Hedging Cryptos with Bitcoin Futures

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Abstract

The introduction of derivatives on Bitcoin enables investors to hedge risk exposures in cryptocurrencies. Because of volatility swings and jumps in cryptocurrency prices, the traditional variance-based approach to obtain hedge ratios is infeasible. As a consequence, we consider two extensions of the traditional approach: first, different dependence structures are modelled by different copulae, such as the Gaussian, Student-t, Normal Inverse Gaussian and Archimedean copulae; second, different risk measures, such as value-at-risk, expected shortfall and spectral risk measures are employed to find the optimal hedge ratio. Extensive out-of-sample tests in the time period December 2017 until May 2021 give insights in the practice of hedging various cryptos and crypto indices, including Bitcoin, Ethereum, Cardano, the CRIX index and a number of crypto-portfolios. Evidence shows that BTC futures can effectively hedge BTC and BTC-involved indices. This promising result is consistent across different risk measures and copulae except for the Frank copula. On the other hand, we observe complex and diverse dependence structures between non-BTC-related cryptoassets and the BTC futures. As a consequence, the hedge performance of non-BTC-related cryptoassets is mixed and even infeasible for some assets.

JEL classification: G11, G13

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1 Introduction

Cryptocurrencies (CC's) are a fast-growing asset class, with many more CCs now available on the market since the first cryptocurrency Bitcoin (BTC) surfaced (Nakamoto, 2009). In response to the rapid development of the CC market, the CME Group launched exchange-traded BTC futures contracts in December 2017. At the time of writing, the CME is the only exchanged offering regulated crypto futures. The average daily volume and open interest of the CME BTC futures are \$2,518 M and \$2,836 M respectively.*[Add an approximate date. Where are these figures from?]* Because it is regulated, the CME BTC derivatives market is an attractive way for institutional investors to participate in or manage their exposure in the crypto market. As more individual and institutional investors are adding CCs and CC derivatives to their portfolios, the need to understand downside risks and find suitable ways to hedge against extreme risks is created. Fom a risk management perspective, the roller-coaster ride of crypto prices may create significant basis risk, even when using simple hedges involving crypto portfolios and BTC futures. This requires analysing the dependence structure of cryptos and futures beyond linear correlation.

In this paper, we examine static hedges of crypto portfolios with Bitcoin futures. Owing to the asymmetry of crypto returns as well as the occurrence of extreme events, we consider different dependence structures via a variety of copula models. We then optimise the hedge ratio using different risk measures. A similar study was conducted by (Barbi and Romagnoli, 2014) for equity and FX portfolios. Barbi and Romagnoli (2014)'s work is based on Cherubini et al. (2011) to derive the distribution of linear combinations of margins with copulae describing the dependence structure. We slightly extend their results and come up with a formula for the linear combination of random variables for our purpose.

The hedge ratio is the appropriate amount of futures contracts to hold in order to eliminate the risk exposure in the underlying security. The determination of the optimal hedge ratio relies primarily on the dependence between BTC and futures prices. Financial asset returns have long known to be non-Gaussian, see e.g. (Fama, 1963; Cont, 2001). Specifically, Gaussian models cannot produce the heavy tails and the asymmetry observed in asset returns, which in turn implies a consistent underestimation of financial risks. Therefore, to minimize downside risk, one cannot solely rely on second-order moment calculations. Moreover, variance as a risk measure does not account for the variety of investors' utility functions. In particular, it is known that investors are tail-risk averse, see Menezes et al. (1980). Copulae provide the flexibility to model multivariate random variables separately by their margins and dependence structure. The concept of copulae was originally developed (but not under this name) by Wassily Hoeffding (Hoeffding, 1940a) and later popularised by the work of Abe Sklar (Sklar, 1959).

Different risk measures account for investors' risk attitudes. They serve as loss functions in the search process of the optimal hedge ratio. Of the vast literature discussing the relationship between risk measures and investors' risk attitudes, we refer readers to Artzner et al. (1999) for an axiomatic approach of risk measure construction; Embrechts et al. (2002) for reasoning of using expected shortfall (ES) and spectral risk measures (SRM) in addition to value-at-risk (VaR); Acerbi (2002) for direct linkages between risk measures and investor's risk attitudes using the concept of a "risk aversion function".

In order to capture a variety of risk preferences, in addition to variance, we include the risk measures value-at-risk (VaR), expected shortfall (ES), and spectral risk measures (SRM). VaR is widely used by the finance industry and easy to understand. ES and SRM are chosen because of their coherence property, in particular, they recognize diversification benefits. SRM can also be directly related to

an individual's utility function. Examples are the exponential SRM and power SRM introduced by Dowd et al. (2008).

In this work, we study the effectiveness of hedging various CC's and crypto indices using Bitcoin futures under copula models and different risk preferences. In an extensive back-test,[1] we find the ability of the BTC futures to hedge BTC and BTC-related indices promising, regardless of the choices of the copula (with the exception of the Frank copula) and risk measure. On the other hand, the ability of BTC futures to hedge other cryptos *depends on various factors, such as ... (was: is inconclusive) [Something more useful should be said here. "is inconclusive" means: "stop reading here"]*. Instead of suggesting a particular copula or risk measures, we discuss the characteristics of different settings.

The paper is organized as follows. Section 2 introduces the notion of an optimal hedge ratio; Section 3 decribes the method of estimation of copulae; Section 4 provides the empirical result; Section 5 concludes. All calculations in this work can be reproduced with the data and code available at www.quantlet.com Q.

2 Optimal hedge ratio

2.1 Distribution of hedge portfolio

We form a portfolio with two assets, consisting of one unit in the spot asset and a short position of h units of a futures contract, for example one Bitcoin and a short position in a CME Bitcoin futures contract. The objective is to minimize the risk of the exposure in the spot. Let R^S and R^F be the (discrete) returns of the spot and futures price. The (discrete) return of the portfolio is[2]

$$R^h = R^S - hR^F.$$

[I fixed this, please check.] [We need to discuss the footnote. Generally, the portfolio return is $R_p = \sum_{i=1}^{n} w_i R_i$. With the futures contract, the notional investment in the futures is zero, so the portfolio return is $(S_0(1 + R^S) - hF_0 R^F)/S_0 - 1 = R^S - hR^F$, if $S_0 = F_0$.]

To measure risk, we define a risk measure ρ to be a mapping from a financial position or its return, such as R^h, to a real number, which is often interpreted as the amount of money to make the position acceptable (e.g. to a regulator), see e.g. (Föllmer and Schied, 2002). For example, a widely used risk measure is value-at-risk (VaR), which, at the confidence level α, is derived from the $1 - \alpha$ quantile of the return distribution.

If the portfolio reduces the risk of the spot position, then we call this a hedge portfolio. An optimal hedge ratio (OHR) h^* is a parameter that minimizes the risk of the aforementioned portfolio

$$h^* = \underset{h}{\operatorname{argmin}} \, \rho(R^h).$$

Obviously the cdf and pdf of R^h and the risk measure depend on the joint distribution of R^S and $-hR^F$. However, optimising h according to $f_{R^S, -hR^F}$ is unfavorable since one would need to calibrate the joint pdf $f_{R^S, -hR^F}$ whenever updating h. Another problem of using the joint pdf is that one lacks the flexibility to model the margins separately from the dependence structure. Copulae allow to

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[1] We thank the data provider Tiingo (https://www.tiingo.com/) for providing the crypto price data.

[2] In practice, as the nominal investment in the futures is zero, R^F is understood as the return on the notional amount underlying the futures contract. In other words, if both the spot price S_{t-1} and the futures price F_{t-1} are normalised to 1, then the portfolio return will be identical to the portfolio value change $\Delta V = \Delta S - h\Delta F$, where $\Delta S = S_t - S_{t-1}$, etc.

overcome both of these problems.

The advantage of using copulae is two-fold. First, copulae are invariant under strictly monotone increasing function (Schweizer et al., 1981), a property used in Lemma 1 below. Second, copulae allow us to model the margins and dependence structure separately, a result known as Sklar's Theorem (Sklar, 1959), which is given as Theorem 1 below. See also (Nelsen, 1999; Joe, 1997; McNeil et al., 2005) for Sklar's Theorem and more properties of copulae.

[I find it tricky that we give Sklar's Theorem, but no definition of a copula. This should be added.]

Theorem 1 (Hoeffding-Sklar-Theorem) *Let F be a joint distribution function with marginal distributions F_X and F_Y. Then, there exists a copula $C : [0,1]^2 \mapsto [0,1]$ such that, for all $x, y \in \mathbb{R}$*

$$F(x,y) = C\{F_X(x), F_Y(y)\}. \tag{1}$$

If the margins are continuous, then C is unique; otherwise C is unique on the range of the margins.

Conversely, if C is a copula and F_X, F_Y are univariate distribution functions, then the function F defined by (1) is a joint distribution function with margins F_X, F_Y.

Indeed, many basic results about copulae can be traced back to early works of Wassily Hoeffding (Hoeffding, 1940b, 1941). The works aimed to derive a measure of relationship of variables, which is invariant under change of scale. See also Fisher and Sen (2012) for English translations of the original papers written in German.

Lemma 1 *Let $h > 0$ and let X and Y be continuous random variables. Then, the joint distribution of the portfolio positions can be expressed via the joint distribution of the securities as follows:*

$$C_{X,hY}\left(F_X(s), F_{hY}(t)\right) = C_{X,Y}\left(F_X(s), F_Y(t/h)\right), \quad s, t \in \mathbb{R}. \tag{2}$$

Proof. Since copulae are invariant under strictly monotone increasing function (Schweizer et al., 1981, Theorem 3 (i)) or (Nelsen, 1999, Theorem 2.4.3),

$$C_{X,hY}\left(F_X(s), F_{hY}(t)\right) = C_{X,Y}\left(F_X(s), F_{hY}(t)\right).$$

Re-writing the second argument of the copula gives

$$F_{hY}(t) = \mathbb{P}(hY \leq t) = \mathbb{P}(Y \leq t/h) = F_Y(t/h).$$

∎

Leveraging these two features of copulae, Barbi and Romagnoli (2014) introduce the distribution of linear combinations of random variables using copulae. We slightly edit their Corollary 2.1 of their work and yield the following expression of the distribution.

