	**0.5701*****	**1.0934*****	**0.7216*****	**0.5435*****	**0.8569*****
	(0.1069)	(0.2369)	(0.1806)	(0.1616)	(0.2281)	(0.2216)	(0.1664)	(0.2038)
δ_1	0.0074	0.0115	-0.0113	-0.0194	-0.0361	0.0502	0.0187	-0.0083
	(0.0415)	(0.0646)	(0.0589)	(0.0526)	(0.0732)	(0.0623)	(0.0662)	(0.0677)
γ_1	0.2356	0.4050	0.2858	0.1118	0.2415	0.4184	0.3652	**0.7722*****
	(0.1503)	(0.3318)	(0.2764)	(0.2177)	(0.2843)	(0.2871)	(0.2403)	(0.2906)
$\beta_2(0.05)$	**0.5175***	0.6893	-0.1815	0.5018	**0.9567****	**0.7614***	**0.5352***	0.2940
	(0.2701)	(0.4017)	(0.4302)	(0.3579)	(0.4269)	(0.4436)	(0.2979)	(0.4734)
$\beta_2(0.01)$	**0.9843****	**1.1469****	**1.3824****	0.8053	0.9272	0.4728	**1.1837*****	0.8757
	(0.4022)	(0.5154)	(0.6200)	(0.5022)	(0.6563)	(0.6553)	(0.4529)	(0.5771)
$\delta_2(0.05)$	-0.0020	-0.2483	-0.0855	-0.0935	**-0.2595***	-0.2294	-0.1874	-0.0919
	(0.1041)	(0.1607)	(0.1273)	(0.1510)	(0.1485)	(0.1422)	(0.1721)	(0.1395)
$\delta_2(0.01)$	-0.2325	-0.0160	-0.0007	-0.0231	0.0640	0.0138	-0.0375	-0.0134
	(0.1441)	(0.1774)	(0.1660)	(0.1831)	(0.1709)	(0.1961)	(0.2166)	(0.1667)
$\gamma_2(0.05)$	-0.2128	0.0452	0.4819	-0.4911	0.4003	-0.1193	0.2386	-0.5158
	(0.3666)	(0.5212)	(0.5370)	(0.5163)	(0.6401)	(0.5511)	(0.5037)	(0.6190)
$\gamma_2(0.01)$	0.5170	0.5181	0.4388	**1.0521****	0.0172	1.0514	-0.1583	0.9355
	(0.4199)	(0.5376)	(0.5895)	(0.5013)	(0.7753)	(0.6456)	(0.6605)	(0.6389)
AIC	-3.2490	-2.3197	-2.1564	-2.4618	-2.2122	-2.2832	-2.3268	-2.2884
SIC	-3.2259	-2.2908	-2.1193	-2.4387	-2.1743	-2.2462	-2.3014	-2.2517
Log L.	4110.2	2248.5	1538.9	3116.8	1533.1	1629.9	2624.2	1650.8

Notes: $R_{c,t} = \alpha + \beta_1 R_{s,t} + \delta_1 R_{b,t} + \gamma_1 R_{g,t} + \beta_2 R_{s,t(\tau)} + \delta_2 R_{b,t(\tau)} + \gamma_2 R_{g,t(\tau)} + \epsilon_t$. Where $R_{c,t}$, $R_{s,t}$, $R_{b,t}$ and $R_{g,t}$ denote returns on a cryptocurrency, stock, bond, and gold prices, respectively. $R_{s,t(\tau)}$, $R_{b,t(\tau)}$ and $R_{g,t(\tau)}$ account for crashes in the stock, bond, and gold markets, respectively. These can be defined as returns less than τ quantile (τ = 0.05 and 0.01). The robust standard deviations are given in parentheses. ***, **, and * represent levels of significance at the 1%, 5% and 10%, respectively.

