Market uncertainty and correlation between Bitcoin and Ether

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Abstract

This study investigates whether market states impact the Bitcoin-Ether correlation. We observe an increase in the average correlation due to a rise in popularity of Ether. We also find that an increase in uncertainty leads to the low Bitcoin-Ether correlation, suggesting that investors revise the relative valuation during high market uncertainty periods. The relationship between the Bitcoin-Ether correlation and uncertainty is nonlinear, and our search volume results show that investors' attention to both cryptocurrencies increases during the uncertainty periods.

Keywords: VIX, ADCC GARCH, Cryptocurrencies, Gold, Quantile regression

1. Introduction

Cryptocurrency markets have received capital flows and become important financial markets for both investors and regulators. As of January 2022, Bitcoin (BTC) has the largest asset capitalization (US$1.6 trillion). BTC is the most important cryptocurrency while its dominance is declining. For instance, the market share was more than 80% in January 2017, but it is about 40% in

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January 2022.[2] Ether (ETH) now plays a key role as an alternative cryptocurrency and the market share is about 18%. ETH is built by Ethereum, which is Blockchain technology with its smart contract system. Ethereum receives attention as decentralized finance (DeFi) and one of the application examples is the stablecoin DAI. This Ethereum characteristic indicates that ETH has a different intrinsic value from BTC.

This study focuses on a correlation of two major cryptocurrencies, BTC and ETH. Some investors start to regard ETH as an alternative asset of BTC due to an increase in the market share of ETH. Previous studies have investigated correlations between equities and bonds.[3] For example, Connolly et al. (2005) revealed that market uncertainty was associated with more frequent revisions of expected returns for investors, resulting in negative equity and bond correlations. Furthermore, Adrian et al. (2019) reported that equity and bond correlations depended on the level of Chicago Board Options Exchange Volatility Index (VIX). We explore whether the correlation between BTC and ETH is linked to market states. Investors frequently revise their values during market uncertainty periods and their values are affected by differences in Blockchain technologies, network effects and current price levels.[4] Therefore, it is reasonable to consider that the BTC-ETH correlation becomes low with an increase in market uncertainty, which is similar to equity and bond correlations.

The first contribution of this study is that we investigate whether market states are nonlinearly associated with the BTC and ETH correlation. The previous studies uncover that market states have nonlinear impacts on the BTC

[2] `https://https://coinmarketcap.com/charts/`

[3] See, Connolly et al. (2005), Connolly et al. (2007), Baele et al. (2010), and Baele et al. (2020).

[4] For instance, Cong et al. (2021) and Liu & Tsyvinski (2021) provide theoretical and empirical evidence that the cryptocurrency value depends on the network externality to settle transactions. Liu & Tsyvinski (2021) also provide a valuation ratio for cryptocurrencies based on the network variables and the current market price. Sockin & Xiong (2020) demonstrate that network effects and speculation determine the cryptocurrency demand.

price. For instance, high market uncertainty causes a low crash risk of BTC (Kalyvas et al. (2020)). Umar et al. (2021) reveal that a rise in political uncertainty leads to an increase in the BTC price, while the relationship is negative during normal states (Demir et al. (2018)).[5] The current study complements these studies since we focus on the correlation, not the price of BTC.

Our second contribution is that we extend a relationship between gold and cryptocurrencies. Cryptocurrencies are considered as new gold and many studies investigate whether the gold price is associated with cryptocurrency prices. Baur et al. (2018) highlight that the properties of BTC depend on the sample period. Klein et al. (2018) and Shahzad et al. (2020) report that gold entails a safe haven property, but BTC does not. Nakagawa & Sakemoto (2021) find that BTC network effects have positive impacts on both BTC and gold prices. These studies focus on a bi-directional relationship between BTC and gold, while we consider three elements: BTC, ETH, and gold. We test whether an increase in market uncertainty of gold weakens the BTC-ETH correlation due to the differences of fundamental values for BTC and ETH. We capture gold market uncertainty using the CBOE gold volatility index (GVZ). This is based on implied volatility such as VIX, which reflects investor's expectation and entails different information contents from historical volatility.[6]

Previous literature has explored relationship between BTC and ETH markets (Ciaian et al. (2018), Borri (2019), Sifat et al. (2019)). The important deviation of our study is that we are motivated by Connolly et al. (2005) and Adrian et al. (2019), and focus on the relationship between the BTC-ETH correlation and market states. Our aim is not to test whether ETH acts as a hedge against BTC, but to explore whether an increase in market uncertainty leads to changes in the correlation, which is observed in the equity-bond correlations. Another important difference is that we include data when BTC dominance declines.

[5] Wu et al. (2019) investigate a nonlinear relationship between the BTC price and uncertainty, but they do not observe a clear pattern.

[6] For instance, see Goyal & Saretto (2009)

The value of cryptocurrencies depends on network effects (Cong et al. (2021), Liu & Tsyvinski (2021)) and a rise in the market share of ETH suggests that the network value is greater than that of the previous studies.

Our main findings are the following two points. First, we find the nonlinear relationship between the cryptocurrency correlation and market uncertainty. Importantly, the conditional correlation between BTC and ETH is high when market uncertainty in the stock and gold markets is low. This unique result is not observed when we focus on volatilities on BTC and ETH. [7] Our new correlation result implies that the difference between BTC and ETH is more focused during high market uncertainty periods. To support this interpretation, we provide empirical evidence that google search volumes of BTC and ETH are negatively related to the correlation between BTC and ETH.

Second, we observe that the conditional correlation between BTC and ETH tended to be high after 2018, which indicates that the cryptocurrency market structure has changed during this period. Extending the data period in the analysis is worthwhile, because the cryptocurrency market is new and the data contain a shorter period compared with other assets. The previous studies such as Ciaian et al. (2018), Borri (2019), and Sifat et al. (2019) did not cover the period after 2018.

The remainder of this paper is organized as follows. Section 2 describes the dataset and methodology. Section 3 presents our empirical results, and Section 4 is the conclusion.

2. Dataset and Methodology

2.1. Dataset

We employ three cryptocurrency prices of BTC, and ETH. We adopt two volatility indices for capturing market uncertainty: VIX and GVZ. The VIX is

[7] Figures B.6 and B.7 provide relationships between cryptocurrency volatility and market uncertainty. We also find that market uncertainty in the gold market does not influence the cryptocurrency returns (Figures B.4 and B.5).

the one of the most important market uncertainty indices (e.g., Adrian et al. (2019)). The GVZ is the volatility index based on gold prices that are associated with the cryptocurrency markets (Nakagawa & Sakemoto (2021)). We adopt returns for the cryptocurrency and prices for the volatility indices at a daily frequency. The prices are obtained from CoinDesk and the volatility indices are downloaded from CBOE Global Markets.[8] The full sample is from December 20, 2016 to April 28, 2022 (1,267 days).

Table 1: Summary Descriptive

Variable	N	Mean	St. Dev.	Min	Max	DF
BTC	1,349	0.004	0.049	−0.388	0.285	-25.131***
ETH	1,349	0.007	0.067	−0.441	0.523	-24.482***
ADCC	1,349	0.735	0.173	0.079	0.979	-3.964**
VIX	1,349	18.792	8.730	9.140	82.690	-4.186***
GVZ	1,349	15.257	4.977	8.880	48.980	-4.298***

Notes: This table reports the number of observations (N), mean, standard deviations, minimum, maximum, and augmented Dickey Fuller statistic (DF). BTH amd ETH are calculated as returns of the prices. ADCC is the dynamic correlations between BTH and ETH. *p<0.1; **p<0.05; ***p<0.01.