Proposition 2 *Let X and Y be two real-valued continuous random variables on a probability space $(\Omega, \mathcal{F}, \mathbf{P})$ with absolutely continuous copula $C_{X,Y}$ and marginal distribution functions F_X and F_Y. Then, the distribution function of Z* [What is Z?] *is given by*

$$F_Z(z) = 1 - \int_0^1 D_1 C_{X,Y}\left[u, F_Y\left\{\frac{F_X^{(-1)}(u) - z}{h}\right\}\right] du, \tag{3}$$

5

where, $F^{(-1)}$ denotes the inverse of F, i.e., the quantile function. [Please check, but this holds only for $h > 0$.]

Here, $D_1 C(u, v) = \dfrac{\partial}{\partial u} C(u, v)$ and, see e.g. Equation (5.15) of (McNeil et al., 2005),

$$D_1 C_{X,Y}\{F_X(x), F_Y(y)\} = \mathbf{P}(Y \leq y | X = x). \tag{4}$$

Proof. Using the identity (4) gives

$$F_Z(z) = \mathbf{P}(X - hY \leq z) = \mathbb{E}\left\{\mathbf{P}\left(Y \geq \frac{X - z}{h}\Big| X\right)\right\}$$

$$= 1 - \mathbb{E}\left\{\mathbf{P}\left(Y \leq \frac{X - z}{h}\Big| X\right)\right\} = 1 - \int_0^1 D_1 C_{X,Y}\left[u, F_Y\left\{\frac{F_X^{(-1)}(u) - z}{h}\right\}\right]\, du.$$

$\blacksquare$

Corollary 1 *Given the formulation of random variables* [What exactly does this mean?], *the pdf of Z can be written as* [Since $h > 0$, it is sufficient to write $1/h$. Order of arguments in $c_{X,Y}$ must be flipped.]

$$f_Z(z) = \left|\frac{1}{h}\right| \int_0^1 c_{X,Y}\left[F_Y\left\{\frac{F_X^{(-1)}(u) - z}{h}\right\}, u\right] \cdot f_Y\left\{\frac{F_X^{(-1)}(u) - z}{h}\right\}\, du, \tag{5}$$

or

$$f_Z(z) = \int_0^1 c_{X,Y}\left[F_X\left\{z + hF_Y^{(-1)}(u)\right\}, u\right] \cdot f_X\left\{z + hF_Y^{(-1)}(u)\right\}\, du. \tag{6}$$

The two expressions are equivalent. *[This is obvious as their LHS's agree... I think you want to say something else. How is the second expression obtained?]* Note that the pdf of Z in the above proposition can be assessed via numerical integration as long as we have the copula density and the marginal densities. A generic expression *[Of what?]* and proof can be found in the appendix. *[Reference appendix properly.]*

2.2 Procedure to determine optimal hedge ratio

We introduce the empirical procedure to obtain the optimal hedge ratio (OHR) being used in this work. *[This is really the backtesting procedure. I think it'd be good if the word "backtest" appeared somwewhere.]* First, we split the time series of spot and futures into sets of training and testing data. *[test data?]* The training data makes up the first 300 observations and its corresponding testing data consists of the consecutive 5 observations. We then roll 5 observations forward (step size of 5) to obtain the next training and test data sets and repeat this until the end of the time series. Note that the testing data are non-overlapping since the step size is equal to test size.

Next, we obtain the OHR as follows:

1. **Construct Univariate Kernel Density Function (KDE)**. From the training data we calibrate the spot and futures' univariate kernel density functions using the Gaussian kernel with bandwidth determined by the refined plug-in method (Härdle et al., 2004, section 3.3.3).

2. **Calibrate Copulae**. We then calibrate the copulae outlined in section 3.1 via the method of moments described in section 3.2.1.

3. **Select Copula**. We compute the Akaike Information Criterion. The copula with the best (i.e., lowest) AIC is used for the next step. A discussion of this step is found in 3.2.3.

4. **Determine OHR**. We determine the OHRs numerically using different risk measures as the loss function by drawing samples from the selected copula and KDEs. The risk measures used as risk reduction objectives are outlined in 3.3

5. **Obtain testing log-return of hedged portfolio**. *["testing log-return" is a bit confusing. I think "testing" refers to test data set? Find better formulation.]* Finally, we apply the OHRs to the test data $R_h = R_s - h^* R_f$.

3 Copulae and risk measures

3.1 Copulae

To capture different aspects of the dependence structure, we consider a set of different copulas, which are layed out in detail below. These are the Gaussian-, t-, Frank-, Gumbel-, Clayton-, mixture, NIG factor, and Plackett-copula.

As this hedging backtest concerns only portfolios with two assets, we focus on the bivariate version of each copula and bivariate copula measures, such as Kendall's τ_K and Spearman's ρ_S.

3.1.1 Copula measures

Kendall's τ and Spearman's ρ are measures of association in terms of concordance, see Kruskal (1958). *[A number of definitions follow. It usually helps the reader if they are put in a definition block rather than just flowing with the text.]* Let (x_i, y_i) and (x_j, y_j) denote two realisations of a vector (X, Y) of continuous random variables. A pair of observations is concordant if $x_i < x_j$ and $y_i < y_j$, discordant if $x_i > x_j$ and $y_i < y_j$ or if $x_i < x_j$ and $y_i > y_j$. *[What about the case $x_i > x_j$ and $y_i > y_j$?]* For a bivariate random variable of n observations, there are $\binom{n}{2}$ distinct pairs. *[I struggled with understanding what "distinct pairs" refers to, but found the answer in Nelsen. Perhaps add a little more test. Also, as this paragraph seems to be taken directly from Nelsen, it must be cited accordingly!]*

Let c denote the number of concordant pairs, and d the number of discordant pairs. Kendall's tau is defined as follows: (Nelsen, 1999)

$$\tau_K := \frac{c - d}{c + d} = \frac{c - d}{\binom{n}{2}}.$$

Let F_X and F_Y be the cdfs of X and Y respectively, Spearman's ρ is *[These are two sentences, so please separate them into two sentences. Also, formulas belong syntactically to the sentence, so if they end the sentence, there should be a full stop.]*

$$\rho_S := 12\mathbb{E}(F_X(X)F_Y(Y)) - 3.$$

[Is there a particular reason to switch between sample and populationo versions?]

Upper tail dependence is defined as *[Typeset terms that are defined, e.g. upper tail dependence, in italics.]*

$$\lambda_U := \lim_{q \to 1^-} \mathbf{P}\{X > F_X^{(-1)}(q) | Y > F_Y^{(-1)}(q)\};$$

Lower tail dependence is defined as

$$\lambda_L := \lim_{q \to 0^+} \mathbf{P}\{X \leq F_X^{(-1)}(q) | Y \leq F_Y^{(-1)}(q)\}.$$

Furthermore, we denote the Fréchet-Hoeffding lower bound by $\boldsymbol{W}$, the product copula by $\boldsymbol{\Pi}$, and the Fréchet-Hoeffding upper bound by $\boldsymbol{M}$. They represent cases of perfect negative dependence, independence, and perfect positive dependence, respectively. For further details, we refer readers to Joe (1997) and Nelsen (1999); see also Härdle and Okhrin (2010).

The symmetry property of copulae is also important for modelling financial data. In particular, we are interested in radial symmetry among various concepts of symmetry, see Nelsen (1999). *[Why?]*

Definition 3 *Let $(U_1, ..., U_d)$ be random variables.* [uniform on $[0, 1]$?] *The random variables is radially symmetric if the joint cdf of $(U_1, ..., U_d)$ is same as the joint cdf of $(1 - U_1, ..., 1 - U_d)$*

3.1.2 Gaussian and t Copulae

The Gaussian and t copulae are dervived from Gaussian and t distributions. As the Gaussian and t distributions belong to the family of elliptical distributions, their copulae belong to the family of elliptical copulae. *[I personally would remove the reference to the elliptical family, as this is not important for what is to come. If it must stay, then briefly explain what elliptical distributions are ("Empirical distributions are characeterised by...".]*

The bivariate Gaussian copula is defined as

$$\begin{aligned} \boldsymbol{C}(u, v) &= \Phi_{2,\rho}\{\Phi^{(-1)}(u), \Phi^{(-1)}(v)\} \\ &= \int_{-\infty}^{\Phi^{(-1)}(u)} \int_{-\infty}^{\Phi^{(-1)}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left\{\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right\} \mathrm{d}s\,\mathrm{d}t, \quad , u, v \in [0, 1], \end{aligned}$$

where $\Phi_{2,\rho}$ is the bivariate Normal cdf with zero mean, unit variance, and correlation coefficient ρ, and $\Phi^{(-1)}$ is the quantile function of the univariate standard normal distribution. The Gaussian copula is fully specified by the correlation parameter ρ. [3] Like all elliptical copulas, it is symmetric. *[Remove reference to elliptic copula.]* It has no tail dependence, which, in a finance context, implies that it often underestimates tail risk.

The Gaussian copula density is

$$\boldsymbol{c}_\rho(u, v) = \frac{\boldsymbol{\varphi}_{2,\rho}\{\Phi^{(-1)}(u), \Phi^{(-1)}(v)\}}{\varphi\{\Phi^{(-1)}(u)\} \cdot \varphi\{\Phi^{(-1)}(v)\}} = \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left\{-\frac{u^2 - 2\rho uv + v^2}{2(1-\rho^2)}\right\},$$

where $\boldsymbol{\varphi}_{2,\rho}(\cdot)$ is the pdf corresponding to $\Phi_{2,\rho}$, and $\varphi(\cdot)$ the standard normal pdf. *[I think the abbreviations cdf and pdf where not introduced. Please double-check.]*

To illustrate the various copulae and their differences, Figure 1 shows scatter plots of random samples of each of the copulae treated.