Table 3: Estimation results of the GARCH regression model

	BTC	ETH	BNB	LTC	LINK	BCH	XMR	EOS
α	0.0014	0.0013	0.0014	-0.0007	0.0021	-0.0026	0.0014	-0.0027
	(0.0008)	(0.0014)	(0.0013)	(0.0011)	(0.0020)	(0.0016)	(0.0013)	(0.0019)
β_1	**0.4236*****	**0.9784*****	**0.8862*****	**0.5231*****	**1.1284*****	**0.9084*****	**0.4548*****	**0.9522*****
	(0.0947)	(0.1540)	(0.1397)	(0.1267)	(0.1744)	(0.1557)	(0.1432)	(0.1574)
δ_1	0.0175	0.0910	0.0046	0.0245	-0.0176	0.0727	0.0594	0.0288
	(0.0350)	(0.0596)	(0.0548)	(0.0493)	(0.0675)	(0.0625)	(0.0527)	(0.0640)
γ_1	**0.3185****	**0.4476***	**0.5021*****	0.1295	0.2543	**0.5639****	**0.5040****	**0.5990****
	(0.1258)	(0.2479)	(0.1936)	(0.1620)	(0.2954)	(0.2396)	(0.2147)	(0.2579)
$\beta_2(0.05)$	0.3561	0.3272	0.1514	0.3556	0.6968	0.3991	0.3796	0.0179
	(0.3001)	(0.3815)	(0.3494)	(0.3847)	(0.4256)	(0.4273)	(0.3139)	(0.4154)
$\beta_2(0.01)$	**1.1897****	**1.2079***	**1.2535***	**1.0981****	1.1428	0.7627	**1.4653****	1.1408
	(0.5293)	(0.6711)	(0.6552)	(0.5576)	(1.0262)	(0.8465)	(0.5938)	(0.7697)
$\delta_2(0.05)$	0.0407	-0.1590	-0.0557	0.0209	-0.1900	-0.1247	-0.1577	-0.0968
	(0.1052)	(0.1302)	(0.1099)	(0.1322)	(0.1374)	(0.1386)	(0.1194)	(0.1246)
$\delta_2(0.01)$	**-0.3044***	-0.1993	-0.0747	-0.2097	0.0186	-0.1092	-0.0856	-0.0606
	(0.1563)	(0.1842)	(0.2020)	(0.1708)	(0.2105)	(0.2370)	(0.1700)	(0.1807)
$\gamma_2(0.05)$	-0.1421	0.3883	0.2059	-0.3252	0.2057	-0.4409	-0.2018	-0.6059
	(0.2525)	(0.4693)	(0.5385)	(0.3329)	(0.5584)	(0.5509)	(0.4297)	(0.6678)
$\gamma_2(0.01)$	0.3878	0.3189	0.5329	**1.0997****	0.2033	1.1610	0.6564	**1.2734***
	(0.3418)	(0.6362)	(0.6334)	(0.5117)	(0.8714)	(0.7982)	(0.5468)	(0.7328)
c_0	**0.0001*****	**0.0003*****	**0.0001****	**0.0002****	**0.0002****	**0.0001****	**0.0002*****	0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
c_1	**0.1126*****	**0.1349*****	**0.1517*****	**0.1073*****	**0.0999*****	**0.0845*****	**0.1188*****	**0.0589*****
	(0.0207)	(0.0261)	(0.0428)	(0.0253)	(0.0220)	(0.0218)	(0.0379)	(0.0228)
c_2	**0.8497*****	**0.7997*****	**0.8353*****	**0.8441*****	**0.8789*****	**0.8934*****	**0.8594*****	**0.9239*****
	(0.0257)	(0.0221)	(0.0374)	(0.0294)	(0.0273)	(0.0250)	(0.0410)	(0.0306)
AIC	-3.4495	-2.6742	-2.7580	-2.7301	-2.3711	-2.5371	-2.5624	-2.4857
BIC	-3.4194	-2.6367	-2.7098	-2.7001	-2.3217	-2.4889	-2.5293	-2.4379
Log L.	4366.2	2593.6	1968.4	3458.4	1645.5	1813.0	2891.8	1795.2

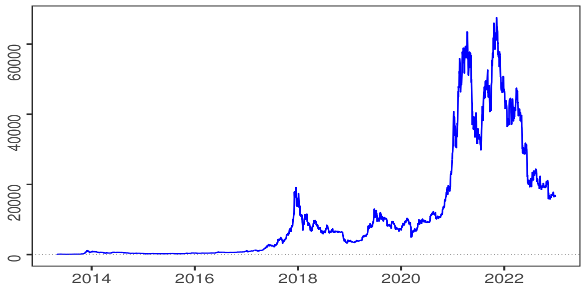
Notes: $R_{c,t} = \alpha + \beta_1 R_{s,t} + \delta_1 R_{b,t} + \gamma_1 R_{g,t} + \beta_2 R_{s,t(\tau)} + \delta_2 R_{b,t(\tau)} + \gamma_2 R_{g,t(\tau)} + \epsilon_t$. $h_t^2 = c_0 + c_1 \varepsilon_{t-1}^2 + c_2 h_{t-1}^2$. Where $R_{c,t}$, $R_{s,t}$, $R_{b,t}$ and $R_{g,t}$ denote returns on a cryptocurrency, stock, bond, and gold prices, respectively. $R_{s,t(\tau)}$, $R_{b,t(\tau)}$ and $R_{g,t(\tau)}$ account for crashes in the stock, bond, and gold markets, respectively. These can be defined as returns less than τ quantile ($\tau = 0.05$ and 0.01). The robust standard deviations are given in parentheses. ***, **, and * represent levels of significance at the 1%, 5% and 10%, respectively.