2.2. Asymmetric Dynamic Conditional Correlation Model

First, we use the Asymmetric Dynamic Conditional Correlation (ADCC) model of Cappiello et al. (2006) to describe the volatility dynamics and obtain conditional correlations. This model is based on the DCC model proposed by Engle (2002) and allows us to capture an asymmetric response of a change in the correlation.

Let r_t be a $n \times 1$ vector of asset returns, and it follows:

$$r_t \mid \Omega_{t-1} \overset{iid}{\sim} N(\mu_t, H_t) \tag{1}$$

[8] (`https://www.coindesk.com/markets/`) and (`https://www.cboe.com/`)

where Ω_{t-1} is the information set up to time $t-1$. The conditional mean process μ_t is obtained by the AR(1) model as: $\mu_t = c + ar_{t-1}$, where c is the $n \times 1$ estimated constant parameter vector and $a = \text{diag}(a_1, ..., a_n)$ is the diagonal matrix and the diagonal indicates estimated parameters. The conditional covariance matrix H_t is decomposed as $H_t = D_t R_t D_t$, where D_t is the diagonal matrix of the standard deviations of returns on the diagonal and R_t is the conditional correlation matrix of standardized residuals of returns. $D_t = \text{diag}(h_{1,t}^{1/2}, ..., h_{n,t}^{1/2})$ is the diagonal matrix and the diagonal is obtained by the univariate GARCH model with a t-distribution as: $h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}$, and ν is the shape parameter of the t-distribution.

The vector of the standardized residuals z_t is modeled as:

$$z_t = H_t^{-1/2} \varepsilon_t, \quad z_t \overset{iid}{\sim} N(0, I_n) \tag{2}$$

where ε_t is obtained as the vector of the residuals as: $\varepsilon_t = r_t - \mu_t$. The conditional correlation matrix R_t can be decomposed as $R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2}$ and the dynamics of Q_t in the ADCC model is given by:

$$Q_t = (\bar{Q} - A\bar{Q} - B\bar{Q} - G\bar{Q}^-) + A z_{t-1} z_{t-1}^\top + B Q_{t-1} + G z_{t-1}^- z_{t-1}^{-\top} \tag{3}$$

where A, B and G are scalar parameters, and z_t^- are zero-threshold standardized errors which are equal to z_t when less than zero, and otherwise zero. This term captures asymmetric shocks of z_t. The terms $\bar{Q}$ and $\bar{Q}^-$ are the unconditional matrices of z_t and z_t^-, respectively.[9]

2.3. Quantile Regression

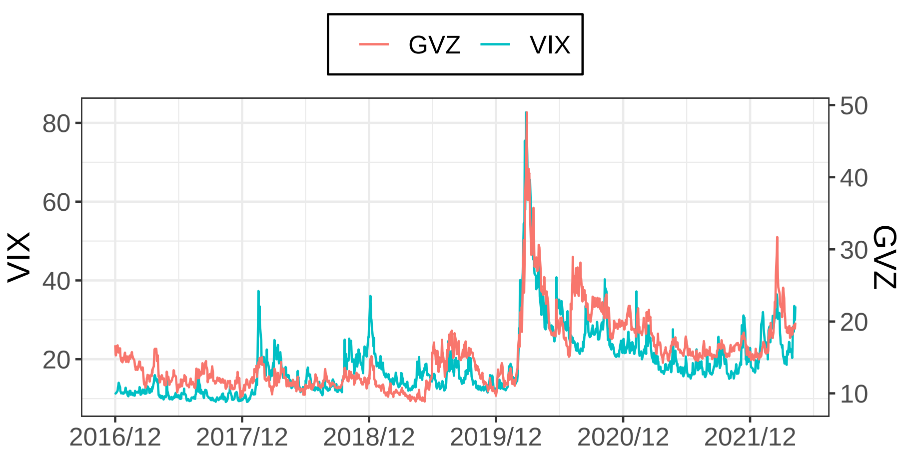
We employ a quantile regression approach (Koenker & Bassett (1978)) and explore whether market states captured by the VIX or the GVZ impact the correlations between BTC and ETH. The quantile regression allows us to evaluate nonlinear and asymmetric relationships (e.g., Umar et al. (2021)). Generally,

[9] We estimate the ADCC model using the rmgarch package (`https://cran.r-project.org/web/packages/rmgarch/index.html`).

Figure 1: Time-varying correlation between BTC and ETH

Notes: This correlation is obtained by the ADCC model.

Figure 2: VIX and GVZ prices



the quantile regression model is described by the equation as:

$$Y_t = X_t\beta_\theta^\top + e_t \tag{4}$$

where Y_t is the dependent variable, X_t is regressors, and β_θ represents the vector of unknown parameters associated with the θth quantile. The quantile estimator β_θ is obtained by solving the following optimization problem as:

$$\min \sum_{t\in\{Y_t\geq X_t\beta_\theta^\top\}} \theta|Y_t - X_t\beta_\theta^\top| + \sum_{t\in\{Y_t<X_t\beta_\theta^\top\}} (1-\theta)|Y_t - X_t\beta_\theta^\top| \tag{5}$$

We examine 19 different quantiles, namely from $\theta = 0.05$ to $\theta = 0.95$. The standard errors are calculated using the wild bootstrap approach proposed by Feng et al. (2011).

3. Empirical Results

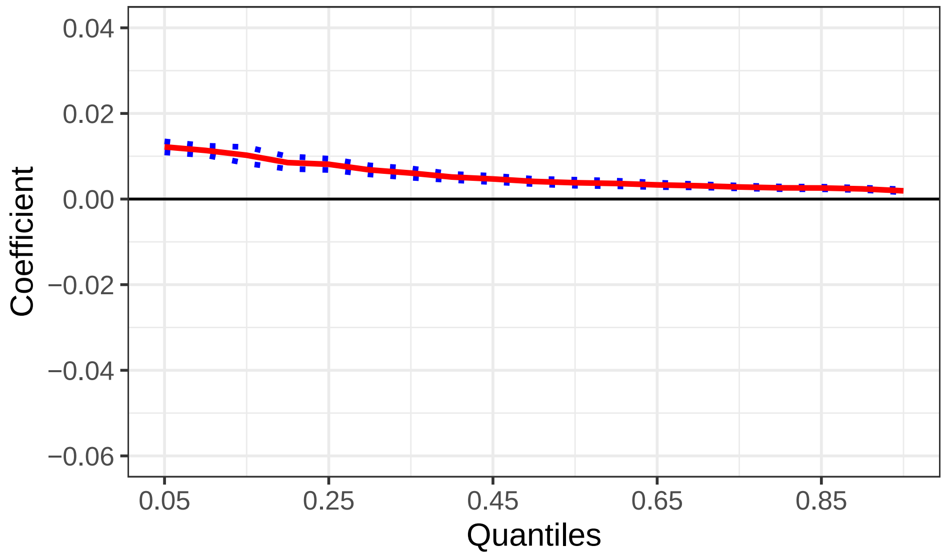
3.1. Conditional Correlations

We begin with the time-varying correlation between BTC and ETH estimated using the ADCC model.[10] Figure 1 demonstrates that the correlation varies over time and the fluctuation is larger in the early period than that in the later period. The correlation was close to zero twice in 2017, which is consistent with the finding in Aslanidis et al. (2019). In contrast, it became higher from 2018, indicating that the cryptocurrency markets were more integrated. This market integration is related to a decline in the BTC market share and an increase in the ETH market share, which suggests that ETH is becoming an important alternative asset for BTC investors. Our results also demonstrate that the sample periods have a large impact on estimation results, which is in line with Baur et al. (2018).