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[3]The symbol ρ is used to denote both the correlation parameter as well as a general risk measure. However, it will be clear from the context, what ρ refers to.
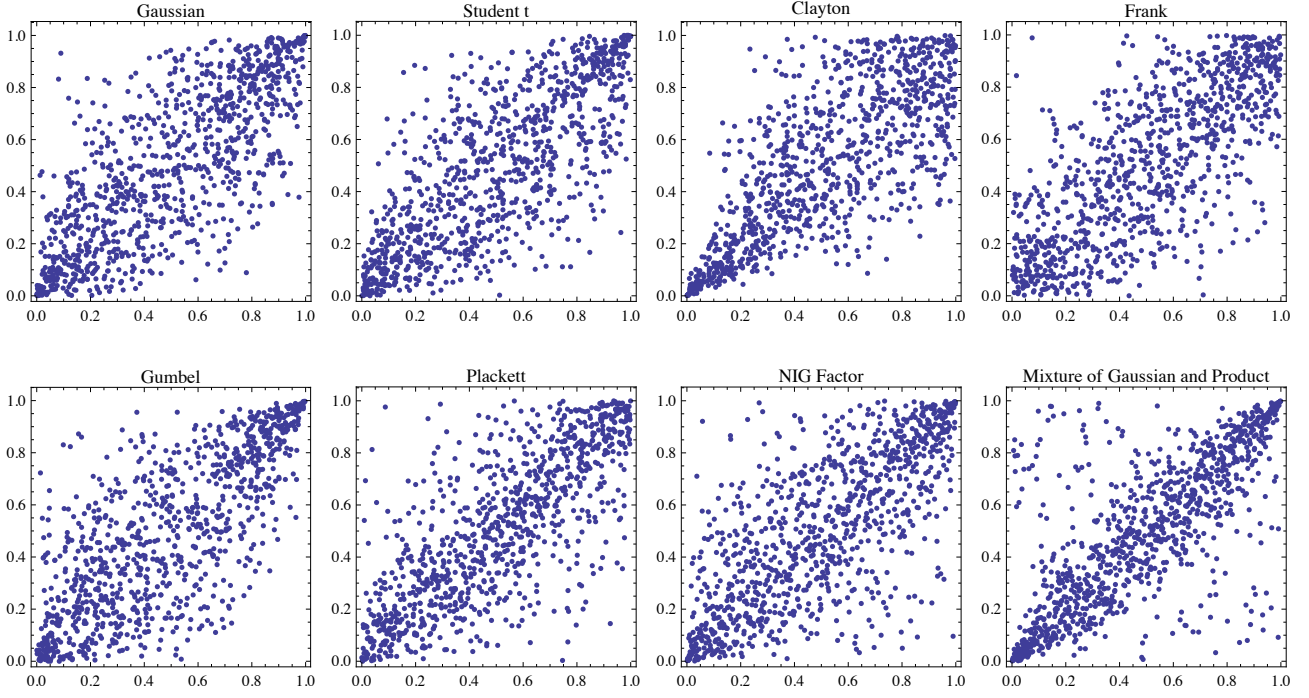
Figure 1: Scatterplots of samples drawn from various copulae. All copulae are calibrated to Spearman's ρ of 0.75 before sampling.

Kendall's τ_K and Spearman's ρ_S of the bivariate Gaussian copula are

$$\tau_K(\rho) = \frac{2}{\pi} \arcsin \rho$$

$$\rho_S(\rho) = \frac{6}{\pi} \arcsin \frac{\rho}{2}.$$

The t-copula has the form

$$
\begin{aligned}
\boldsymbol{C}(u,v) &= \boldsymbol{T}_{2,\rho,\nu}\{T_\nu^{(-1)}(u), T_\nu^{(-1)}(v)\} \\
&= \int_{-\infty}^{T_\nu^{(-1)}(u)} \int_{-\infty}^{T_\nu^{(-1)}(v)} \frac{\Gamma\left(\frac{\nu+2}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\pi\nu\sqrt{1-\rho^2}} \left(1 + \frac{s^2 - 2st\rho + t^2}{\nu}\right)^{-\frac{\nu+2}{2}} \mathrm{d}s\,\mathrm{d}t,
\end{aligned}
$$

where $\boldsymbol{T}_{2,\rho,\nu}$ denotes the bivariate t cdf with dependence parameter ρ *[Is this Spearman's Rho? If so, then say so.]* and degrees of freedom parameter ν, $\nu > 2$, and where $T_\nu^{(-1)}(\cdot)$ is the quantile function of a standard t distribution with parameter ν.

Contrary to the Gaussian copula, the t-copula has a non-zero tail dependence coefficient, which makes it more appropriate for dependence modelling in finance. The Gaussian copula arises as $\nu \to \infty$.

The copula density is

$$\boldsymbol{c}(u,v) = \frac{\boldsymbol{t}_{2,\rho,\nu}\{T_\nu^{(-1)}(u), T_\nu^{(-1)}(v)\}}{t_\nu\{T_\nu^{(-1)}(u)\} \cdot t_\nu\{T_\nu^{(-1)}(v)\}},$$

where $\boldsymbol{t}_{2,\rho,\nu}$ is the pdf of $\boldsymbol{T}_{2,\rho,\nu}$ and t_ν the density of standard t distribution.

The t-copula and Gaussian copula with parameter ρ have equal Kendall's τ, a property shared by all so-called elliptical copulas (see Demarta and McNeil, 2005, and references therein). (was: Like all

3.1.3 Archimedean copulae

The family of Archimedean copulae forms a large class of copulae with many convenient features. Archimedean copulas are determined via a simple parametric form of the dependence structure. A prominent feature is the ability to model asymmetric dependence structures.

In general, they take a form

$$\boldsymbol{C}(u,v) = \psi^{(-1)}\{\psi(u), \psi(v)\},$$

where $\psi : [0,1] \to [0,\infty)$ is a continuous, strictly decreasing and convex function such that $\psi(1) = 0$ for any permissible dependence parameter θ. ψ is also called generator. $\psi^{(-1)}$ is the inverse of the generator.

The Frank copula (B3 in Joe (1997)) is a radial symmetric copula and cannot produce any tail dependence. It takes the form

$$\boldsymbol{C}_\theta(u,v) = \frac{1}{\theta}\log\left\{1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1}\right\}$$

where $\theta \in [0,\infty]$ is the dependency parameter. $\boldsymbol{C}_{-\infty} = \boldsymbol{M}$, $\boldsymbol{C}_1 = \boldsymbol{\Pi}$, and $\boldsymbol{C}_\infty = \boldsymbol{W}$.

The Copula density is

$$\boldsymbol{c}_\theta(u,v) = \frac{\theta e^{\theta(u+v)}(e^\theta - 1)}{\left\{e^\theta - e^{\theta u} - e^{\theta v} + e^{\theta(u+v)}\right\}^2}$$

Frank copula has Kendall's τ and Spearman's ρ as follow:

$$\tau_K(\theta) = 1 - 4\frac{D_1\{-\log(\theta)\}}{\log(\theta)},$$

and

$$\rho_S(\theta) = 1 - 12\frac{D_2\{-\log(\theta)\} - D_1\{\log(\theta)\}}{\log(\theta)},$$

where D_1 and D_2 are the Debye function of order 1 and 2. Debye function is $D_n = \frac{n}{x^n}\int_0^x \frac{t^n}{e^t - 1}dt$.

The Gumbel copula (B6 in Joe (1997)) has upper tail dependence with the dependence parameter $\lambda^U = 2 - 2^{\frac{1}{\theta}}$ and displays no lower tail dependence.

$$\boldsymbol{C}_\theta(u,v) = \exp-\{(-\log(u))^\theta + (-\log(v))^\theta\}^{\frac{1}{\theta}},$$

where $\theta \in [1,\infty)$ is the dependence parameter.

While the Gumbel copula cannot model perfect counter-dependence (Nelsen, 2002), $\boldsymbol{C}_1 = \boldsymbol{\Pi}$ models the independence, and $\lim_\theta^\infty \boldsymbol{C}_\theta = \boldsymbol{W}$ models the perfect dependence. The copula density takes the form

$$\tau_K(\theta) = \frac{\theta - 1}{\theta}.$$

The Clayton copula, by contrast to Gumbel copula, generates lower tail dependence of the form

$\lambda^L = 2^{-\frac{1}{\theta}}$, but cannot generate upper tail dependence. The Clayton copula takes the form

$$\boldsymbol{C}_\theta(u,v) = \left\{ \max(u^{-\theta} + v^{-\theta} - 1, 0) \right\}^{-\frac{1}{\theta}},$$

where $\theta \in (-\infty, \infty)$ is the dependence parameter. Moreover, $\lim_\theta^{-\infty} \boldsymbol{C}_\theta = \boldsymbol{M}$, $\boldsymbol{C}_0 = \boldsymbol{\Pi}$, and $\lim_\theta^\infty \boldsymbol{C}_\theta = \boldsymbol{W}$. Kendall's τ of the Clayton copula is given by

$$\tau_K(\theta) = \frac{\theta}{\theta + 2}.$$

3.1.4 Mixture Copula

The mixture copula is a linear combination of copulae. For a 2-dimensional random variable $\boldsymbol{X} = (X_1, X_2)^\top$, its distribution can be written as linear combination of K copulae

$$C(u,v) = \sum_{k=1}^K p^{(k)} \cdot \boldsymbol{C}^{(k)} \{ F_{X_1}^{(-1)}(u), F_{X_2}^{(-1)}(v); \boldsymbol{\theta}^{(k)} \}.$$

The copula density is again a linear combination of copula densities

$$c(u,v) = \sum_{k=1}^K p^{(k)} \cdot \boldsymbol{c}^{(k)} \{ F_{X_1}^{(-1)}(u), F_{X_2}^{(-1)}(v); \boldsymbol{\theta}^{(k)} \}.$$

While Kendall's τ of mixture copula is not known in closed form, Spearman's ρ is specified by the following statement.

Proposition 4 *Let $\rho_S^{(k)}$ be Spearman's ρ of the k-th component Spearman's ρ of the mixture copula is given by*

$$\rho_S = \sum_{k=1}^K p^{(k)} \cdot \rho_S^{(k)}$$

Proof. Since Spearman's ρ is defined as (Nelsen, 1999)

$$\rho_S = 12 \int_{\mathbb{I}^2} \boldsymbol{C}(s,t) ds dt - 3,$$

Spearman's ρ of the the mixture copula is given by summation of the components

$$\rho_S = 12 \int_{\mathbb{I}^2} \sum_{k=1}^K p^{(k)} \cdot \boldsymbol{C}^{(k)}(s,t) ds dt - 3.$$

$\blacksquare$

An example of a mixture copula is the Fr'echet class of copulas, which are given by convex combinations of $\boldsymbol{W}$, $\boldsymbol{\Pi}$, and $\boldsymbol{M}$ (Nelsen, 1999).