Table 4: Estimation results of the semi-parametric models

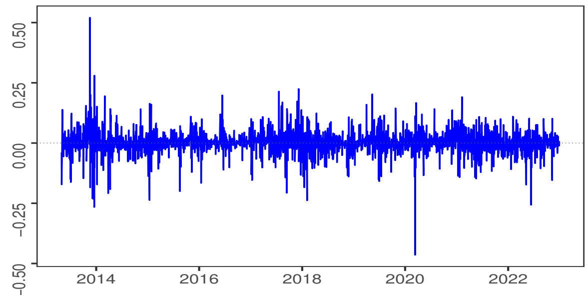
	BTC	ETH	BNB	LTC	LINK	BCH	XMR	EOS
$\beta_2(0.05)$	**0.8585*****	**2.0872*****	**1.2034*****	**0.9235*****	**2.2504*****	**1.2353*****	**0.8332*****	0.3677
	(0.2566)	(0.3767)	(0.3560)	(0.3234)	(0.3867)	(0.3790)	(0.2640)	(0.4524)
$\beta_2(0.01)$	0.0902	0.1012	0.1230	0.0932	0.0881	-0.0099	**0.4126****	0.3058
	(0.1154)	(0.1798)	(0.1385)	(0.1447)	(0.1711)	(0.1687)	(0.1696)	(0.1976)
$\delta_2(0.05)$	**1.3509*****	**1.5024****	**1.2297***	**1.4041*****	0.9285	1.2007	**1.8279*****	**1.6412****
	(0.4794)	(0.6883)	(0.7329)	(0.5211)	(0.8596)	(0.8128)	(0.6019)	(0.7566)
$\delta_2(0.01)$	**-0.6748*****	**0.9048****	**0.9420****	**-0.8559*****	**1.6554*****	-0.0239	**-0.6214***	0.5455
	(0.2319)	(0.4528)	(0.4686)	(0.3276)	(0.6284)	(0.5343)	(0.3740)	(0.6400)
$\gamma_2(0.05)$	**-0.1522***	0.1426	**-0.2575****	-0.1376	-0.1829	0.0154	-0.1206	**-0.2105***
	(0.0907)	(0.1244)	(0.1025)	(0.1195)	(0.1146)	(0.1501)	(0.1102)	(0.1184)
$\gamma_2(0.01)$	**0.9996*****	0.7876	0.9066	**1.3807*****	0.0346	0.9804	**1.2730*****	**1.4526***
	(0.3088)	(0.6972)	(0.5876)	(0.3956)	(0.9357)	(0.7060)	(0.4856)	(0.7526)

Notes: $R_{c,t} = \alpha + \beta_1(t/T)R_{s,t} + \delta_1(t/T)R_{b,t} + \gamma_1(t/T)R_{g,t} + \beta_2 R_{s,t(\tau)} + \delta_2 R_{b,t(\tau)} + \gamma_2 R_{g,t(\tau)} + \epsilon_t$. Where $R_{c,t}$, $R_{s,t}$, $R_{b,t}$ and $R_{g,t}$ denote returns on a cryptocurrency, stock, bond, and gold prices, respectively. $R_{s,t(\tau)}$, $R_{b,t(\tau)}$ and $R_{g,t(\tau)}$ account for crashes in the stock, bond, and gold markets, respectively. These can be defined as returns less than τ quantile (τ = 0.05 and 0.01). ***, **, and * represent levels of significance at the 1%, 5% and 10%, respectively. The numbers in parentheses are standard errors.

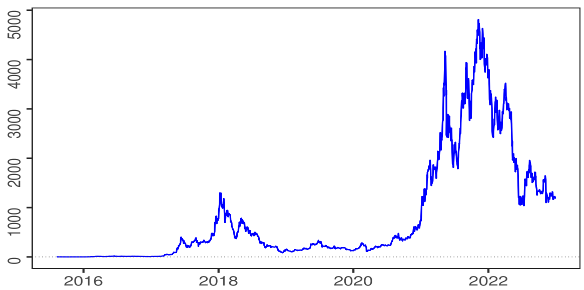
Figure 1: TIME SERIES VARIABLES OF LEVELS AND RETURNS



