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Risk aversion and Bitcoin returns in extreme quantiles

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Abstract

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1. Introduction

Based on the assumption that all investors are rational (i.e., risk averse), the classical finance literature underlines the importance of risk aversion. Accordingly, market premiums are generally interpreted as risk premiums. Several studies consider the role of risk aversion in the equity premium puzzle (Epstein and Zin, 1990; Benartzi and Thaler, 1995) and portfolio optimization (Beiglböck et al., 2012; Bernard et al., 2015). In fact, risk aversion measures the willingness of investors to take financial risks, and thereby hold risky assets. Economic intuition suggests that the level of risk aversion affects portfolio payoff and its distribution (Dybvig and Wang, 2012). The level of risk aversion is cited by market participants and policymakers as a key driver of the trend dynamics in risk premiums (Londono and Wilson, 2018), reinforcing its ability to affect the return dynamics in financial markets. However, the ability of risk aversion to drive Bitcoin returns remains unexplored, although Bitcoin is often seen as a shelter from global market uncertainty (Bouri et al., 2017).

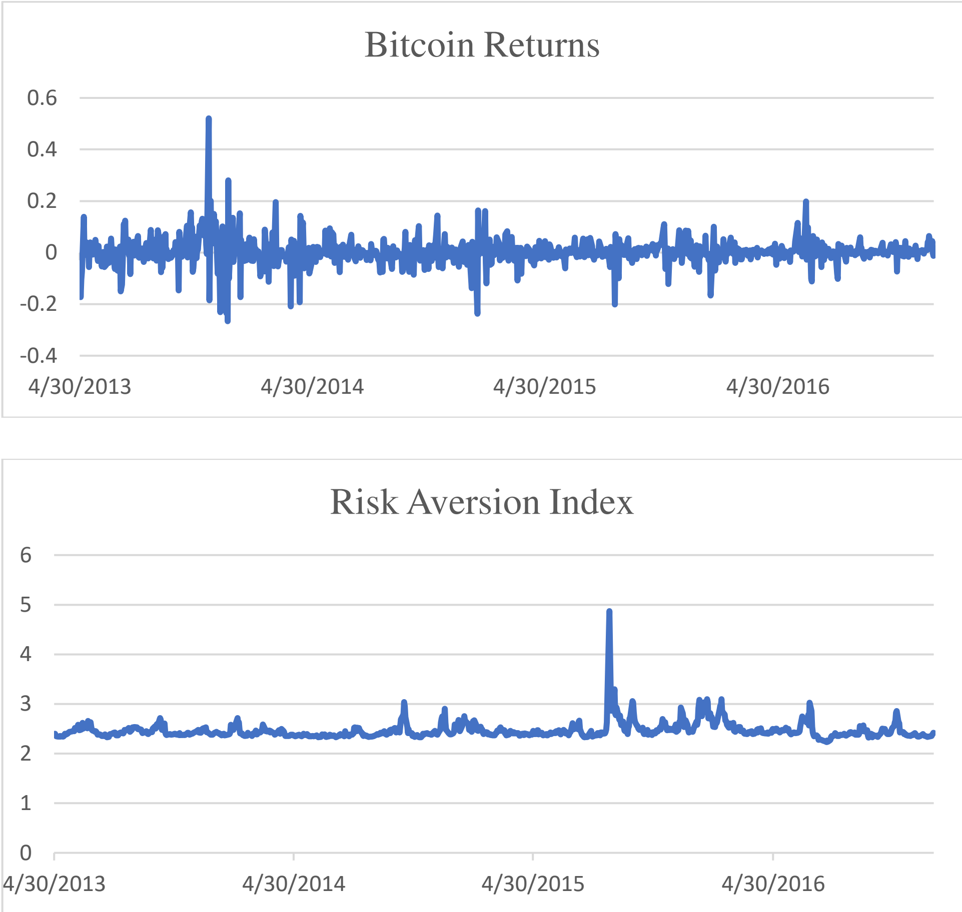
With the growing popularity of Bitcoin as an alternative digital asset, numerous studies examine the safe-haven role of this protocol-governed currency for equities (e.g., Bouri, 2017; Baur et al., 2018), embracing its detachment from the global financial system (Corbet et al., 2018; Shahzad et al., 2020), mostly due its independence from any third-party control such as a government or a central bank. Other studies (e.g., Klein et al., 2018; Selmi et al., 2018; Smales, 2019) provide an opposing view, with some researchers pointing to Bitcoin's high volatility, illiquidity, and high transaction costs. Interestingly, the hedging ability of Bitcoin is affected by the level of global EPU (Fang et al., 2019), and Bitcoin shows some ability to hedge financial market uncertainty (Bouri et al., 2017), economic policy uncertainty (EPU) (Demir et al., 2018; Wang et al., 2019), and trade uncertainty (Bouri et al., 2020). However, risk aversion is different from economic uncertainty, with the latter representing the amount of risk, and the former representing the price of risk.