We use a mixture of Gaussian and independent copulas in our analysis, i.e.,

$$\boldsymbol{C}(u,v) = p \cdot \boldsymbol{C}^{\text{Gaussian}}(u,v) + (1-p)(uv),$$

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with corresponding density is

$$\boldsymbol{c}(u,v) = p \cdot \boldsymbol{c}^{\text{Gaussian}}(u,v) + (1-p).$$

This mixture models the amount of "random noise" that appears in the dependence structure. In the hedging exercise, the "random noise" adds an unhedgable component to the two-asset portfolio, whose weight $(1-p)$ is calibrated from market data.

3.1.5   NIG factor copula

The *normal inverse Gaussian (NIG)* distribution, introduced by (Barndorff-Nielsen, 1997), has density function

$$g(x; \alpha, \beta, \mu, \delta) = \frac{\alpha}{\pi} \mathbf{e}^{\delta \sqrt{\alpha^2 - \beta^2} - \beta\mu} \frac{1}{q((x-\mu)/\delta)} K_1 \left[\delta\alpha q \left(\frac{x-\mu}{\delta} \right) \right] \mathbf{e}^{\beta x}, \quad x > 0,$$

where $q(x) = \sqrt{1 + x^2}$ and where K_1 is the modified Bessel function of third order and index 1. The parameters satisfy $0 \leq |\beta| \leq \alpha$, $\mu \in \mathbb{R}$ and $\delta > 0$. The parameters have the following interpretation: μ and δ are location and scale parameters, respectively, α determines the heaviness of the tails and β determines the degree of asymmetry. If $\beta = 0$, then the distribution is symmetric around μ.

The moment-generating function of the NIG distribution is given by

$$M(u; \alpha, \beta, \mu, \delta) = \exp\left(\delta \left(\sqrt{\alpha^2 - \beta^2} - \sqrt{\alpha^2 - (\beta + u)^2} \right) + \mu u \right).$$

As a direct consequence, moments are easily calculated with the expectation and variance of the NIG distribution being

$$\mathbb{E}X = \mu + \frac{\delta\beta}{\sqrt{\alpha^2 - \beta^2}}$$

$$\text{Var}(X) = \frac{\alpha^2 \delta}{(\alpha^2 - \beta^2)^{3/2}}. \tag{7}$$

The NIG$(\alpha, \beta, \mu\,\delta)$ distribution belongs to the class of so-called *normal variance-mean mixture*, (see Section 3.2 of (McNeil et al., 2005)): X follows an NIG$(\alpha, \beta, \mu, \delta)$ distribution if X conditional on W follows a normal distribution with mean $\mu + \beta W$ and variance W, i.e.,

$$X|W \overset{\mathcal{L}}{\sim} \text{N}(\mu + \beta W, W),$$

where W follows an *inverse Gaussian distribution*, denoted by IG$(\delta, \sqrt{\alpha^2 - \beta^2})$.

It is easily seen from the moment-generating function that the NIG distribution is preserved under linear combinations, provided the variables share the parameters α and β. For this and other reasons, the NIG distribution is popular in many areas of financial modelling; for example, it gives rise to the normal inverse Gaussian Lévy process, which may be represented as a Brownian motion with a time change.

In the setting here, we consider the *NIG factor copula*. This is not directly derived from the multivariate NIG distribution, but determined through a factor structure instead. The factor structure, which was applied e.g. in (Kalemanova et al., 2007) for calibrating CDO's, gives additionaly flexibility

as it does not force the components to have a mixing variable W. The following proposition introduces the NIG factor model and some of its properties.

Proposition 5 *Let $Z \sim NIG(\alpha, \beta, \mu, \delta)$ and $Z_i \sim NIG(\alpha, \beta, \mu_i, \delta_i)$, $i = 1, \ldots, n$ be independent NIG-distributed random variables. Then:*

1. $X_i = Z + Z_i \sim NIG(\alpha, \beta, \mu + \mu_i, \delta + \delta_i)$,

2. *and*

$$Cov(X_i, X_j) = Var(Z),$$
$$Corr(X_i, X_j) = \frac{\delta}{\sqrt{(\delta + \delta_i)(\delta + \delta_j)}}. \tag{8}$$

Proof.

1. This follows directly from the moment-generating function.

2. For the covariance,

$$\mathrm{Cov}(X_i, X_j) = \mathbb{E}[(Z + Z_i)(Z + Z_j)] - \mathbb{E}[Z + Z_i]\mathbb{E}[Z + Z_j]$$
$$= \mathbb{E}[Z^2] - (\mathbb{E}Z)^2.$$

The correlation is determined directly from 7.

∎

The NIG factor copula is obtained by transforming the margins to uniforms (see Sklar's Theorem), giving (e.g. (Krupskii and Joe, 2013)):

$$C_{r^S, r^F}(F_{r^S}(r^S), F_{r^F}(r^F)) = \int_{\mathbb{R}} F_{Z_1}(F_{X_1}^{(-1)} \circ F_{r^S}(r^S) - z) \cdot F_{Z_2}(F_{X_2}^{(-1)} \circ F_{r^F}(r^F) - z) \cdot f_Z(z) dz$$

If the margins are continuous, then Spearman's rho of NIG factor copula is

$$\rho_S = 12 \int \int \int_{\mathbb{R}^3} F_{X_1}(x_1) \cdot F_{X_2}(x_2) \cdot f_{Z_1}(x_1 - z) \cdot f_{Z_2}(x_2 - z) \cdot f_Z(z) dx_1 dx_2 dz - \frac{1}{48}.$$

3.1.6 Plackett copula

The Plackett copula has an expression

$$C_\theta(u, v) = \frac{1 + (\theta - 1)(u + v)}{2(\theta - 1)} - \frac{\sqrt{\{1 + (\theta - 1)(u + v)\}^2 - 4uv\theta(\theta - 1)}}{2(\theta - 1)}$$

$$\rho_S(\theta) = \frac{\theta + 1}{\theta - 1} - \frac{2\theta \log \theta}{(\theta - 1)^2}$$

We include Placket copula in our analysis as it possesses a special property, the cross-product ratio

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is equal to the dependence parameter

$$\cdot \, \frac{\mathbf{P}(U \leq u, V \leq v) \cdot \mathbf{P}(U > u, V > v)}{\mathbf{P}(U \leq u, V > v) \cdot \mathbf{P}(U > u, V \leq v)}$$

$$= \frac{C_\theta(u,v)\{1 - u - v + C_\theta(u,v)\}}{\{u - C_\theta(u,v)\}\{v - C_\theta(u,v)}$$

$$= \theta. \tag{9}$$

That is, the dependence parameter is equal to the ratio between number of concordance pairs and number of discordance pairs of a bivariate random variable.

3.2 Calibration and selection of copulae

We introduce the method to calibrate copulae to our data in this section. In general, there are two types of calibration procedures to calibrate copulae: maximum likelihood (MLE) and method of moments (MM). We decide to deploy the latter since it calibrates according to the moments desired.

In the following subsection, we present the configuration of the method of moments procedures in this work. In the subsection after, we argue that MM is more suitable to this work by comparing MM with MLE.

3.2.1 Method of moments

We trace back the usage of MM to calibrate copulae to Genest (1987); Genest and Rivest (1993). The moments mainly refer to Kendall's τ or Spearman's ρ. We extend MM to quantile dependence measures denoted by λ_q for quantile level q.

Spearman's ρ, Kendall's τ, and quantile dependence of the copula C are defined as

$$\rho_S = 12 \int \int_{I^2} C_{\boldsymbol{\theta}}(u,v) \, \mathrm{d}u \, \mathrm{d}v - 3$$

$$\tau_K = 4\mathbb{E}[C_{\boldsymbol{\theta}}\{F_X(x), F_Y(y)\}] - 1,$$

$$\lambda_q = \begin{cases} \mathbf{P}(F_X(X) \leq q | F_Y(Y) \leq q) = \dfrac{C_{\boldsymbol{\theta}}(q,q)}{q}, & \text{if } q \in (0, 0.5], \\ \mathbf{P}(F_X(X) > q | F_Y(Y) > q) = \dfrac{1 - 2q + C_{\boldsymbol{\theta}}(q,q)}{1 - q}, & \text{if } q \in (0.5, 1). \end{cases}$$

The empirical counterparts are

$$\hat{\rho}_S = \frac{12}{n} \sum_{k=1}^{n} \hat{F}_X(x_k) \hat{F}_Y(y_k) - 3,$$

$$\hat{\tau}_K = \frac{4}{n} \sum_{k=1}^{n} \hat{C}\{\hat{F}_X(x_i), \hat{F}_X(y_i)\} - 1,$$

$$\hat{\lambda}_q = \begin{cases} \dfrac{1}{n} \sum_{k=1}^{n} \dfrac{\mathbf{1}_{\{\hat{F}_X(x_k) \leq q, \hat{F}_Y(y_k) \leq q\}}}{q}, & \text{if } q \in (0, 0.5], \\ \dfrac{1}{n} \sum_{k=1}^{n} \dfrac{\mathbf{1}_{\{\hat{F}_X(x_k) > q, \hat{F}_Y(y_k) > q\}}}{1 - q}, & \text{if } q \in (0.5, 1), \end{cases}$$

where $\hat{F}(x) = \dfrac{1}{n} \sum_{k=1}^{n} 1_{\{x_i \leq x\}}$ and $\hat{C}(u,v) = \dfrac{1}{n} \sum_{k=1}^{n} 1_{\{u_i \leq u, v_i \leq v\}}$.