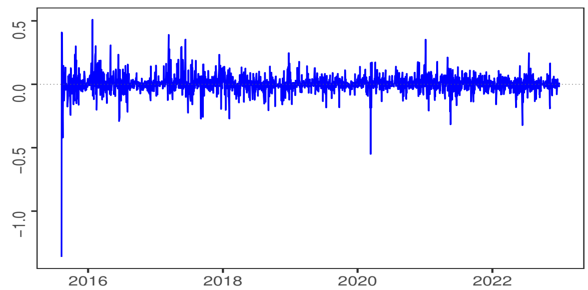
(a) Bitcoin level



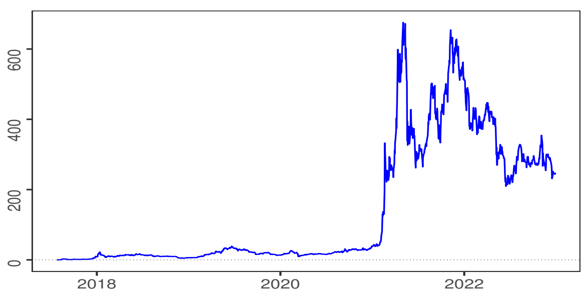
(b) Bitcoin return



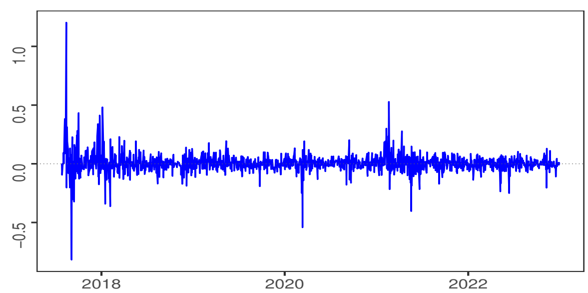
(c) Ethereum level



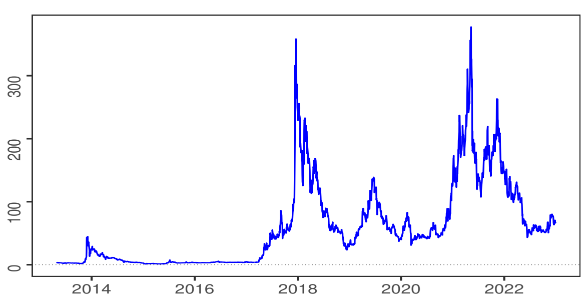
(d) Ethereum return



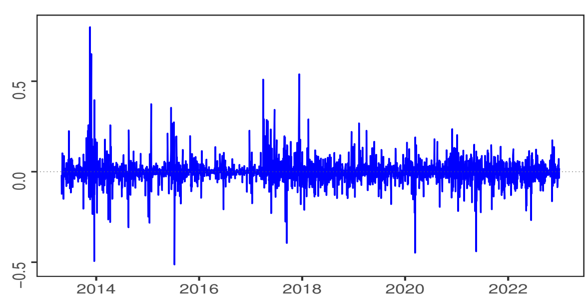
(e) Binance level



(f) Binance return

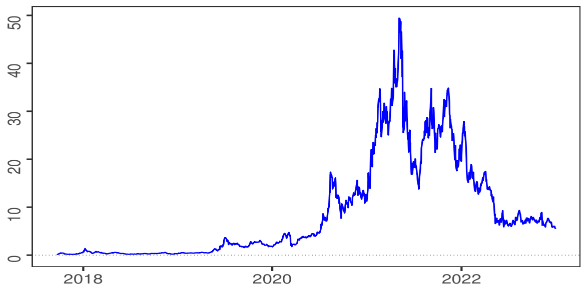


(g) Litecoin level

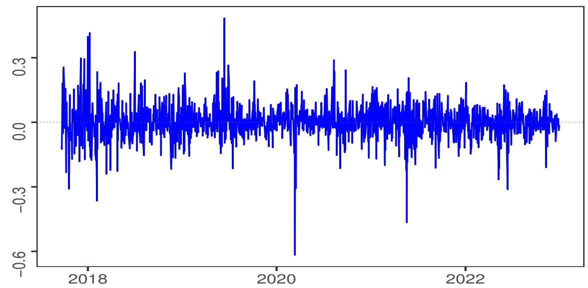


(h) Litecoin return

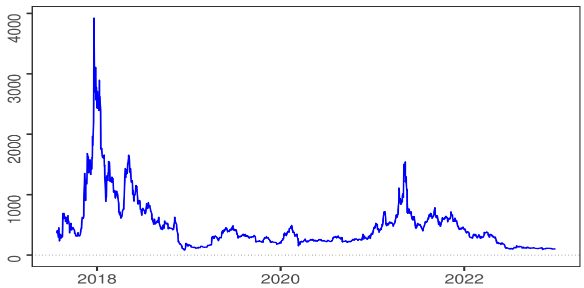
Figure 2: TIME SERIES VARIABLES OF LEVELS AND RETURNS (CONTINUE)