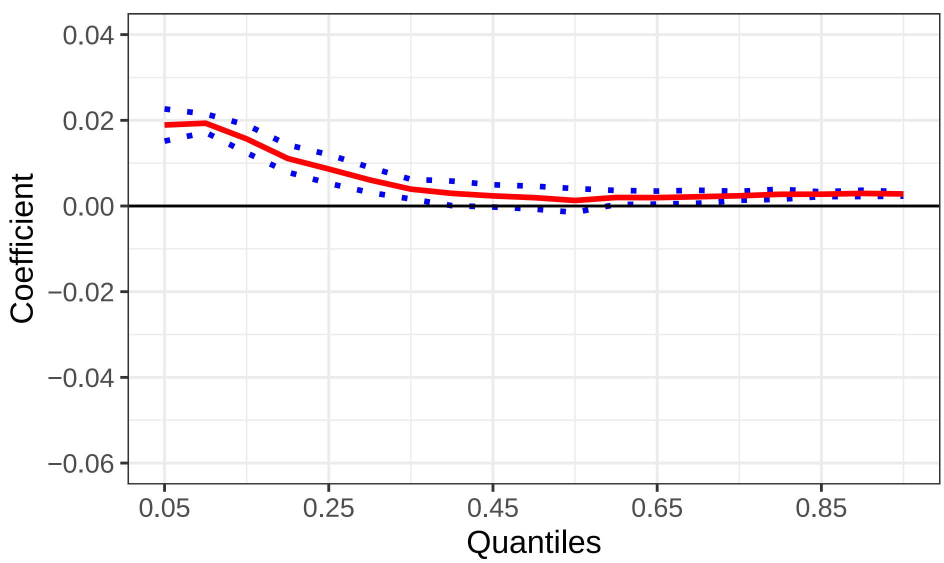
Figure 2 presents the time series plot of the VIX and the GVZ, and we observe several spikes. In particular, the spike in the beginning of 2020 was the

[10]The parameter estimates of the ADCC model are reported in Table A.1 in Online Appendix.

Figure 3: Quantile dependence: BTC-ETH correlations and uncertainty

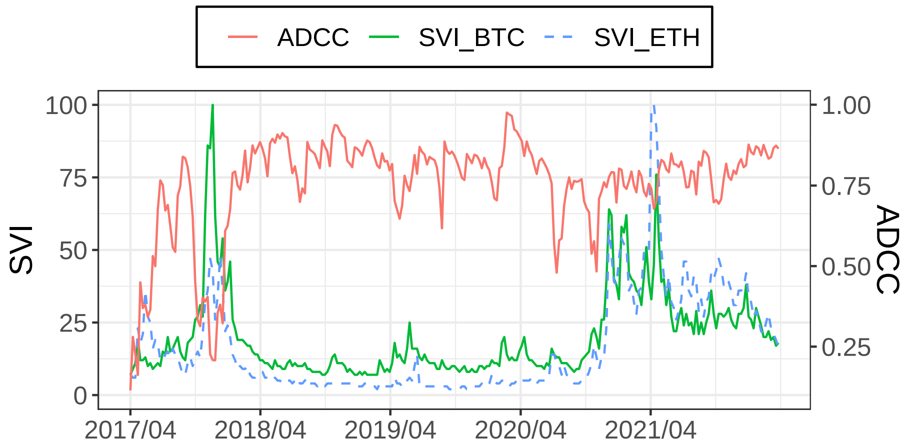


(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-ETH correlations and VIX.



(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-ETH correlations and GVZ.

Figure 4: Search volume indices and the time-varying correlation between BTC and ETH



Notes: SVIs are obtained as a Google search volume index (SVI) at a weekly frequency using a term as "Bitcoin" or "Ethereum".

largest, which was related to the COVID-19 outbreak. Figure 2 also illustrates the time series plot of the GVZ. We observe that a spike is rare, and the value is more stable than that of the VIX.

3.2. Quantile Regressions: BTC-ETH

To explore the negative relationship between market uncertainty and the BTC-ETH correlation, we employ the quantile regression in equation (4). Figure 3a illustrates the relationship between the VIX and the BTC-ETH correlation with 95% confidence intervals. The relationship is positively more dependent at a lower tail, which indicates that a decline in the VIX leads to the high BTC-ETH correlation.[11] This contrasts with the results of Borri (2019) who does not observe tail dependence between BTC and the VIX. The difference stems from the facts that Borri (2019) does not focus on the BTC-ETH correla-

[11] We do not observe this pattern when we replace ETH with Ripple, Litecoin or Dash. See Figure B.1 and the other results are available from the authors.

tion, and the observations do not cover from the period of 2019. We note that the correlation structure changed after 2018, as illustrated in Figure 1.

Figure 3b demonstrates the relationship between the GVZ and the BTC-ETH correlation and we can find the same pattern as Figure 3a. The nonlinearity is clearer for the GVZ than that for the VIX, since the dependence is not statistically significant in the middle of the distribution. Jareño et al. (2020) do not find a clear relationship between BTC and gold adopting the quantile regression. We employ the BTC-ETH correlation and implied volatility in the gold market, which leads to the new findings.

Our results indicate that when market uncertainty is low, investors do not focus on the difference between BTC-ETH. In contrast, an increase in market uncertainty causes frequent revisions of BTC and ETH valuations, which is observed for stock and bond markets (Connolly et al. (2005)). Investors tend to differentiate these two cryptocurrencies in high market uncertainty states. Both BTC and ETH have large shares in the cryptocurrency market and ETH has wider application examples than BTC, which leads to the value difference between BTC and ETH.[12] To support this interpretation, we follow Bleher & Dimpfl (2019) and obtain a Google search volume index (SVI) at a weekly frequency. We use a term as "Bitcoin" or "Ethereum" to obtain the SVI. We find that the SVIs negatively comove with the BTC-ETH correlation, as demonstrated by Figure 4.

4. Conclusion

Given a rise in the market share of ETH due to its Blockchain technology with its smart contract system, we investigate whether a BTC-ETH correlation is associated with market uncertainty. This research question is motivated by the equity-bond correlation studies such as Connolly et al. (2005) and Adrian

[12] The valuation of cryptocurrencies depends on Blockchain technologies that generate network effects and investors' speculation, see, Sockin & Xiong (2020), Cong et al. (2021), and Liu & Tsyvinski (2021)."

et al. (2019). First, we estimate the conditional correlation between BTC and ETH, and reveal an increase in the average correlation after 2018. Second, we adopt the quantile regression and observe that the correlation increases only when market uncertainty is low. This is clearer when we use gold market uncertainty. Our results suggest that investors focus on the difference of fundamental values between BTC and ETH with high market uncertainty states.

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Online Supplement, Not for Publication

This online appendix includes detail of empirical results that are not reported in the main text.

Appendix A. Parameter Estimates of ADCC Model

Table A.1: Parameter estimates of the ADCC model: BTC-ETH and BTC-XRP.

Appendix B. Quantile Regression Results

Tables B.1-B.2 : Details of quantile dependence between BTC-XRP correlations and uncertainty.

Tables B.3-B.4: Subsample results.

Figure B.1: Quantile dependence: BTC-XRP.

Figures B.2-B.3: Subsample results.

Figures B.4-B.5: Quantile dependence between returns and uncertainty.