Denote by $\boldsymbol{m}(\boldsymbol{\theta})$ the m-dimensional vector of dependence measures according the dependence parameters $\boldsymbol{\theta}$, and let $\hat{\boldsymbol{m}}$ be the corresponding empirical counterpart. The difference between dependence measures and their counterpart is denoted by

$$g(\boldsymbol{\theta}) = \hat{\boldsymbol{m}} - \boldsymbol{m}(\boldsymbol{\theta}).$$

The MM estimator is

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta} \in \boldsymbol{\Theta}}{\operatorname{argmin}} \, g(\boldsymbol{\theta})^\top \hat{\boldsymbol{W}} g(\boldsymbol{\theta}),$$

where $\hat{W}$ is some positive definite weight matrix. In this work, we use $\boldsymbol{m}(\boldsymbol{\theta}) = (\rho_S, \lambda_{0.05}, \lambda_{0.1}, \lambda_{0.9}, \lambda_{0.95})^\top$ for calibration. $\hat{W}$ is set to identity matrix.

3.2.2 Comparison between method of moments and maximum likelihood

By the Hoeffding-Sklar theorem, the joint density of a d-dimensional random variable $\boldsymbol{X}$ with sample size n can be written as

$$\boldsymbol{f_X}(x_1, ..., x_d) = \boldsymbol{c}\{F_{X_1}(x_1), ..., F_{X_d}(x_d)\} \prod_{j=1}^{d} f_{X_i}(x_i).$$

We follow the treatment of MLE documented in section 10.1 of Joe (1997), namely the *inference functions for margins (IFM) method*. The log-likelihood $\sum_{i=1}^{n} f_{\boldsymbol{X}}(X_{i,1}, ..., X_{i,d})$ can be decomposed into a dependence part and a marginal part,

$$L(\boldsymbol{\theta}) = \sum_{i=1}^{n} \boldsymbol{c}\{F_{X_1}(x_{i,1}; \boldsymbol{\delta}_1), ..., F_{X_d}(x_{i,d}; \boldsymbol{\delta}_d); \boldsymbol{\gamma}\} + \sum_{i=1}^{n} \sum_{j=1}^{d} f_{X_j}(x_{i,j}; \boldsymbol{\delta}_j)$$

$$= L_C(\boldsymbol{\delta}_1, ..., \boldsymbol{\delta}_d, \boldsymbol{\gamma}) + \sum_{j=1}^{d} L_j(\boldsymbol{\delta}_j)$$

where $\boldsymbol{\delta}_j$ are the parameters of the j-th margin, $\boldsymbol{\gamma}$ is the parameter of the parametric copula, and $\boldsymbol{\theta} = (\boldsymbol{\delta}_1, ..., \boldsymbol{\delta}_d, \boldsymbol{\gamma})$. Instead of searching the $\boldsymbol{\theta}$ in a high dimensional space, Joe (1997) suggests to search for $\hat{\boldsymbol{\delta}}_1, ..., \hat{\boldsymbol{\delta}}_d$ that maximize $L_1(\boldsymbol{\delta}_1), ..., L_d(\boldsymbol{\delta}_d)$, then search for $\hat{\boldsymbol{\gamma}}$ that maximize $L_C(\hat{\boldsymbol{\delta}}_1, ..., \hat{\boldsymbol{\delta}}_d, \boldsymbol{\gamma})$.

We follow Genest et al. (1995) who suggest to replace the estimation of marginals parameters estimation by non-parameteric estimation. Given non-parametric estimator $\hat{F}_i$ of the margins F_i, the estimator of the dependence parameters $\boldsymbol{\gamma}$ is

$$\hat{\boldsymbol{\gamma}} = \underset{\boldsymbol{\gamma}}{\operatorname{argmax}} \sum_{i=1}^{n} \boldsymbol{c}\{\hat{F}_{X_1}(x_{i,1}), ..., \hat{F}_{X_d}(x_{i,d}); \boldsymbol{\gamma}\}.$$

Both the simulated method of moments and the maximum likelihood estimation are unbiased. The question though which procedure is more suitable for hedging.

Figure 2 shows the empirical quantile dependence of Bitcoin and CME future and the copula implied quantile dependence of the MLE and MM calibration procedures. Although the MLE is a better fit to a range of quantile dependence in the middle, it fails to address the situation in the tails. We find that our data empirically has low quantile dependence in the lower ends ($q < 10\%$). We argue that MM is preferred as it produces a better fit to the dependence structure in the tail behaviour,
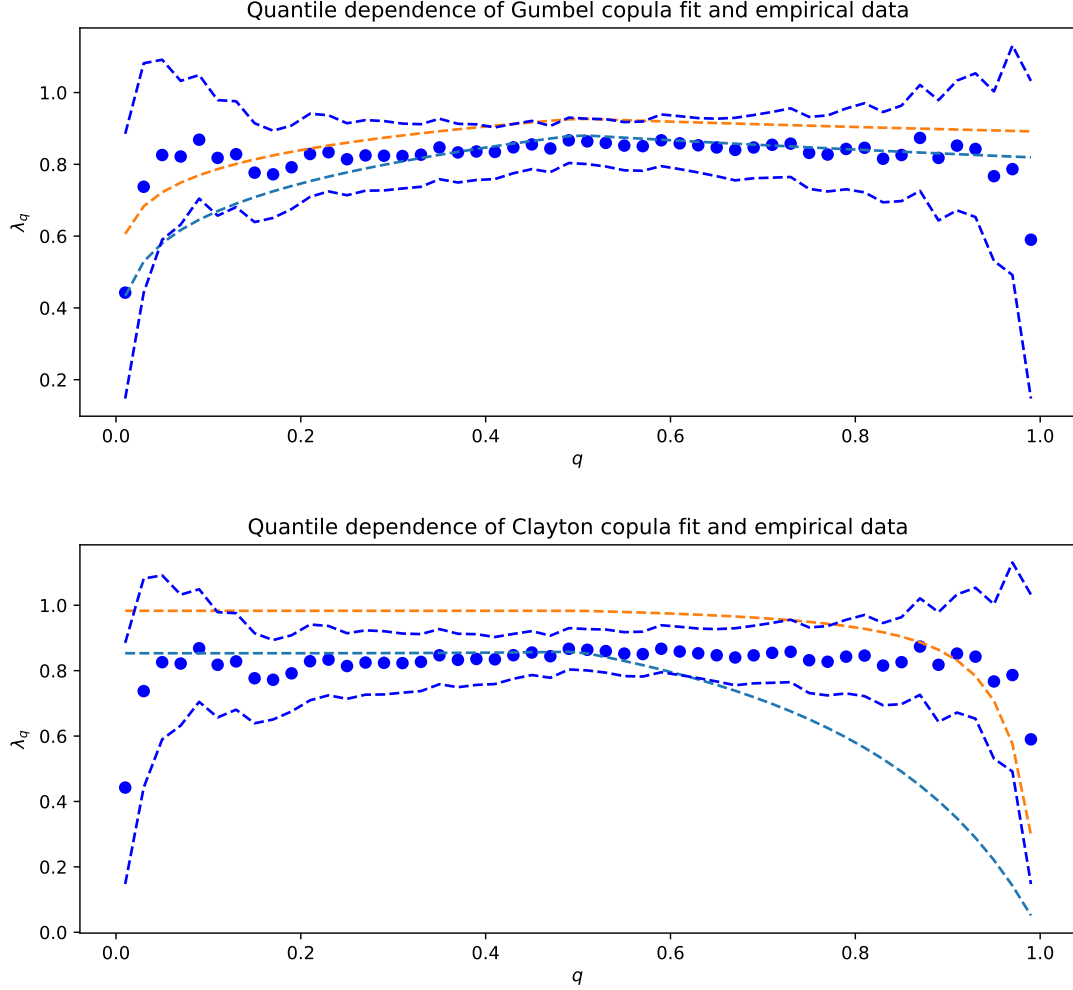
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Figure 2: Quantile dependences of Gumbel, and Clayton Copula. The blue circle dots are the quantile dependence estimates of Bitcoin and CME future, blue dotted lines are the estimates' 90% confidence interval. Orange dotted line is the copula implied quantile dependence by MM estimation. Light blue dotted line is the copula implied quantile dependence by MLE estimation.

contrary to MLE.

Therefore, we deploy the method of moments throughout the analysis. We choose the 5th-, 10th-, 90th-, 95th-quantile, and Spearman's ρ as the moments.

3.2.3 Copula selection

The dependence structure of price data changes across time, in which both the dependency parameters and the type of dependence. For this reason, we allow for a flexible choice of the best-fitting copula, by re-calibrating periodically and re-evaluating performance of the various copulas. We select the best-fitting copula, characterised by the lowest *Akaike Information Criterion (AIC)*,

$$\text{AIC} = 2k - 2\log(L),$$

where k is the number of estimated parameteres and L is the likelihood (Akaike, 1973).

Other model selection criteria, such as the TIC (Takeuchi, 1976) or likelihood ratio test could be used instead. For a survey of model selection and inference, see Anderson et al. (1998). Among various copula selection procedures, AIC is a popular choice for its applicability, see e.g. Breymann

et al. (2003). In our case, the AICs are calculated only with dependency likelihood since the marginals are modelled via kernel density estimators. The selected copula will then be enter the calculation of the optimal hedge ratio.

3.3 Risk measures

The optimal hedge ratio is determined for the following variety of risk measures: variance, Value-at-Risk (VaR), Expected Shortfall (ES), and Exponential Risk Measure (ERM). A summary of risk measures being used in portfolio selection problem can be found in Härdle et al. (2008). The risk measures here serve as risk minimization objectives, i.e. loss functions for searching the optimal hedge ratio.

The risk measures are defined as follows. Let Z be a random variable with distribution function F_Z.

1. Variance: $\text{Var}(Z) = \mathbb{E}[(Z - \mathbb{E}Z)^2]$.

2. VaR at confidence level α: $\text{VaR}_\alpha(Z) = -F_Z^{(-1)}(1 - \alpha)$

3. ES at confidence level α: $\text{ES}(F_Z) = -\frac{1}{1-\alpha} \int_0^{1-\alpha} F_Z^{(-1)}(p) dp$

4. ERM with Arrow-Pratt coefficient of absolute risk aversion k:

$$\text{ERM}_k(F_Z) = \int_0^{1-\alpha} \phi(p) F_Z^{(-1)}(p) dp,$$

where ϕ is a weight function described in (3.3) below.