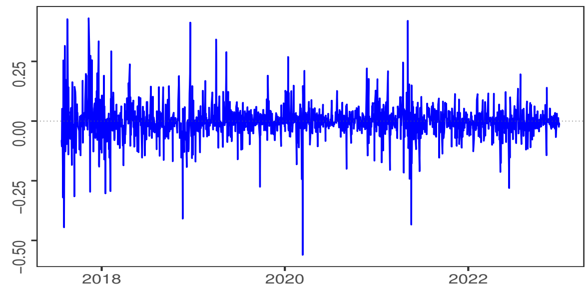
(a) Chainlink level



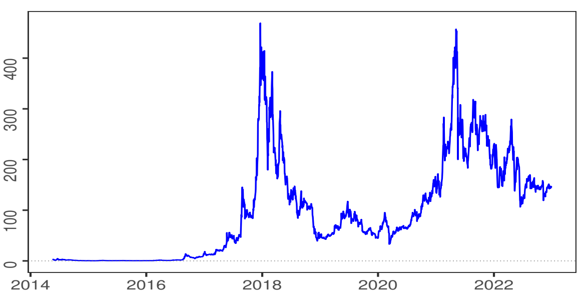
(b) Chainlink return



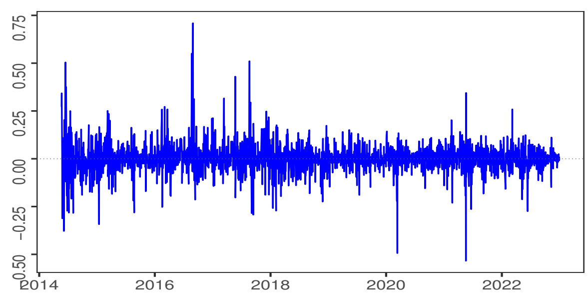
(c) Bitcoin Cash level



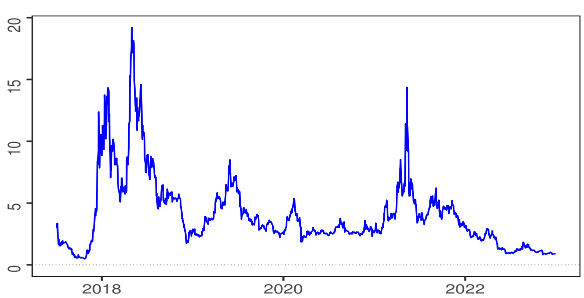
(d) Bitcoin Cash return



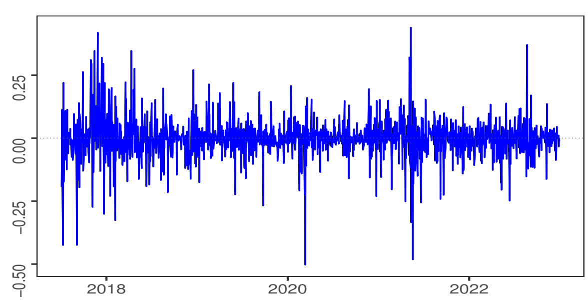
(e) Monero level



(f) Monero return

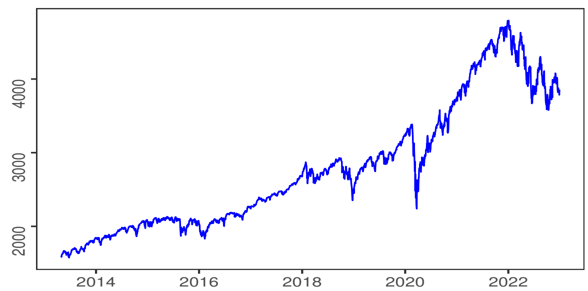


(g) EOS level

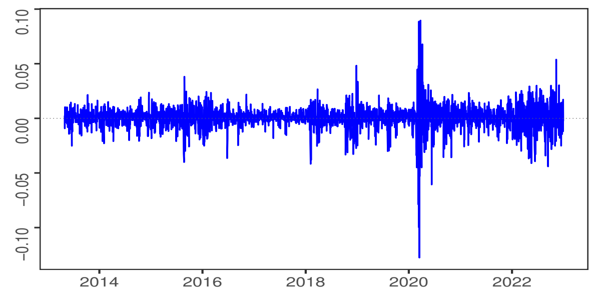


(h) EOS return

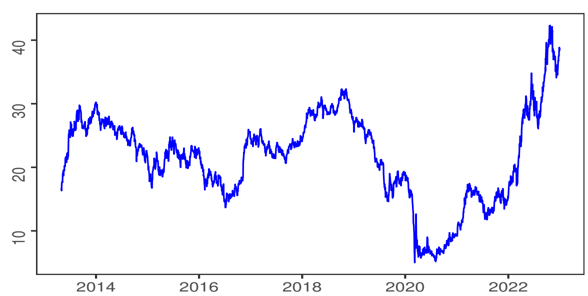
Figure 3: Time series variables of levels and returns (continue)