Given the ability of risk aversion to drive the trend dynamics in financial markets and the mixed views on the role of Bitcoin as a safe haven, one wonders about the ability of the level of risk aversion to drive Bitcoin returns. This is where we aim to contribute.

2. Data

The data used are the daily Bitcoin price (https://coinmarketcap.com/) and the risk aversion index of Bekaert et al. (2017) (available at https://www.nancyxu.net/). Bekaert et al. (2017) develop a new measure of time-varying risk aversion based on observable financial information (involving the term spread, credit spread, a detrended dividend yield, realized and risk-neutral equity return variance and realized corporate bond return variance) at daily frequencies. An important feature of this measure is that it distinguishes time variation in economic uncertainty (the amount of risk) from time variation in risk aversion (the price of risk), and thus provides an unbiased representation for time-varying risk aversion based on a utility function in the hyperbolic absolute risk aversion (HARA) class. Our analysis covers the period 30th April, 2013 to 30th December, 2016, a total of 919 observations, with the start and end dates based on data availability of Bitcoin prices and the risk aversion index. While the risk aversion index is stationary by design, we compute the log-returns of the Bitcoin prices for our analysis, given that the econometric approach used requires mean-reverting data. The data is plotted in Figure 1 and summarized in Table A1 in the Appendix. The results of the augmented Dickey and Fuller (ADF) test confirm the stationarity of the two variables under study, and the strong evidence of non-normality warrants a quantiles-based approach.

Figure 1. Data Plots



3. Methodology and results

We use the GCD test of Lee and Yang (2014) to examine the ability of the level of risk aversion to predict Bitcoin returns in low, medium and upper quantiles. We then apply the cross-quantilogram approach of Han et al. (2016) to reveal the sign of predictability[1].

3.1. Granger causality in distribution (GCD) test of Lee and Yang (2014)

We examine the dynamic causality between the returns of Bitcoin (RBC) and the risk aversion index (RAI) through quantile forecasts which are largely reliant on inversion concerning parametric conditional copula distribution from Lee and Yang's (2014) model. It is realistic for market practitioners to view causality anticipated at high RBC and RAI quantiles, since RBC can be a safe haven in case of panic in the global financial

[1] Bouri et al. (2018) apply quite similar methods while studying the dependence between global financial stress and Bitcoin.

market (i.e. risk aversion is high). We test the null hypothesis in which RBC_t in the distribution is not Granger caused by RAI_t: H0: c(u, v) = 1 where c(u, v) represents conditional copula density function and u and v represent RAI_t and RBC_t conditional probability integral transforms respectively. The following formulas are used to compute the proposed conditional variance for $\{RAI_t\}$ and $\{RBC_t\}$, $\hat{h}_{RAI,t+1}$ and $\hat{h}_{RBC,t+1}$:

$$\hat{h}_{RAI,t+1} = \hat{\beta}_{RAI0} + \hat{\beta}_{RAI1} RAI_t^2 + \hat{\beta}_{RAI2} \hat{h}_{RAI,t}$$

$$\hat{h}_{RBC,t+1} = \hat{\beta}_{RBC0} + \hat{\beta}_{RBC1} RBC_t^2 + \hat{\beta}_{RBC2} \hat{h}_{RBC,t} \quad (1)$$

The empirical distribution function (EDF) is used to calculate the cumulative distribution function (CDF) values of $\hat{u}_{t+1}$ and $\hat{v}_{t+1}$ for RBC_{t+1} and RAI_{t+1}. On the other hand, pared EDF values $\{\hat{u}_{t+1}, \hat{v}_{t+1}\}_{t=R}^{T-1}$ are used to estimate a nonparametric copula function through the use of a quartic kernel function:

$$k(u) = \frac{15}{16}(1-u^2)^2 I(|u| \leq 1) \quad (2)$$

The GCD result of test statistics established by Hong and Li (2005) for $\{RAI_{t+1}, RBC_{t+1}\}_{t=R}^{T-1}$ is 36.158, which is significant at the level of 1%, showing that there exists an important GCD between RBC and RAI. On the other hand, the GCD test evidence is not a reflection of Granger causality in every conditional quantile. Our empirical study focuses on 3 main regions of distribution: the right tail (99% quantile, 95% quantile, and 90% quantile), central region (60% quantile, median, and 40% quantile), and the left tail (10% quantile, 5% quantile, and 1% quantile), which is similar to Lee and Yang (2014)[2].