VaR, ES, and ERM fall into the class of spectral risk measures (SRM), which have the from (Acerbi, 2002)

$$\rho_\phi(r^h) = -\int_0^1 \phi(p) F_Z^{(-1)}(p) dp,$$

where p is the loss quantile and $\phi(p)$ is a user-defined weighting function defined on $[0, 1]$. We consider only so-called admissible risk spectra $\phi(p)$, i.e., fulfilling

(i) ϕ is positive,

(ii) ϕ is decreasing,

(iii)   and $\int \phi = 1$.

The VaR's $\phi(p)$ gives all its weight on the $1 - \alpha$ quantile of Z and zero elsewhere, i.e. the weighting function is a Dirac delta function, and hence it violates the (ii) property of admissible risk spectra. The ES' $\phi(p)$ gives all tail quantiles the same weight of $\frac{1}{1-\alpha}$ and non-tail quantiles zero weight. The ERM assumes investors' risk preference are in the form of an exponential utility function $U(x) = 1 - e^{kx}$, so its corresponding risk spectrum is defined as

$$\phi(p) = \frac{ke^{-k(1-p)}}{1 - e^{-k}},$$

where k is the Arrow-Pratt coefficient of absolute risk aversion. The parameter k has an economic interpretation as being the ratio between the second derivative and first derivative of investor's utility
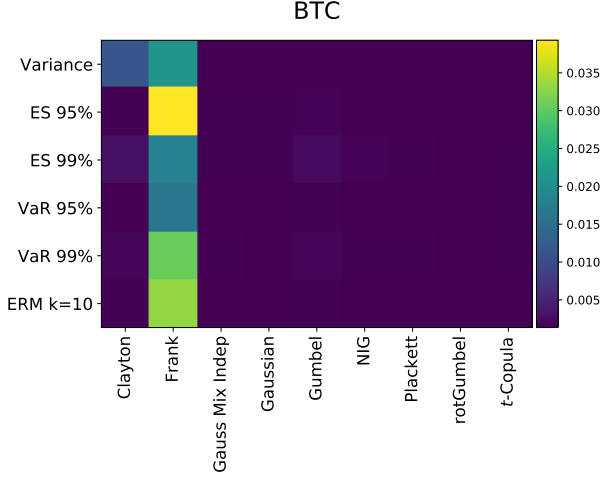
Figure 3: Out-of-sample mean square errors of BTC-BTCF portfolios constructed with different copula and risk minimization objectives. The Frank copula is inferior in the BTC-involved portfolios.
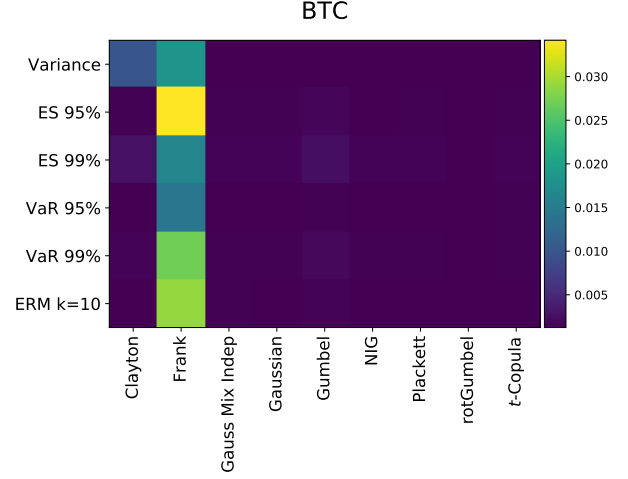
Figure 4: Out-of-sample lower semivariance of BTC-BTCF portfolios constructed with different copula and risk minimization objectives. The Frank copula is obviously inferior.

function on an risky asset,

$$k = -\frac{U''(x)}{U'(x)},$$

for x in all possible outcomes. In case of the exponential utility, k is the the constant absolute risk aversion (CARA).

4 Empirical Results

4.1 Data

In the empirical analysis, we consider the risk reduction capability of CME Bitcoin Futures (BTCF) on five cryptos, namely Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), Litecoin (LTC) and Ripple (XRP), as well as five crypto indexes, namely BITX, BITW100, CRIX, BITW20, and BITW70. ETH, ADA, LTC, and XRP are popular cryptos tradable in various exchanges and have large market capitalization. BITX, BITW100, and CRIX are market-cap weighted crypto indexes with BTC as constituent. BITX and BITW100 track the total return of the 10 and 100 cryptos with largest market-cap, respectively. CRIX decides the number of constituents by AIC and tracks that number of cryptos with largest market-cap. In our case, the number of constituents in CRIX is 5. BITW20 is also a market-cap weighted crypto index but with the 20 largest market-cap cryptos outside the constituents of BITX. BITW70 has the same construction as BITW20 but with the 70 largest market-cap cryptos outside BITX and BITW20. Therefore, BTC is excluded as a constituent in BITW20 and BITW70.

For each of the 10 hedging portfolios, a crypto or index is considered as the spot and held in a unit size long position, while the front BTCF is held in a short position with units corresponding to the OHR in order to reduce the risk of the spot. Except for the hedge of BTC, all hedging portfolios are considered to be cross-asset hedges.

We collect the spots' and BTCF's daily prices at 15:00 US Central Time (CT). The reason for choosing this particular time is that the CME group determines the daily settlements for BTCF's based on the trading activities on CME Globex between 14:59 and 15:00 CT. This is also the reporting time

of the daily closing price by Bloomberg. The crypto spot data is collected from the data provider called Tiingo (https://www.tiingo.com/). Tiingo aggregates crypto OHLC (open, high, low, and close) prices fed by APIs from various exchanges. It covers major exchanges, such as Binance, Gemini, Poloniex etc., so Tiingo's aggregated OHLC price is a good representation a tradable market price. For each crypto, we match the opening price at 15:00 CT from Tiingo with the daily BTCF closing price from Bloomberg. Since CRIX is not available at 15:00 CT, we recalculated an hourly CRIX using the monthly constituents weights and the hourly OHLC price data collected from Tiingo. BITX, BITW20, BITW70, and BITW100 are collected from the official website of their publisher Bitwise.com. The daily reporting time of the Bitwise indexes is 15:00 CT.

At the time of writing, the CRIX is undergoing the listing process on the S&P Dow Jones Indices, the official CRIX data will then be calculated with Lukka Prime Data and available to the public via S&P.

4.2   Overview of the out-of-sample data

For every asset and hedge portfolio, we concatenate the out-of-sample data to form a time series for analysis. The date range of the out-of-sample time series is from 2019-10-21 to 2021-05-27, in total of 405 data points in each time series. We analyse these time series throughout the whole result section.

We introduce the out-of-sample data in this subsection before we proceed to analysing the hedged portfolio results. Figure 5 presents the BTC and BTCF price in USD in the first panel and the arithmetic difference between the daily return of BTC and BTCF, i.e. $R_s - R_f$, in the second panel. In the first panel, the black vertical lines with capital letter labels indicate the days of the five most negative daily return of BTC during out-pf-sample period. Table 1 summarizes the relevant news headlines and events of those days.

Figures 6 and 7 are the cumulative returns of the indices and individual cryptos respectively. The black vertical lines labeled by assets name are the largest daily price drop of the assets in the out-of-sample data.

The out-of-sample data covers the pre-COVID19 period, 2019-10-21 to 2020-03-09, as well as the COVID19 period, 2019-03-19 onwards. We can observe an overall upward trend of crypto prices in both periods. Nonetheless, the volatilities of assets are high (annualized around 100%) regardless of COVID19.
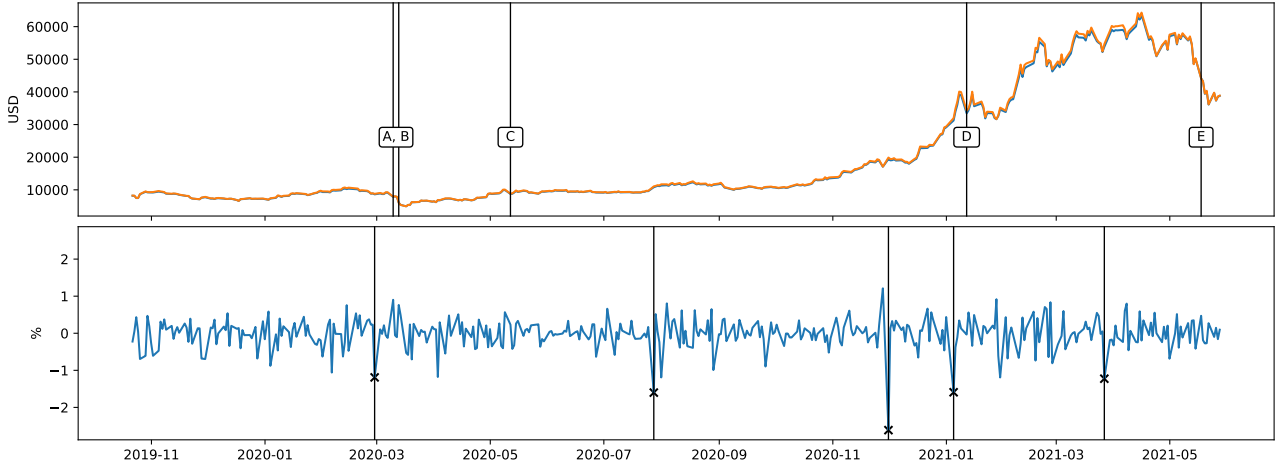
Figure 5: Out-of-sample BTC and BTCF price. The first panel presents the price of BTC in blue line and that of BTCF in orange line. The black vertical lines with capital letter labels indicate the five most negative daily return of BTC in the out-of-sample data. The second panel presents the difference between the % return of BTC and BTCF. The black vertical lines indicate the five most negative returns. The crosses locate the level the returns.