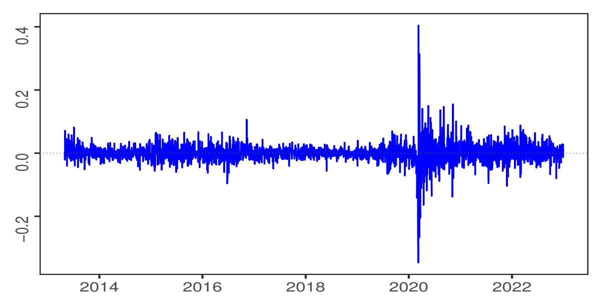
(a) Stock level



(b) Stock return

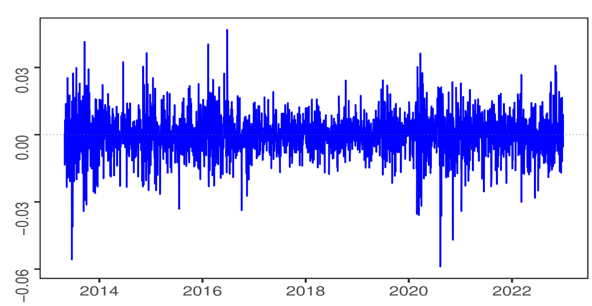


(c) Bond level



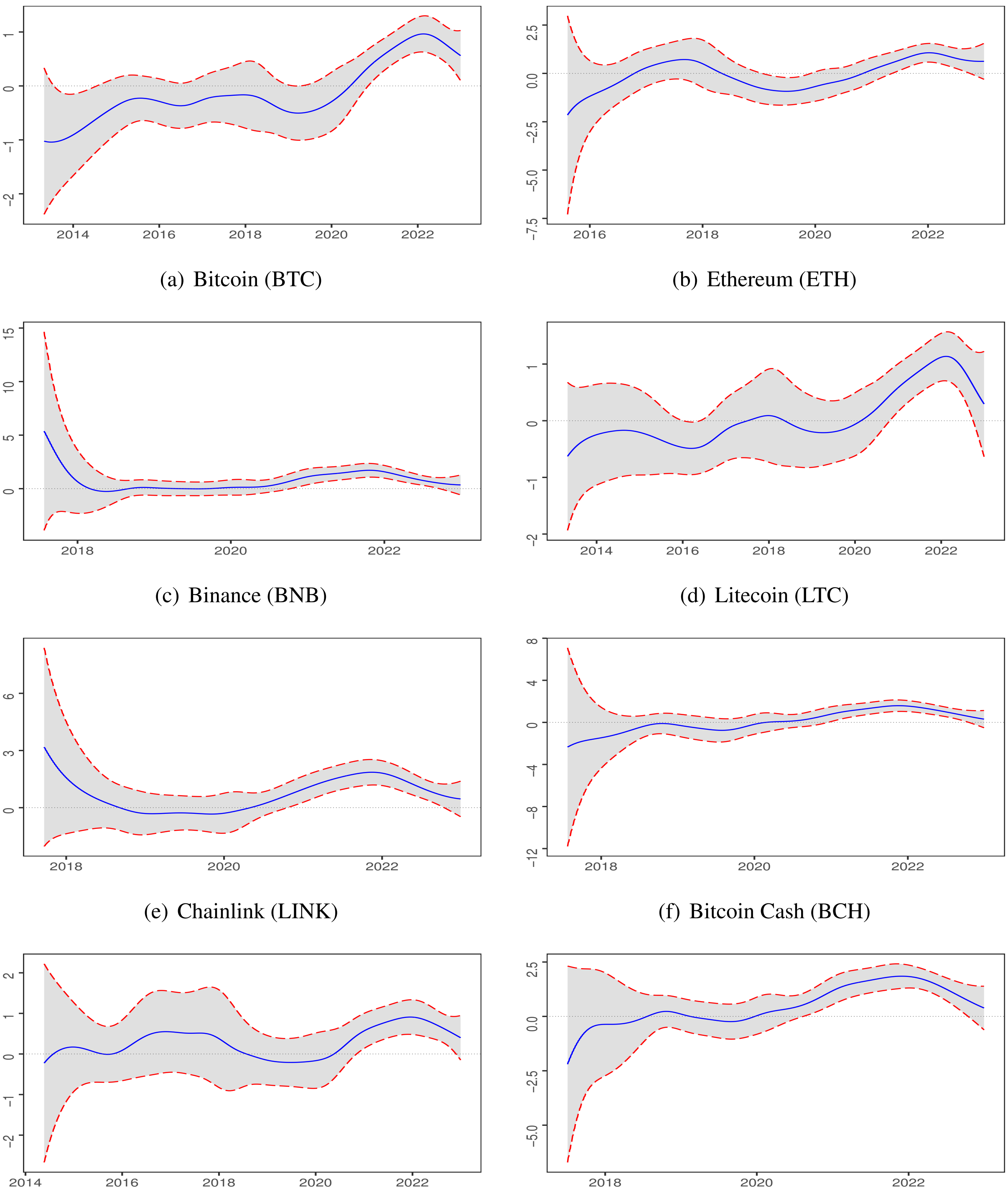
(d) Bond return

(e) Gold level



(f) Gold return

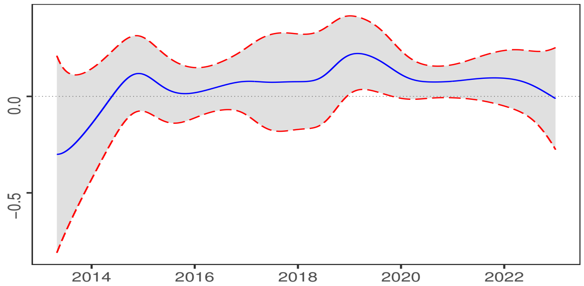
Figure 4: Semi-parametric varying-coefficients partial linear models for Stock