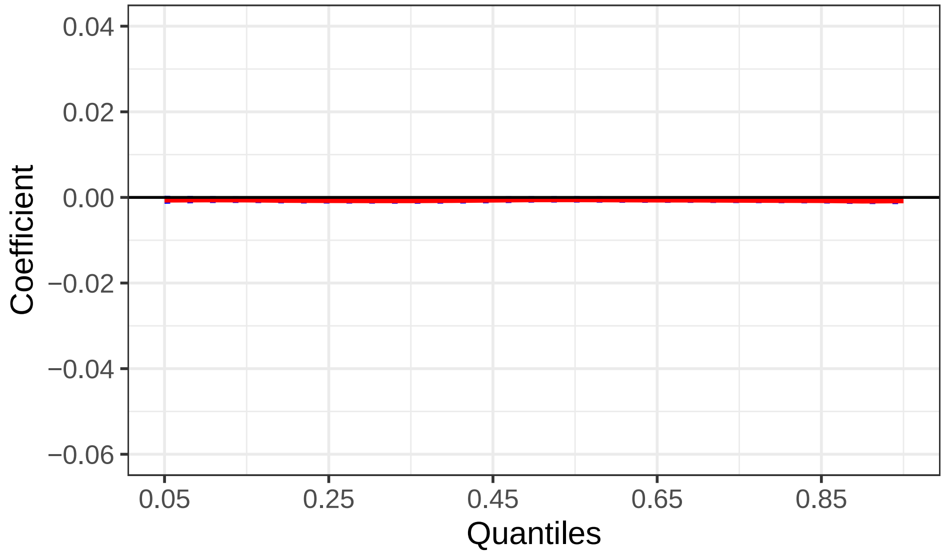
Figures B.6-B.7: Quantile dependence between volatilities and uncertainty.

Table A.1: Parameter Estimates of ADCC Model

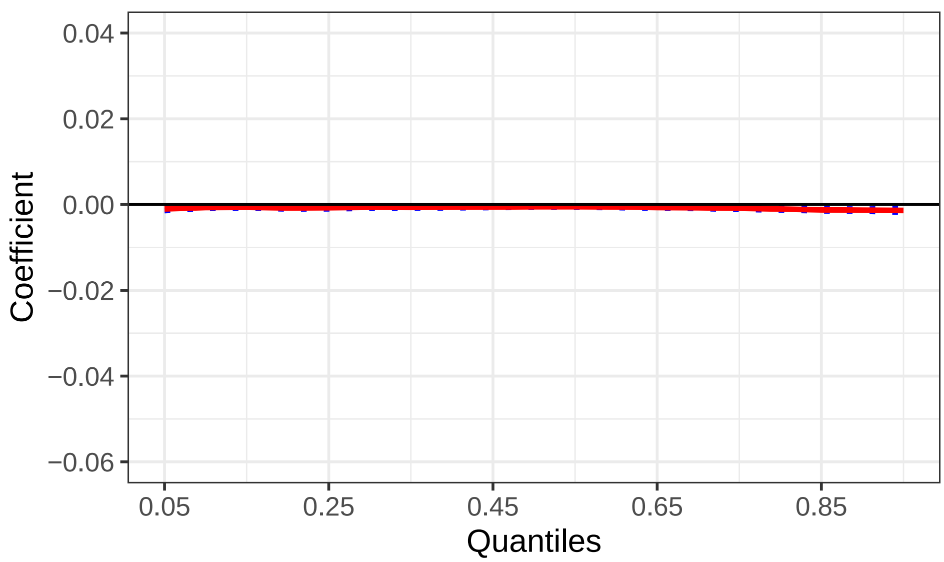
	Coef.	S.E.	t	Prob		Coef.	S.E.	t	Prob
c_{BTC}	0.003	0.001	3.133	0.002	c_{BTC}	0.003	0.001	3.133	0.002
a_{BTC}	-0.005	0.026	-0.190	0.849	a_{BTC}	-0.005	0.026	-0.190	0.849
ω_{BTC}	0.000	0.000	1.033	0.302	ω_{BTC}	0.000	0.000	1.033	0.302
α_{BTC}	0.085	0.023	3.714	0.000	α_{BTC}	0.085	0.023	3.714	0.000
β_{BTC}	0.914	0.023	39.500	0.000	β_{BTC}	0.914	0.023	39.500	0.000
ν_{BTC}	3.527	0.399	8.846	0.000	ν_{BTC}	3.527	0.399	8.846	0.000
μ_{ETH}	0.003	0.001	2.263	0.024	μ_{XRP}	0.003	0.001	2.263	0.024
a_{ETH}	-0.010	0.027	-0.363	0.717	a_{XRP}	-0.010	0.027	-0.363	0.717
ω_{ETH}	0.001	0.000	2.287	0.022	ω_{XRP}	0.001	0.000	2.287	0.022
α_{ETH}	0.172	0.057	2.998	0.003	α_{XRP}	0.172	0.057	2.998	0.003
β_{ETH}	0.748	0.089	8.378	0.000	β_{XRP}	0.748	0.089	8.378	0.000
ν_{ETH}	3.260	0.370	8.811	0.000	ν_{XRP}	3.260	0.370	8.811	0.000
A	0.035	0.028	1.232	0.218	A	0.035	0.028	1.232	0.218
B	0.932	0.035	26.985	0.000	B	0.932	0.035	26.985	0.000
G	0.074	0.059	1.255	0.210	G	0.074	0.059	1.255	0.210
AIC	-6.775				AIC	-21.422			
BIC	-6.713				BIC	-21.342			
Shibata	-6.775				Shibata	-21.422			
H-Q	-6.751				H-Q	-21.391			

Notes: μ_i and a_i are AR(1) parameters. ω_i,α_i,β_i and ν_i are GARCH parameters. A, B, G are ADCC parameters. Estimated coefficients (Coef.), standard errors (S.E.), t-value (t), and p-value (Prob) are reported. AIC indicates Akaike's Information Criterion, BIC denotes Bayesian's Information Criterion, Shibata denotes Shibata Information Criterion and H-Q denotes Hannan-Quinn Information Criterion.

Figure B.1: Quantile dependence: BTC-XRP correlations and uncertainty



(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-XRP correlations and VIX.



(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-XRP correlations and GVZ.

Table B.1: Quantile dependence: BTC-ETH correlations and uncertainty from December 17, 2016 to April 28, 2022.

VIX					GVZ				
Q	Coef.	S.E.	t	Prob	Q	Coef.	S.E.	t	Prob
5%	0.012	0.001	18.948	0.000	5%	0.019	0.002	10.052	0.000
10%	0.011	0.001	20.651	0.000	10%	0.019	0.001	17.968	0.000
15%	0.010	0.001	10.715	0.000	15%	0.016	0.002	9.621	0.000
20%	0.009	0.001	11.665	0.000	20%	0.011	0.002	6.955	0.000
25%	0.008	0.001	12.283	0.000	25%	0.009	0.002	5.136	0.000
30%	0.007	0.001	12.925	0.000	30%	0.006	0.001	4.171	0.000
35%	0.006	0.001	11.110	0.000	35%	0.004	0.001	3.419	0.001
40%	0.005	0.000	14.202	0.000	40%	0.003	0.001	2.059	0.040
45%	0.005	0.000	12.662	0.000	45%	0.002	0.001	1.817	0.069
50%	0.004	0.000	13.370	0.000	50%	0.002	0.001	1.463	0.144
55%	0.004	0.000	10.785	0.000	55%	0.001	0.001	0.927	0.354
60%	0.004	0.000	11.136	0.000	60%	0.002	0.001	2.413	0.016
65%	0.003	0.000	12.829	0.000	65%	0.002	0.001	2.587	0.010
70%	0.003	0.000	16.596	0.000	70%	0.002	0.001	2.865	0.004
75%	0.003	0.000	16.826	0.000	75%	0.002	0.001	4.508	0.000
80%	0.003	0.000	17.014	0.000	80%	0.003	0.001	4.685	0.000
85%	0.003	0.000	17.447	0.000	85%	0.003	0.000	9.811	0.000
90%	0.002	0.000	17.138	0.000	90%	0.003	0.000	7.962	0.000
95%	0.002	0.000	10.990	0.000	95%	0.003	0.000	11.024	0.000

Notes: This table reports the quantile (Q), coefficients (Coef.), standard errors(S.E.), t-statistics (t.), and p-values(Prob.).