Label	Date	% Drop in Price	Summary
A	2020-03-09	13.83	Coronavirus outbreak that affect the global markets; BTC as potential safe-haven was questioned.[1]
B	2020-03-12	22.89	Continuation of the 2020-03-09 drop.
C	2020-05-11	12.11	Price correction (from $10,000 to $8,100) after BTC price surge because of the third supply halving.[2,3]
D	2021-01-11	14.41	Short term correction of BTC hits the $40,000 mark.[4]
E	2021-05-17	11.86	Tesla stopped taking BTC as payment due to environmental concerns about energy use to process transaction.[5]

Table 1: Summary of events that associated with the five most negative daily price drops in out-of-sample BTC price data. The capital letter labels in the first column are the labels in the first panel of figure 5. [1] is reported by the CNBC news `https://cnb.cx/3HZ2x7K`; [2] is from Forbes `https://bit.ly/3rdJPmP`; [3] is from livemint.com `https://bit.ly/3FRi6Na`; [4] is from CNBC `https://cnb.cx/3nU0pp0`; [5] is from Reuters `https://reut.rs/3leCiAv`.
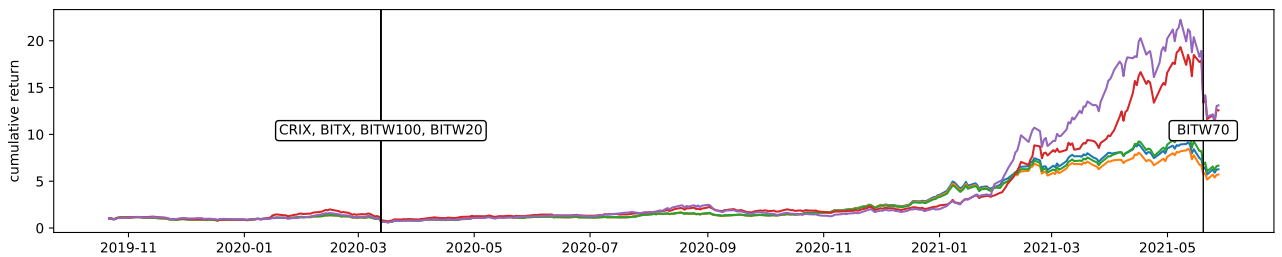
Figure 6: Out-of-sample cumulative return of crypto indices. The black vertical lines indicate largest price drop of indices indicated by the labels. The colouring is as follows: Blue line is CRIX; Orange line is BITX; Green line is BITW100; Red line is BITW20; Purple line is BITW70.
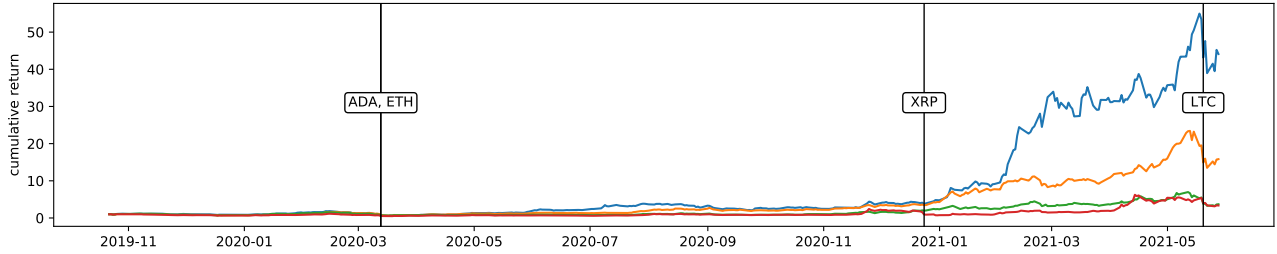
Figure 7: Out-of-sample cumulative return of individual cyptos. The black vertical lines indicate largest price drop of cryptos indicated by the labels. Blue line is ADA; Orange line is ETH; Green line is LTC; Red line is XRP.

Label	Date	% Drop in Price	Summary
CRIX	2020-03-09	23.77	Coronavirus outbreak that affect
BITX		23.68	the global markets including the
BITW100		23.87	crpyto market.
BITW20		26.66	
ADA		23.55	
ETH		27.40	
BITW70	2021-05-19	27.64	The spillover of the BTC shock on 2021-05-17 (label A in figure 5 and table 1)
XRP	2020-12-23	41.00	Top executives were sued by the SEC of misleading investors[1].

Table 2: Summary of events that associated with largest price drops in out-of-sample data. The labels in the first column are the labels in figure 6 and figure 7. CRIX, BITX, BITW100, BITW20, ADA and ETH have the same date the reason of the largest drop. [1] is reported by Bloomberg `https://bloom.bg/3cWdita`.
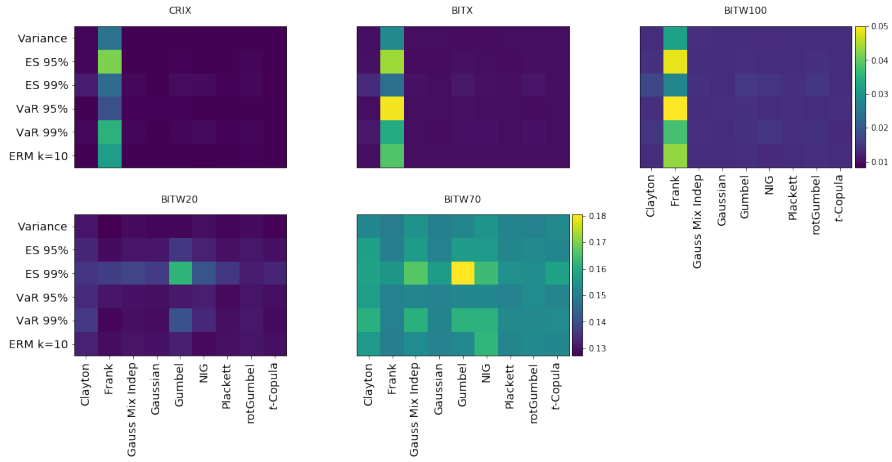
Figure 8: Out-of-sample mean square errors of indices' hedge portfolios. Plots in a row share the same colour scale for comparison.

Figure 9: Out-of-sample mean square errors of cryptos' hedge portfolios. Each plot has its own colour scale.

Figure 10: Out-of-sample lower semi variance of indices' hedge portfolios. Plots in a row share the same colour scale for comparison.

Figure 11: Out-of-sample lower semi variance of cryptos' hedge portfolios. Each plot has its own colour scale.

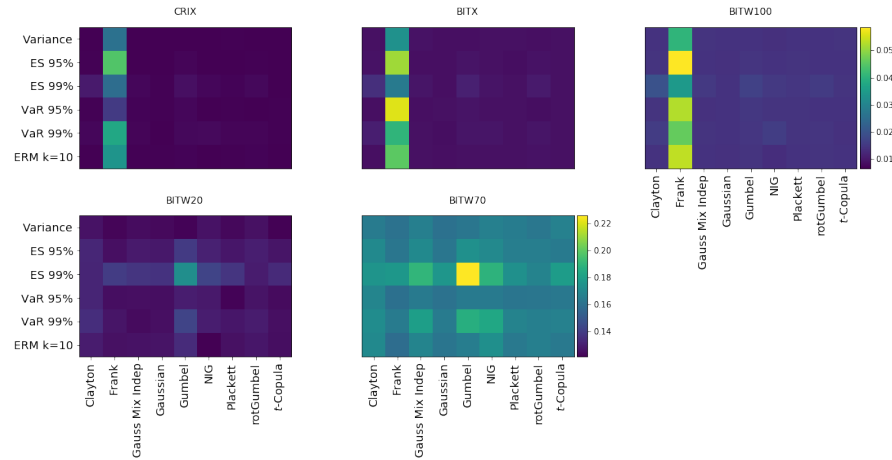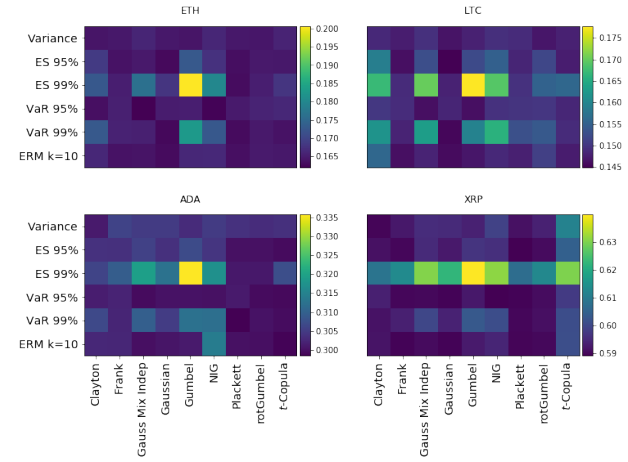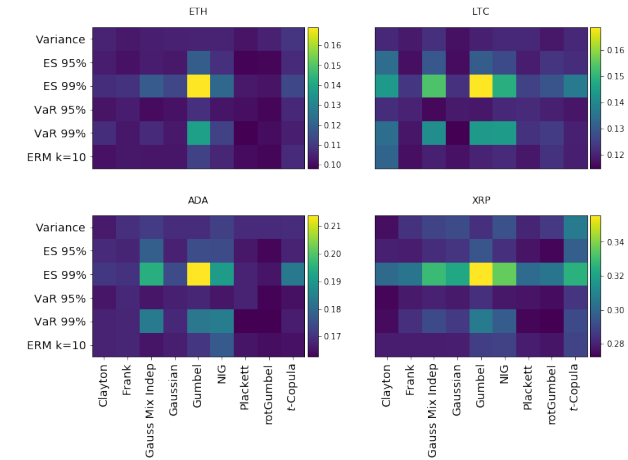| Spot/ Copula	t	Plackett	GMI	rotGumbel	NIG
Individual Cryptos					
BTC	73	4	2	1	31
ETH	3	6	8	94	1
ADA	0	0	0	0	112
LTC	13	0	3	32	64
XRP	0	31	3	78	0
Crypto Indices with BTC Constituent					
BITX	39	0	14	16	12
CRIX	47	0	11	3	27
BITW100	42	0	8	29	2
Crypto Indices without BTC Constituent					
BITW20	0	0	0	78	3
BITW70	0	0	0	80	1

Table 3: Copula selection results (shortened). The values are the counts of a copula chosen by the AIC procedure during the out-of-sample period. Each count represents five trading days since the each testing data consists of five trading days. The table shows only the frequently chosen copula, i.e. t, Plackett, Gaussian Mix Independent (GMI), rotated Gumbel (rotGumbel), and Normal Inverse Gaussian factor copula (NIG).