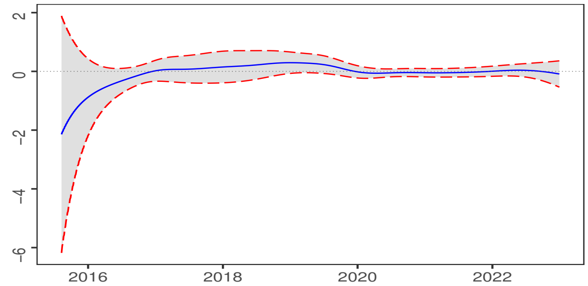
(a) Bitcoin (BTC)
(b) Ethereum (ETH)
(c) Binance (BNB)
(d) Litecoin (LTC)
(e) Chainlink (LINK)
(f) Bitcoin Cash (BCH)
(g) Monero (XMR)
(h) EOS (EOS)

Notes: The solid line represents the estimated coefficients, and the dashed lines represent the corresponding 95% confidence bands. Wild bootstrap method is used to estimate standard errors.

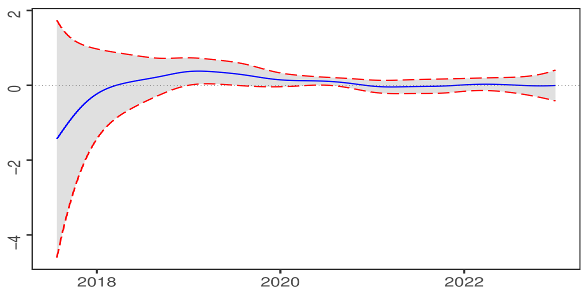
Figure 5: Semi-parametric varying-coefficients partial linear models for Bond



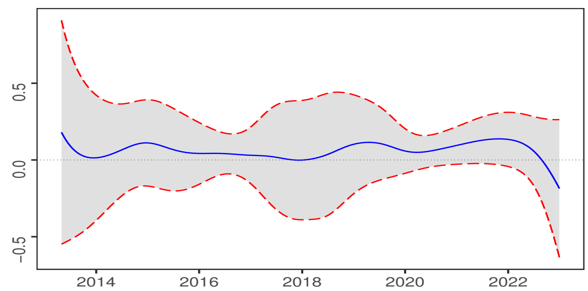
(a) Bitcoin (BTC)



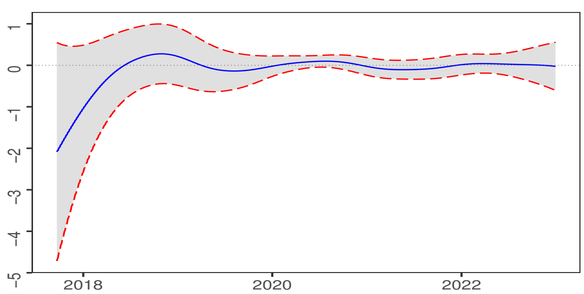
(b) Ethereum (ETH)



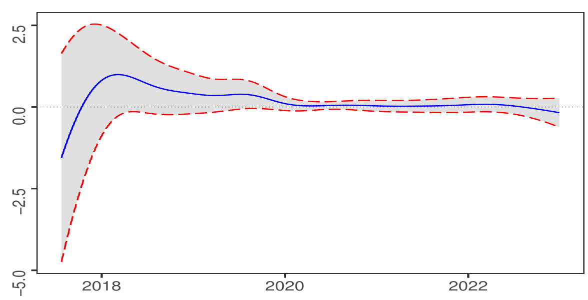
(c) Binance (BNB)



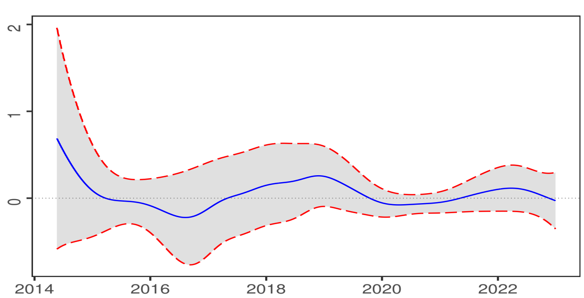
(d) Litecoin (LTC)



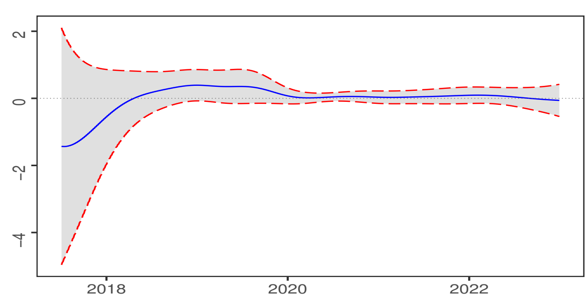
(e) Chainlink (LINK)