Table B.2: Quantile dependence: BTC-XRP correlations and uncertainty from June 4, 2018 to April 28, 2022.

VIX					GVZ				
Q	Coef.	S.E.	t	Prob	Q	Coef.	S.E.	t	Prob
5%	-0.001	0.000	-3.884	0.000	5%	-0.001	0.000	-5.190	0.000
10%	0.000	0.000	-6.619	0.000	10%	-0.001	0.000	-6.721	0.000
15%	-0.001	0.000	-9.332	0.000	15%	-0.001	0.000	-7.258	0.000
20%	-0.001	0.000	-9.868	0.000	20%	-0.001	0.000	-7.094	0.000
25%	-0.001	0.000	-10.997	0.000	25%	-0.001	0.000	-5.927	0.000
30%	-0.001	0.000	-13.090	0.000	30%	-0.001	0.000	-5.679	0.000
35%	-0.001	0.000	-9.861	0.000	35%	-0.001	0.000	-7.861	0.000
40%	-0.001	0.000	-8.537	0.000	40%	-0.001	0.000	-9.304	0.000
45%	-0.001	0.000	-6.892	0.000	45%	-0.001	0.000	-9.709	0.000
50%	0.000	0.000	-10.070	0.000	50%	-0.001	0.000	-9.309	0.000
55%	0.000	0.000	-9.734	0.000	55%	0.000	0.000	-7.902	0.000
60%	0.000	0.000	-10.719	0.000	60%	-0.001	0.000	-6.834	0.000
65%	-0.001	0.000	-14.596	0.000	65%	-0.001	0.000	-9.343	0.000
70%	-0.001	0.000	-14.518	0.000	70%	-0.001	0.000	-8.689	0.000
75%	-0.001	0.000	-14.792	0.000	75%	-0.001	0.000	-6.580	0.000
80%	-0.001	0.000	-18.489	0.000	80%	-0.001	0.000	-9.565	0.000
85%	-0.001	0.000	-13.072	0.000	85%	-0.001	0.000	-11.049	0.000
90%	-0.001	0.000	-14.124	0.000	90%	-0.001	0.000	-12.183	0.000
95%	-0.001	0.000	-7.320	0.000	95%	-0.001	0.000	-6.372	0.000

Notes: This table reports the quantile (Q), coefficients (Coef.), standard errors(S.E.), t-statistics (t.), and p-values(Prob.).

Table B.3: Quantile dependence: BTC-ETH correlations and uncertainty from December 17, 2016 to June 28, 2019.

VIX					GVZ				
Q	Coef.	S.E.	t	Prob	Q	Coef.	S.E.	t	Prob
5%	0.005	0.005	1.155	0.249	5%	-0.019	0.011	-1.659	0.098
10%	-0.003	0.006	-0.447	0.655	10%	-0.032	0.013	-2.572	0.010
15%	-0.010	0.007	-1.518	0.129	15%	-0.029	0.011	-2.675	0.008
20%	-0.015	0.005	-2.890	0.004	20%	-0.028	0.011	-2.624	0.009
25%	-0.020	0.006	-3.500	0.000	25%	-0.018	0.006	-2.871	0.004
30%	-0.020	0.006	-3.077	0.002	30%	-0.016	0.004	-4.203	0.000
35%	-0.012	0.004	-3.333	0.001	35%	-0.015	0.003	-5.822	0.000
40%	-0.012	0.003	-3.804	0.000	40%	-0.014	0.003	-4.954	0.000
45%	-0.008	0.004	-2.107	0.036	45%	-0.009	0.004	-2.229	0.026
50%	-0.007	0.002	-2.941	0.003	50%	-0.009	0.004	-2.544	0.011
55%	-0.006	0.001	-4.976	0.000	55%	-0.006	0.003	-2.128	0.034
60%	-0.006	0.001	-6.343	0.000	60%	-0.003	0.002	-1.454	0.147
65%	-0.006	0.001	-7.469	0.000	65%	-0.003	0.002	-1.375	0.169
70%	-0.006	0.001	-6.831	0.000	70%	0.001	0.002	0.318	0.751
75%	-0.005	0.001	-4.058	0.000	75%	0.002	0.001	1.391	0.165
80%	-0.004	0.001	-2.900	0.004	80%	0.001	0.001	0.740	0.459
85%	-0.003	0.001	-3.055	0.002	85%	0.000	0.002	-0.287	0.774
90%	-0.003	0.001	-2.730	0.007	90%	-0.002	0.001	-1.885	0.060
95%	-0.001	0.001	-0.751	0.453	95%	-0.001	0.002	-0.622	0.534

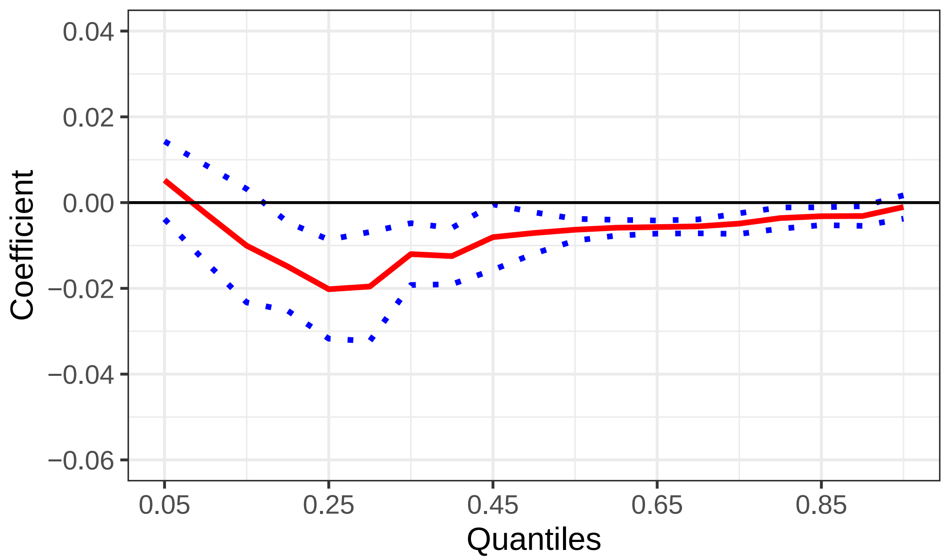
Notes: This table reports the quantile (Q), coefficients (Coef.), standard errors(S.E.), t-statistics (t.), and p-values(Prob.).

Table B.4: Quantile dependence: BTC-ETH correlations and uncertainty from December July 1, 2019 to April 28, 2022.