Table 1. Testing for CGQ

	Left tail					Mid tail			Right tail				
	1%	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%	99%
Bitcoin	0	0	0	0	0	0.001	0.627	0.325	0.048	0.002	0	0	0

Notes: We compute quantile forecasts by inverting the parametric conditional copula distribution. We use six copulas (Gaussian, Frank, Clayton, Clayton Survival, Gumbel and Gumbel Survival copulas). The check loss functions are compared to evaluate the predictive ability of different quantile forecasting using different copula models. The benchmark quantile forecasts are computed using the independent copula, so there is no GCQ. The bootstrap p-values for testing the null hypothesis show that most of the six copula models (which model GCQ) makes a better quantile forecast than the independent copula (which gives no GCQ). The small p values of the reality check indicate rejection of the null hypothesis, indicating that there exists a copula function to model GCQ that makes a better quantile forecast.

Table 1 shows the outcomes of the analysis of GCQ in p-values. The small p-value of the authenticity check indicates the denial of the worthless supposition, demonstrating that there exists a copular task to model GCQ and, in return, yield a good quintile predictor of the RBC based on the RAI. We observe that a quantile forecasting model with no Granger causality in the quantile is rejected in many quantiles, but not the quantiles at 50% and 60%, with evidence at 1% significance level. This result shows that the risk aversion index strongly Granger-causes the Bitcoin returns at the left tail

[2] Details of the method of Lee and Yang (2014) are given in Bouri et al. (2018).

(poor performance) and right tail (superior performance) but not at the mid tail (usual performance) of the distribution of the Bitcoin return, conditional on the risk aversion index. In other words, risk aversion is important primarily at the tails of the conditional distribution, i.e. when the Bitcoin market is at lower quantiles or upper quantiles phases, dependent on the information content of our measure of risk aversion. When the conditional distribution is around the median, i.e. when the market return is in its middle distribution, the predictive content of risk aversion is not significant, which makes sense, since agents operating in the market are likely to be averse to heightened risk when the market is performing poorly or well, rather than when the market return is in its middle distribution.[3]

3.2. Directional predictability test of Han et al. (2016)

Han et al.'s (2016) directional predictability test is used in this study to complement the GCD test. Investors may prefer to use RAI for predicting RBC movement. As such, access to the RBC forecasting performance using RAI as a predictor is necessary. Our null hypothesis posits no directional expectedness for RAI in any other time series. The cross-quantilogram's ability to detect duration, magnitude and spontaneous relationship direction for RAI and RBC is an added advantage over the GCD. However, this is not the only advantage. The model of Han et al. (2016) allows us to choose arbitrary quantiles for both RBC and RAI. Thus, unlike the GCD, there are no pre-set quantiles. Furthermore, the use of the bootstrap technique enhances the large lag in the directional predictability test.

The cross-quantilogram technique of Han et al. (2016), which shows a quantile-to-quantile relationship between RBC and RAI, starts with the linear quantile regression:

$$q_{\alpha(RBC_{t+1}|\mathcal{F}_t)} = \beta_{0,\alpha} + \beta_{1,\alpha}RAI_t + \beta_{2,\alpha}RAI_t q_\alpha(RBC_t|\mathcal{F}_{t-1}) + \beta_{3,\alpha}|RBC_t| \tag{3}$$

where $q_{\alpha(RBC_{t+1}|\mathcal{F}_t)}$ denotes RBC conditional quantile information $\mathcal{F}_t$ at given time t[4]. The sample cross-quantilogram $\hat{p}_\alpha(k)$ is shown in Figure 2, so as identify directional predictability from RAI to RBC[5]. The sample cross-quantilogram $\hat{p}_\alpha(k)$ captures serial dependence between two series at different conditional quantile levels. The sample cross-quantilogram $\hat{p}_\alpha(k)$ is defined (see page 253, Han et al., 2016) as:

$$\frac{\sum_{t=k+1}^{T}\psi_{\alpha 1}(RBC_t-\hat{q}_{1,t}(\alpha_1))\psi_{\alpha 2}(RAI_{t-k}-\hat{q}_{2,t-k}(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T}\psi^2{}_{\alpha 1}(RBC_t-\hat{q}_{1,t}(\alpha_1))}\sqrt{\sum_{t=k+1}^{T}\psi^2\alpha_2(RAI_{t-k}-\hat{q}_{2,t-k}(\alpha_2))}} \tag{4}$$