(f) Bitcoin Cash (BCH)



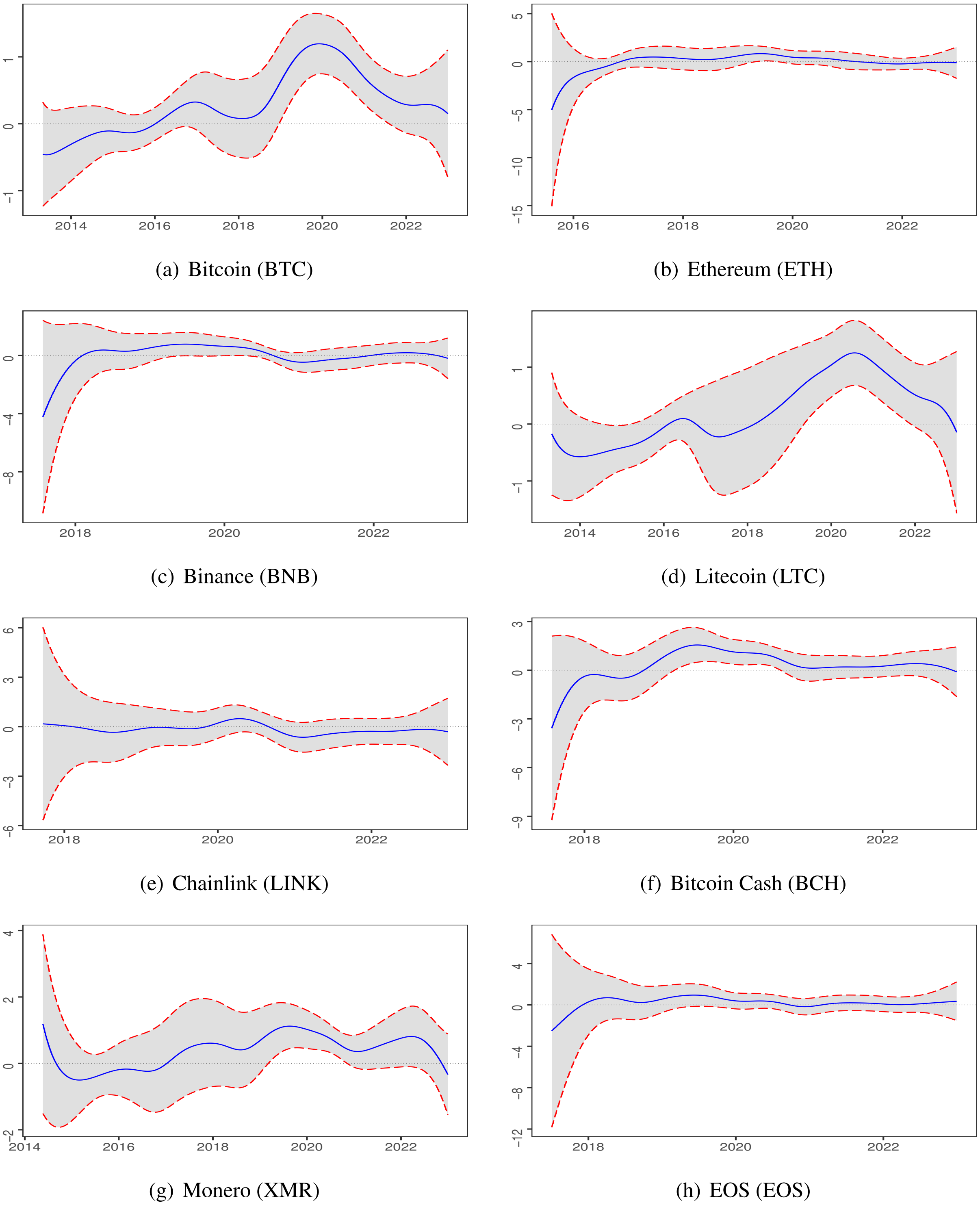
(g) Monero (XMR)



(h) EOS (EOS)

Notes: The solid line represents the estimated coefficients, and the dashed lines represent the corresponding 95% confidence bands. Wild bootstrap method is used to estimate standard errors.

Figure 6: Semi-parametric varying-coefficients partial linear models for Gold



(a) Bitcoin (BTC)

(b) Ethereum (ETH)

(c) Binance (BNB)

(d) Litecoin (LTC)

(e) Chainlink (LINK)

(f) Bitcoin Cash (BCH)

(g) Monero (XMR)

(h) EOS (EOS)

Notes: The solid line represents the estimated coefficients, and the dashed lines represent the corresponding 95% confidence bands. Wild bootstrap method is used to estimate standard errors.