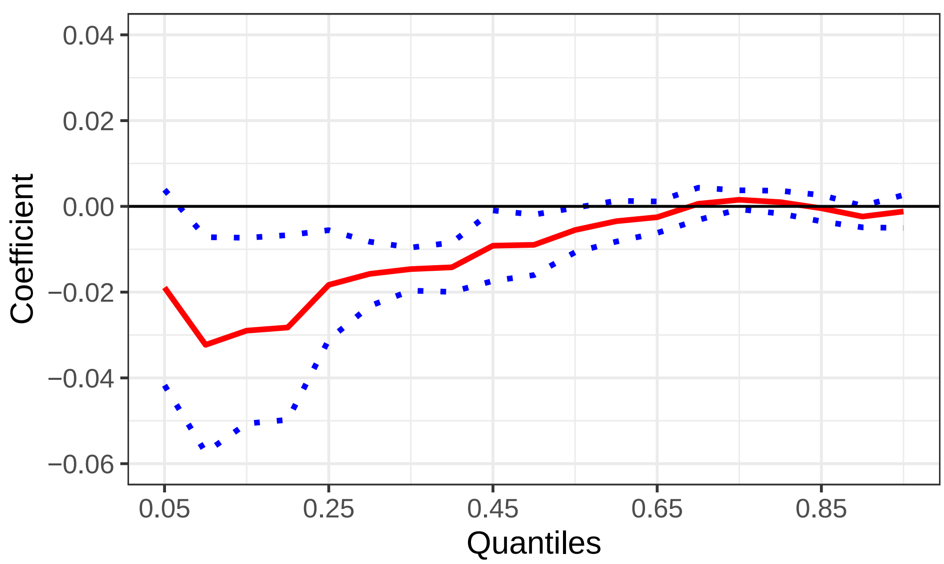
VIX					GVZ				
Q	Coef.	S.E.	t	Prob	Q	Coef.	S.E.	t	Prob
5%	0.004	0.001	6.844	0.000	5%	0.009	0.002	5.315	0.000
10%	0.003	0.001	4.798	0.000	10%	0.006	0.002	3.530	0.000
15%	0.003	0.001	4.584	0.000	15%	0.005	0.001	4.954	0.000
20%	0.001	0.001	1.933	0.054	20%	0.004	0.001	5.265	0.000
25%	0.002	0.001	2.688	0.007	25%	0.004	0.001	4.662	0.000
30%	0.001	0.000	2.745	0.006	30%	0.004	0.001	4.877	0.000
35%	0.001	0.000	4.015	0.000	35%	0.004	0.001	4.970	0.000
40%	0.001	0.000	3.367	0.001	40%	0.003	0.001	5.028	0.000
45%	0.001	0.000	4.189	0.000	45%	0.003	0.001	5.872	0.000
50%	0.001	0.000	4.206	0.000	50%	0.003	0.001	6.032	0.000
55%	0.001	0.000	5.254	0.000	55%	0.003	0.001	5.608	0.000
60%	0.001	0.000	4.786	0.000	60%	0.003	0.001	4.488	0.000
65%	0.001	0.000	3.695	0.000	65%	0.003	0.001	4.032	0.000
70%	0.001	0.000	3.824	0.000	70%	0.003	0.001	4.291	0.000
75%	0.002	0.000	4.311	0.000	75%	0.003	0.001	4.544	0.000
80%	0.002	0.000	4.221	0.000	80%	0.003	0.001	3.746	0.000
85%	0.002	0.001	2.385	0.017	85%	0.003	0.001	3.273	0.001
90%	0.005	0.001	3.928	0.000	90%	0.001	0.001	1.743	0.082
95%	0.006	0.001	9.565	0.000	95%	0.020	0.004	4.946	0.000

Notes: This table reports the quantile (Q), coefficients (Coef.), standard errors(S.E.), t-statistics (t.), and p-values(Prob.).

Figure B.2: Quantile dependence: BTC-ETH correlations and uncertainty from December 17, 2016 to June 28, 2019.

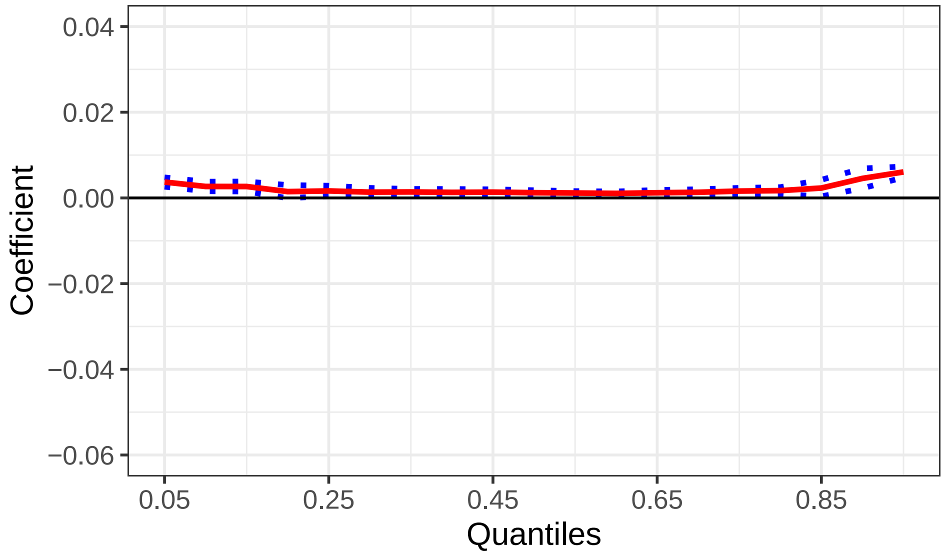


(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-ETH correlations and VIX.

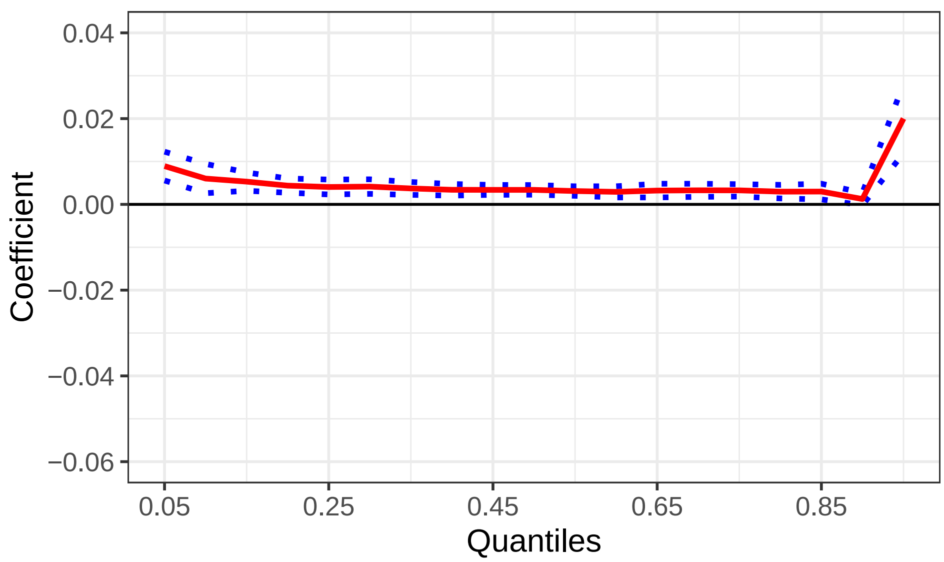


(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-ETH correlations and GVZ.