[3] Following Pástor and Veronesi (2018), who relate risk-aversion with Democratic governments in the US, we use a dummy variable taking the value of 1 under Democratic presidents and zero otherwise (i.e., Republican presidents), and apply the quantiles-based Granger causality test of Jeong et al. (2012) as a robustness check on our analysis. Based on a data sample covering 30th April, 2013 to 1st January, 2019, we obtain qualitatively similar results (i.e., stronger causality at the tails of the conditional distribution (though weaker predictability is observed at the median)) to those reported in Table 1. This is not surprising since, from 2017, the US did have a Republican government, resulting in our risk aversion dummy being zero. Complete details of these results are available upon request from the authors. Note that since the cross-quantilogram requires two continuous variables, we could not use the Democratic dummy variable further for the analysis of directional predictability.

[4] The specification of the quantile estimation function of RAI is the same as that of RBC in Eq.(3).

[5] These quantities contain non-smooth functions, thus the estimation technique of Koenker and Bassett (1978) is adopted (see Han et al., 2016, p.253).

Where $\hat{q}_{i,t}(\alpha_i) = x_{it}^T \hat{\beta}_i(\alpha_i)$, and x_i corresponds to the independent variables in the quantile regressions for RBC and RAI, respectively. For $k = 0, \pm 1, \pm 2, ...$ the sample cross-quantilogram $\hat{p}_\alpha(k)$ measures the directional predictability from RAI to RBC, as it considers dependence in terms of the direction of deviation from conditional quantiles. The case of no directional predictability is represented by $\hat{p}_\alpha(k)$=0, and high dependence between two series is represented by a larger value of $\hat{p}_\alpha(k)$. We also indicate that $\psi_\alpha \equiv 1[u < 0] - \alpha$, where $1[.]$ is the indicator function. Furthermore, $1[x_{i,t} \leq q_i(\alpha_i)]$ is the quantile exceedance process for RBC, with the quantile of RBC_t being $q_i(\alpha_i) = \inf(v: F_i(v) \geq \alpha_i)$, where $F_i(.)$ is the distribution function of $x_{i,t}$. In the present study, $x_{1,t}$ and $x_{2,t}$ represent RBC and RAI, respectively.

We take a range of α_1 into consideration, 0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9 and 0.95 for RBC $q_1(\alpha_1)$ quantiles. We take a range of α_2 into consideration, 0.1, 0.5 and 0.9 for RAI $q_2(\alpha_2)$. Every graph in Figure 2 shows bootstrap confidence intervals of 95% for no predictability on the basis of 1,000 bootstrapped replicates. A 60-day maximum lag is taken (k=60). Estimating critical values from limiting distribution requires nonparametric estimation in line with Politis and Romano's (1994) stationary bootstrap (SB), a block bootstrap technique containing random length blocks with the resample being stationary and conditional on the first sample.

Figure 2(a) shows the case where the aversion index is in the lower quantile, i.e. q2(α2) for α2=0.1. Directional predictability can be detected to RBC from RAI using the sample cross-quantilogram $\hat{p}_\alpha(k)$. Sample cross-quantilograms are denoted by bar graphs while the 95 percent bootstrap confidence intervals are depicted by lines. The result shows cases where risk aversion lies within the lower quantile, i.e. $q2(\alpha_2)$ where α_2=0.1. For α_1=0.2, the cross-quantilogram $\hat{p}_\alpha(k)$ is positive and becomes significant at the 5% significance level only at appropriately 18 days. A positive and significant cross-quantilogram means that, when risk aversion is very low, it is more likely for Bitcoin returns to be at high ranges to have large gains (i.e. Bitcoin has large gains)[6]. However, for low ranges, there is no evidence of significant pattern. That implies that a low risk aversion is not helpful in predicting Bitcoin market's path when Bitcoin return is at low ranges[7].