Figure B.3: Quantile dependence: BTC-ETH correlations and uncertainty from July 1, 2019 to April 28, 2022.

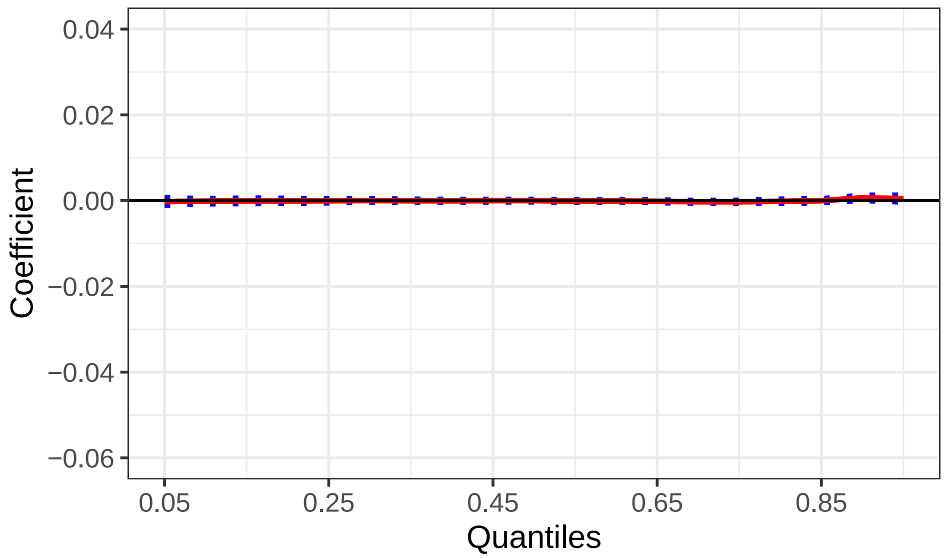


(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-ETH correlations and VIX.

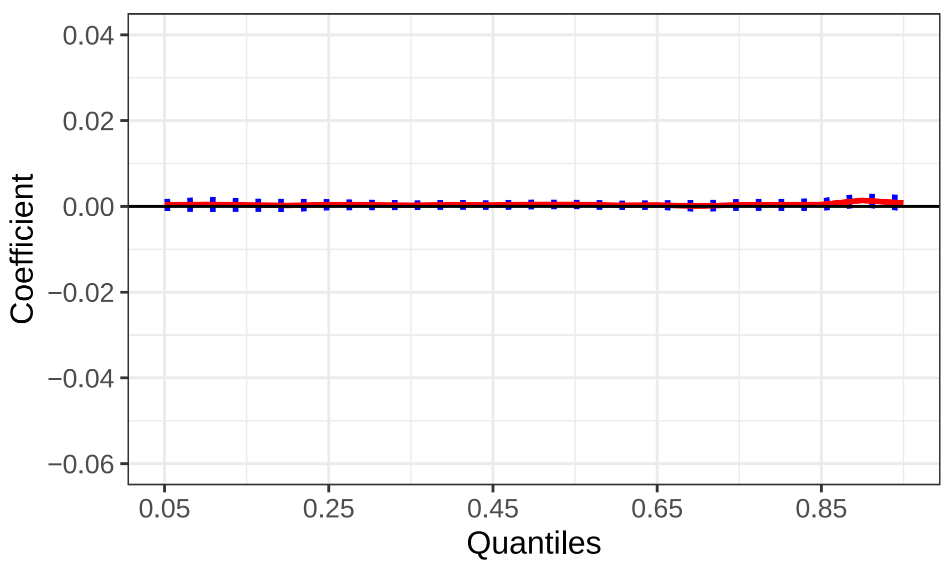


(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC-ETH correlations and GVZ.

Figure B.4: Quantile dependence: BTC return and uncertainty from December 17, 2016 to April 28, 2022.

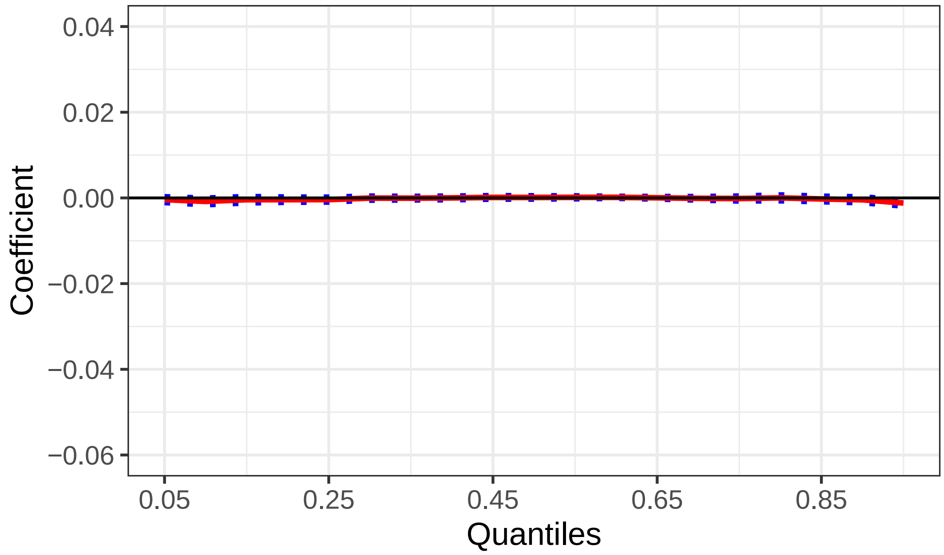


(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC return and VIX.

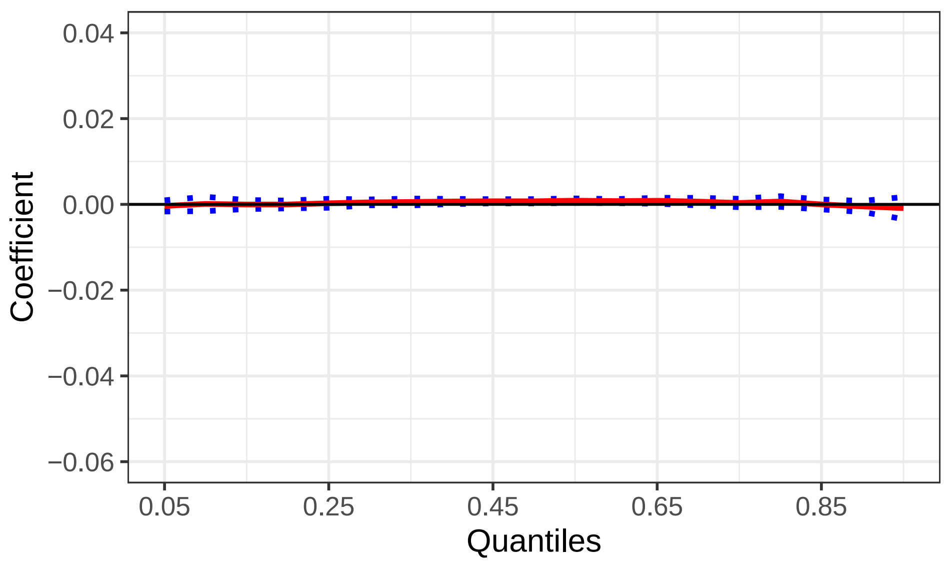


(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC return and GVZ.

Figure B.5: Quantile dependence: ETH return and uncertainty from December 17, 2016 to April 28, 2022.