This also implies the probability of profit is lacking when both Bitcoin returns and risk aversion are at their low levels. Indeed, the quantilogram starts with being negative before 18 days, but it is insignificant at the 5% level, and the impact disappears after day 18. Moreover, most quantilogram values are insignificant across periods. When α_1=0.7, 0.8, 0.9 and 0.95, the cross-quantilogram $\hat{p}_\alpha(k)$ for most lags is positive and significant before 60 days, showing that the likelihood of Bitcoin having large gains during a low risk aversion period is lower. Moreover, we note that when α_2 = 0.1, and α_1 = (0.7, 0.8), the graphs indicate that the cross-quantilogram values are insignificant for most lags after 60 days.

[6] As we can see from Figure 2(a), this conclusion holds for α1=0.7 α1=0.8, α1=0.9, and the duration of this pattern is usually below 60 days.
[7] Because the sample cross-quantilograms are not significant at the 95 percent bootstrap confidence intervals.

Figure 2. The sample cross quantilogram

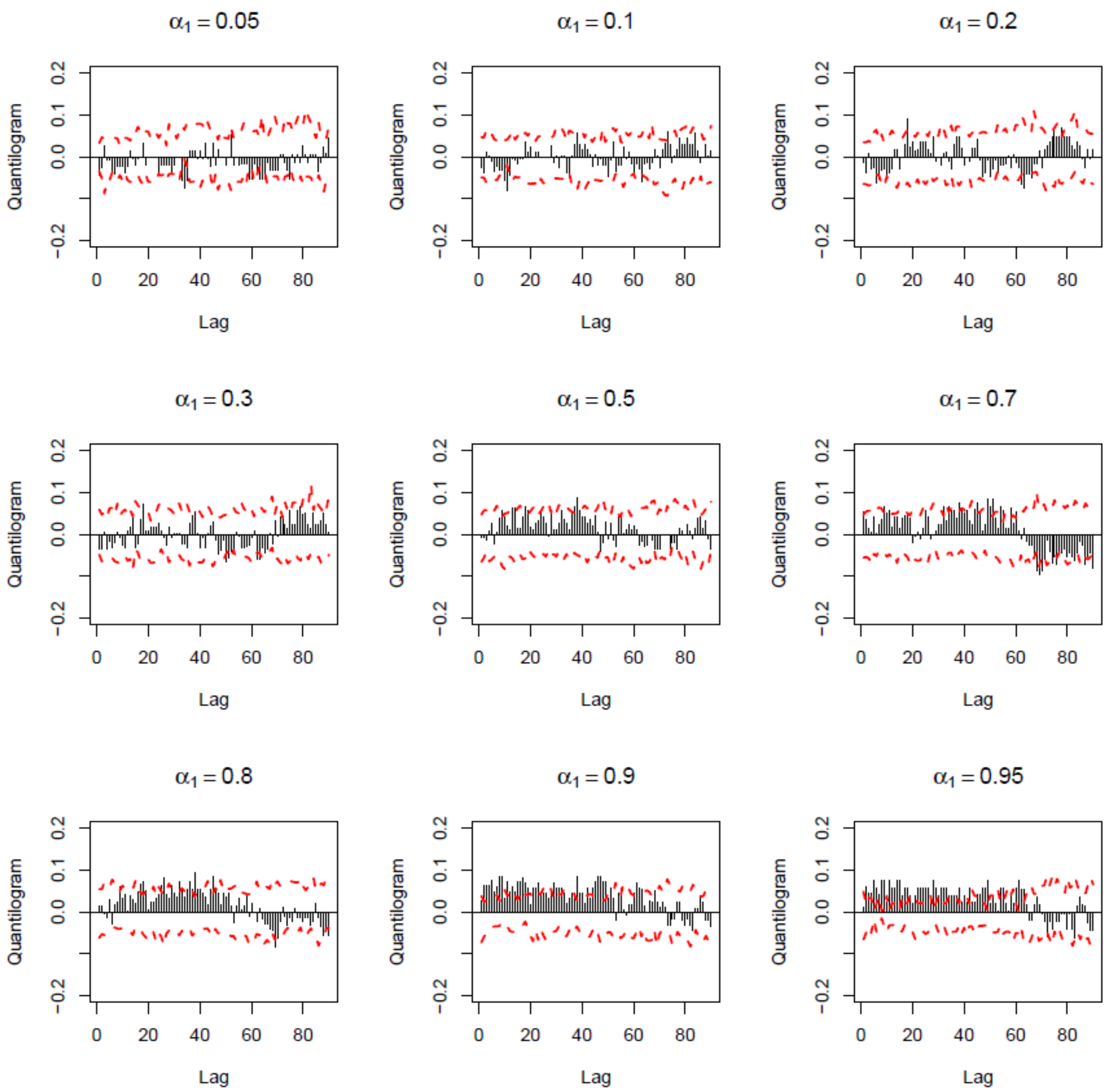


Figure 2(a). The sample cross quantilogram $\hat{\rho}_\alpha(k)$ for α2=0.1 to detect directional predictability from RAI to RBC. Bar graphs describe sample cross quantilograms, and lines are the 95% bootstrap confidence intervals.

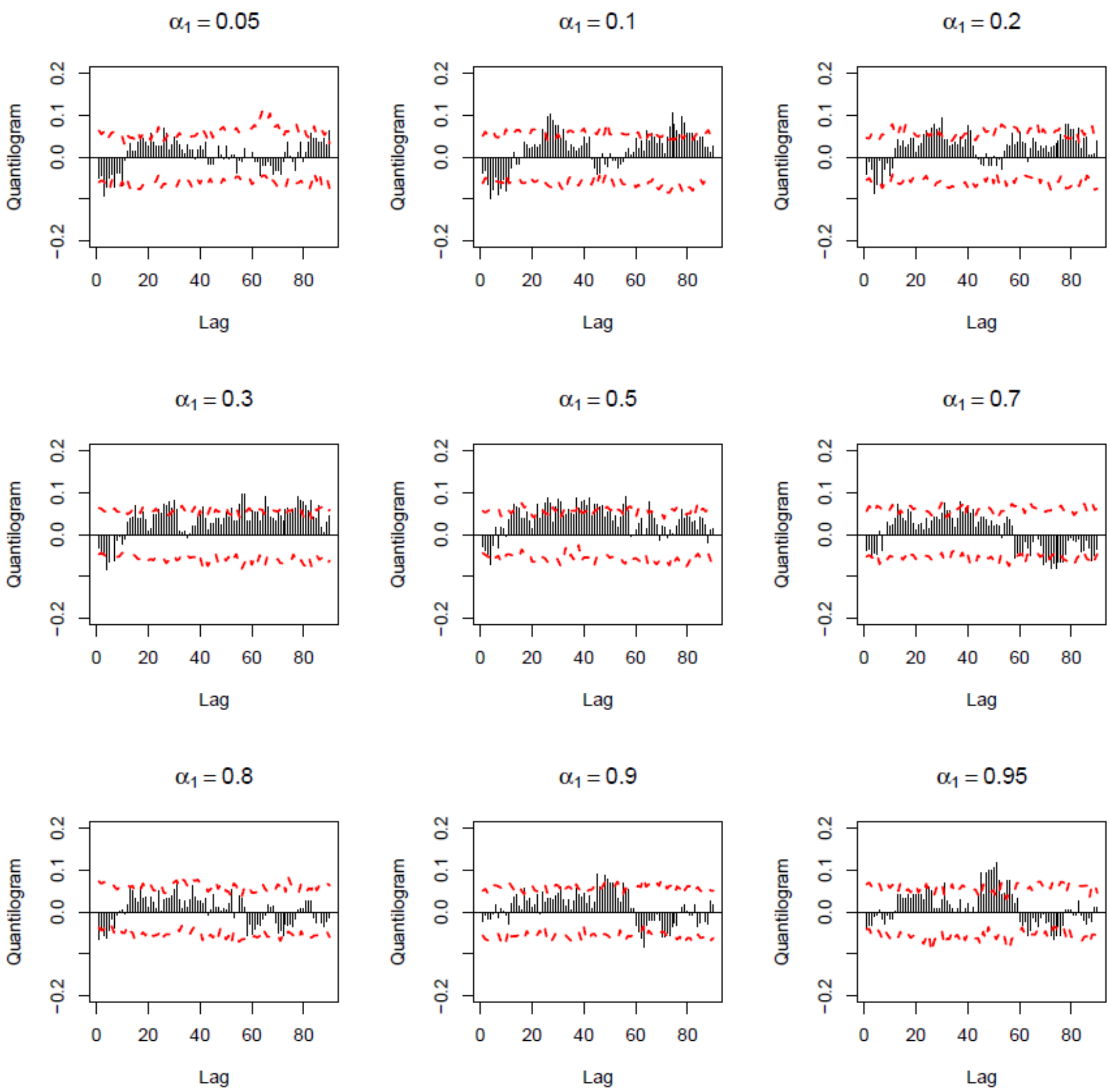


Figure 2(b). The sample cross quantilogram $\hat{\rho}_\alpha(k)$ for α2=0.5 to detect directional predictability from RAI to RBC. Bar graphs describe sample cross quantilograms, and the red dotted lines are the 95% bootstrap confidence intervals.