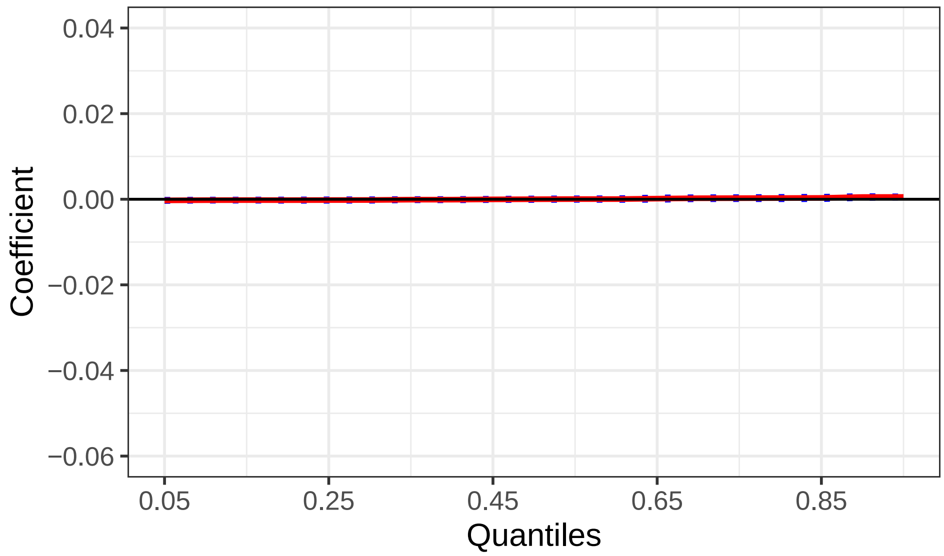


(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between ETH return and VIX.

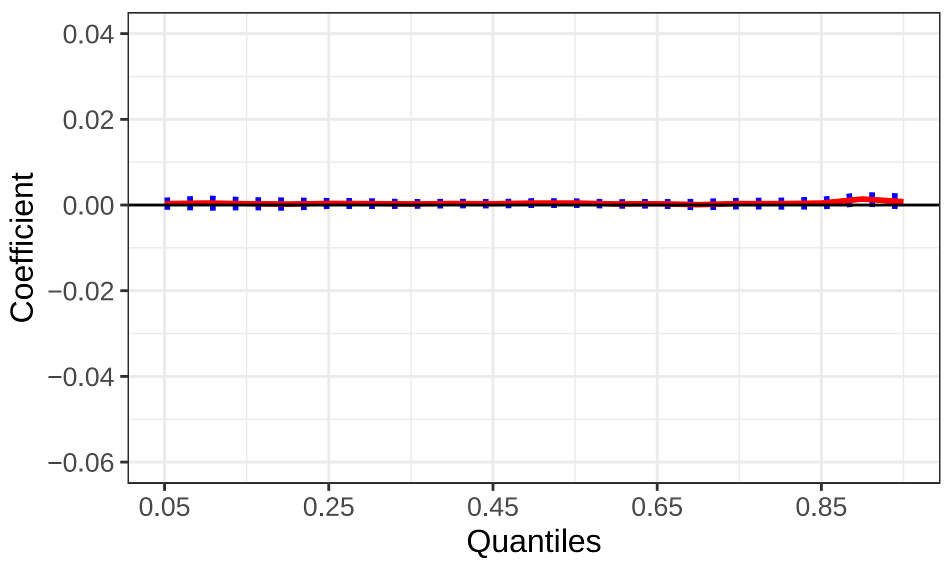


(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between ETH return and GVZ.

Figure B.6: Quantile dependence: BTC volatility and uncertainty from December 17, 2016 to April 28, 2022.

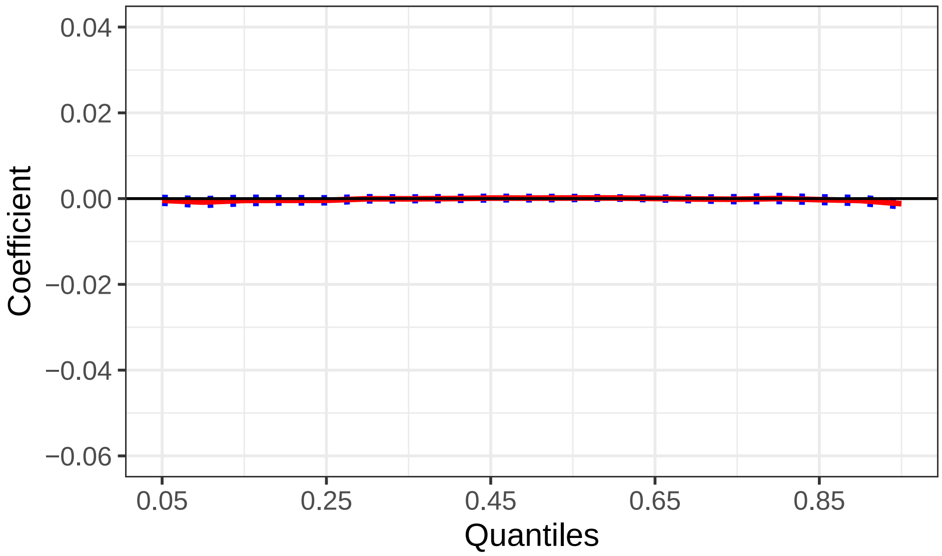


(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC volatility estimated by the GARCH model and VIX.

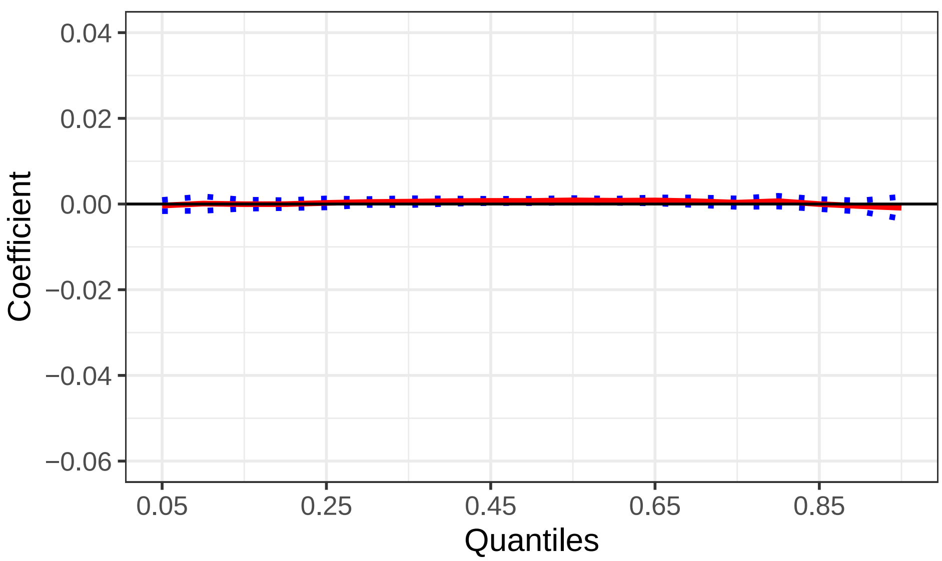


(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between BTC volatility estimated by the GARCH model and GVZ.

Figure B.7: Quantile dependence: ETH volatility and uncertainty from December 17, 2016 to April 28, 2022.



(a) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between ETH volatility estimated by the GARCH model and VIX.



(b) Coefficients(red line) and 95% confidence intervals(bule dots). Quantile dependence between ETH volatility estimated by the GARCH model and GVZ.