Figure 2(b) shows cases where risk aversion lies within the middle quantile, i.e. q2 (α_2) where α_2=0.5. For α2=0.5 and α1=0.1, we first observe a significant negative coefficient for shorter lags, which means that risk aversion above the median is more likely to be associated with Bitcoin returns at the bottom 10% of the distribution. However, in the longer term, the significance pattern turns positive, implying that risk aversion below the median is more likely to be associated with Bitcoin returns at the bottom 10% of the distribution, and risk aversion above the median is more often associated with Bitcoin return at the top 90% of the distribution. It also came to our attention that the cross-quantilogram does not seem to capture the relation between risk aversion and Bitcoin return when risk aversion is at the middle of its distribution (i.e. between 0.4 and 0.5), but rather the relation with Bitcoin return when risk aversion is above or below the median.

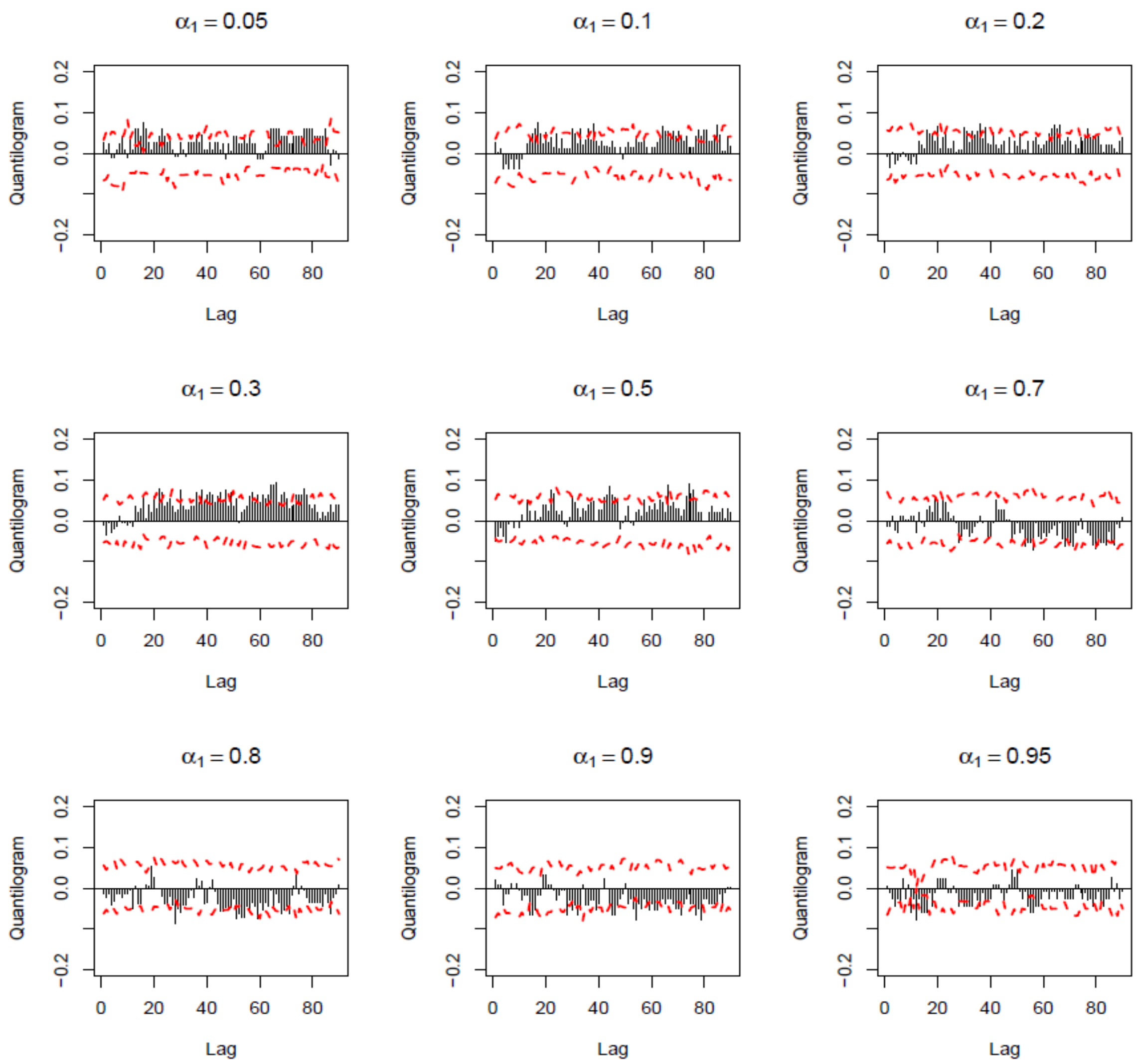


Figure 2(c). The sample cross quantilogram $\hat{p}_{\alpha}(k)$ for α2=0.9 to detect directional predictability from RAI to RBC. Bar graphs describe sample cross quantilograms, and the red dotted lines are the 95% bootstrap confidence intervals.

Figure 2(c) shows cases where risk aversion lies within the high quantile i.e. q2(α2) where α2=0.9. The cross-quantilogram $\hat{p}_{\alpha}(k)$ for α1= (0.05, 0.1, and 0.3) is positive and significant for some lags; specifically, it is only significant for some lags at the 5% level. For example, it is significant for α1 = (0.05, 0.1) for days 60 to 82, as well as for α1 = (0.3) for days 20 to 76. These results imply that when risk aversion is very high, Bitcoin is less likely to have a large loss. However, the positive cross-quantilogram only holds for a limited number of quantiles and lags.

Finally, when the Bitcoin return becomes relatively high (α1=0.8, α1=0.9, α1=0.95) the cross-quantilogram becomes negative and significant, which suggests that when the risk aversion of investors is high (α2=0.9), Bitcoin is less likely to have a large gain when the Bitcoin return is already in higher quantiles, and this is exactly what happens after 2018.

4. Conclusion

We have provided insight into the investment role of Bitcoin by showing the ability of the risk aversion index to predict Bitcoin returns in low or high quantiles. Interestingly, predictability is positive when the risk aversion is very low or at a medium level. However, the predictability becomes negative when both risk aversion and Bitcoin returns are very high, suggesting that when risk aversion is at high levels, Bitcoin is then less likely to have large gains. Overall, this result is not surprising and supports earlier findings (e.g., Bouri et al., 2017) that Bitcoin can act as a safe haven in case of panic in the global financial market (i.e., when the risk aversion is high). In fact, Bitcoin plays a key role in an alternative economy and its price formation depends upon unique non-financial and non-economic factors such as attractiveness, transaction anonymity, and computer-programming enthusiasm (Bouoiyour et al., 2016; Ciaian et al., 2016; Kristoufek, 2015), making it almost detached from the global financial system. Our findings imply that Bitcoin has a weak ability to hedge the amount of risk (e.g., economic uncertainty), which is generally comparable to previous studies considering economic policy uncertainty (EPU) (Demir et al., 2018; Wang et al., 2019) and trade uncertainty (Bouri et al., 2020). The particularity of our findings is that risk aversion is useful to predict Bitcoin returns, although this newly discovered predictive ability is not homogenous across the various quantiles, suggesting the importance of the extreme levels of both risk aversion and Bitcoin returns for the significance and sign of that predictability. For further studies, it is necessary to consider whether risk aversion can generate correlation among the returns of otherwise unrelated assets.

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APPENDIX

Table A1. Summary Statistics

	Bitcoin Returns	Risk Aversion Index
Mean	0.002	24.669
Median	0.001	24.212
Maximum	0.520	48.708
Minimum	-0.266	22.322
Std. Dev.	0.051	0.167
Skewness	0.784	54.119
Kurtosis	192.565	594.517
Jarque-Bera	10213.670*	126513.800*
ADF Test	-31.501*	-9.857*
Observations	919	

Notes: This table provides summary statistics and results of the augmented Dickey-Fuller (ADF) test of stationarity. * indicates the rejection of the null of normality and unit root under the Jarque-Bera test of normality and the ADF test of stationarity.