4.3 An overview of the hedged portfolios without the copula selection step

First, we analyse the results of hedged portfolios without the copula selection step in order to get a better understanding of how a copula affects the hedged portfolio with various risk minimization objectives. To do so, we inspect the hedge performance of copulas by the mean square error and lower semi-variance. The mean square error is the distance between a perfect hedge and the hedged portfolio returns $\text{MSE} = \mathbb{E}(R^2)$. The lower semi-variance is defined as $\text{LSV} = \mathbb{E}\left((R - \mathbb{E}(R))^2 \mathbf{1}_{\{R \leq \mathbb{E}(R)\}}\right)$. All results presentedd here are out-of-sample results obtained without the copula selection step in order to compare the performances across copulae.

Figure 3 and 4 are the mean square error and lower semivariance of BTC-BTCF. We can see that the Frank copula is the worst performing copula: the resulting hedged portfolio returns is far away from a perfect hedge. In Figures **??** and **??**, the phenomenom of Frank copula being inferior to its counterparts can be observed from the results of the CRIX, BITX, BITW100, and BITW20-BTCF portfolios. Interestingly, the spot in those portfolios usually have a strong dependence with the BTCF. In contrast, the inferiority of the Frank copula is less prominent in the BITW70, ADA, ETH, LTC and XRP-BTCF portfolios. We suspect that the Frank copula is not a choice to model assets with strong dependence.

We can also observe from Figures **??** and **??** that the Gumbel copula is not performing as well as other copulas in the ETH, LTC, and XRP-BTCF portfolios. The reason is the Gumbel copula has only upper tail dependence, while the ETH, LTC, and XRP exhibit lower tail dependence with BTCF. We will discuss this in the following section.

4.4 Copula Selection Results

Next, we inspect the copula selection result by the AIC procedure described in section 3.2.3. Although the copula selection is only an intermediate step to obtain the OHRs, the result of this step can help us better understand the dependence feature between BTCF and the assets we study in this work. This gives us valuable information to model the assets in the future. Decisions of the AIC procedure are summarised in Table 3.

Overall, the t-copula, rotated Gumbel (rotGumbel), and the NIG factor copula are the most frequently chosen copulae by the AIC procedure.

The t-copula is frequently chosen to model the dependence between the BTC and BTC-involving-indices, CRIX, BITX, BITW100, and the BTC future. BTC and BTC-involving-indices exhibit strong (upper and lower) tail dependence with BTCF. We interpret tail dependence as a strong tendency for one asset to be extreme when another is extreme and vice versa (McNeil et al., 2015). In fact, the t copula has been recommended in various empirical studies to model financial data, such as Zeevi and Mashal (2002) and Breymann et al. (2003). Those studies suggest that the t-copula is a better model compared to the Gaussian copula as financial data typically exhibit heavy tails and tail dependence.

On the other hand, the radial symmetry of the t-copula appears to be a poor choice to model the remaining hedging pairs. Demarta and McNeil (2005) describe the radial symmetry feature of the t-copula "strong" as it is a radially symmetric distribution. To be specific, if $(U_1, ..., U_d)$ is a vector distributed in t-copula, then $(U_1, ..., U_d) \overset{\mathcal{L}}{=} (1 - U_1, ..., 1 - U_d)$. This symmetry can be justified in the dependence structure between a futures and its underlying by the theory of futures pricing, which suggests the price of a futures is a function of the underlying price (Hull, 2003). However, there is no such relationship between a futures and an asset which is not the underlying. Besides, asset prices tend to crash simultaneously whereas positive development tends to be idiosyncratic.

Among the three popular copulae, rotGumbel copula shows its ability to model the dependence between ETH and BTCF. rotGumbel also performs well when modelling dependence between XRP, BITW20, BITW70, and the BTCF. In particular, the whole time series of the two indices, BITW20 and BITW70, are best fitted solely with the rotated Gumbel copula.

In fact, Clayton's AIC in many of the training sets is the second lowest, just higher than that of rotated Gumbel. This is because the Clayton copula has the same ability to model the lower quantile dependence. However, Clayton's radial like feature does not match the behaviour of the financial data.

It is worth to mention that although the NIG factor copula is penalised heavily due to its three parameters setup, it is frequently chosen to be the best copula to model the dependence between individual cryptos and the BTC future. An extreme case would be ADA, where only NIG factor is chosen in our dataset. Another dependence structure being best described by the NIG factor copula is the pair of LTC-BTCF, with 64 out of 112 training sets best fitted by the NIG factor copula. Indices like BITX and CRIX are sometimes best fitted with the NIG factor copula as well, accounting for modelling 12 and 27 training sets respectively. The popularity of the NIG factor copula reflects the ability of the copula to model very complex dependence structure: the NIG factor copula is able to model the tail, radial asymmetry.

The Frank copula is generally not a good choice to model financial data (as also reported by Barbi and Romagnoli (2014)). Plackett is characterised by its dependence parameter being equal to the

cross-product ratio, see eq. 9. However, apparently, this property does not capture the dependence structure of cryptos and BTCF.

4.5 Hedged portfolios with the copula selection step

	BTC	ETH	ADA	LTC	XRP	BITX	CRIX	BITW100	BITW20	BITW70
Assets										
Mean %	0.3915	0.6819	0.9467	0.3227	0.2987	0.4308	0.4602	0.4683	0.6249	0.6353
Std %	4.4023	6.0103	6.699	6.4781	7.9843	4.5676	4.542	4.6174	5.5021	5.8155
MD %	-25.9965	-32.0144	-26.8528	-37.5913	-52.7652	-27.022	-27.1385	-27.2694	-31.0092	-32.3453
MD date	2020-03-12	2020-03-12	2020-03-12	2021-05-19	2020-12-23	2020-03-12	2020-03-12	2020-03-12	2020-03-12	2021-05-19
Variance minimizing portfolios										
Mean %	0.0215	0.2823	0.5617	-0.0871	-0.0123	0.0561	0.0812	0.0855	0.2429	0.2706
Std %	0.3221	3.8741	5.2722	3.9052	7.1537	0.9954	0.9183	1.1986	3.5846	3.8838
MD %	-1.4393	-17.7421	-13.8687	-28.3029	-52.5236	-7.7567	-7.1025	-11.3866	-21.468	-23.9984
MD date	2020-11-30	2021-05-19	2021-01-08	2021-05-19	2020-12-23	2021-05-19	2021-05-19	2021-05-19	2021-05-19	2021-05-19
VaR 95% minimizing portfolios										
Mean %	0.0253	0.3084	0.5726	-0.0742	0.0208	0.0562	0.0863	0.0846	0.2728	0.2847
Std %	0.3294	3.8944	5.2204	3.9145	7.152	0.993	0.9151	1.198	3.594	3.9133
MD %	-1.5347	-19.175	-14.6974	-28.3672	-52.5667	-7.5639	-6.9744	-11.2582	-22.0733	-24.6513
MD date	2020-11-30	2021-05-19	2021-05-19	2021-05-19	2020-12-23	2021-05-19	2021-05-19	2021-05-19	2021-05-19	2021-05-19
VaR 99% minimizing portfolios										
Mean %	0.0176	0.2977	0.5562	-0.0852	0.0352	0.0593	0.0738	0.0823	0.2499	0.2788
Std %	0.3270	3.9132	5.3466	4.1503	7.1658	1.0178	0.9695	1.2338	3.621	3.9257
MD %	-1.5689	-18.6061	-15.4795	-29.0915	-52.5727	-8.0299	-7.0185	-11.8752	-21.6634	-24.5294
MD date	2020-11-30	2021-05-19	2021-05-19	2021-05-19	2020-12-23	2021-05-19	2021-05-19	2021-05-19	2021-05-19	2021-05-19
ES 95% minimizing portfolios										
Mean %	0.0204	0.3082	0.5525	-0.0808	0.0176	0.0591	0.0777	0.0848	0.2608	0.2785
Std %	0.3234	3.889	5.2673	3.9829	7.1533	1.0065	0.9207	1.2125	3.6115	3.9157
MD %	-1.5629	-18.7819	-14.9647	-28.4608	-52.5698	-7.6211	-6.9894	-11.1357	-21.543	-24.3474
MD date	2020-11-30	2021-05-19	2021-05-19	2021-05-19	2020-12-23	2021-05-19	2021-05-19	2021-05-19	2021-05-19	2021-05-19
ES 99% minimizing portfolios										
Mean %	0.0148	0.308	0.5016	-0.1029	-0.02	0.0598	0.0835	0.0781	0.2538	0.266
Std %	0.3476	3.8954	5.404	4.1581	7.2887	1.0312	0.9461	1.264	3.6323	3.932
MD %	-1.6225	-18.7625	-15.4481	-29.1727	-52.57	-7.7424	-7.0203	-11.9263	-21.9866	-24.4764
MD date	2020-11-30	2021-05-19	2021-05-19	2021-05-19	2020-12-23	2021-05-19	2021-05-19	2021-05-19	2021-05-19	2021-05-19
ERM $k = 10$ minimizing portfolios										
Mean %	0.0223	0.3117	0.5722	-0.0512	0.0155	0.059	0.084	0.0853	0.2564	0.2818
Std %	0.3221	3.8679	5.359	3.8812	7.1579	1.0078	0.9087	1.2032	3.6009	3.9074
MD %	-1.5242	-18.8729	-14.3885	-28.0879	-52.5689	-7.8581	-7.053	-11.1846	-21.592	-24.525
MD date	2020-11-30	2021-05-19	2021-01-08	2021-05-19	2020-12-23	2021-05-19	2021-05-19	2021-05-19	2021-05-19	2021-05-19

Table 4: First two moments, maximum downdown (MD) and date fo MD of assets and hedge portfolios out-of-sample return.

Table 4 presents the first two moments, maximum drawdown (MD) and the date of MD of the hedge portfolios. We observe that the statistics of the portfolios with different objectives are similar to each other. We provide the detail in Tables 6 to 11 in the appendix.

Unsurprisingly, the BTC-involved spots, i.e. BTC, CRIX, BITX, and BITW100, are well hedged by the BTCF regardless of risk minimization objective. Contrarily, BTC-not-involved spots' portfolios are less promising. Those hedge portfolios' returns are as volatile as the assets, see for example ADA and XRP. We will further discuss the effectiveness of hedge in the next section.

4.6 Hedging Effectiveness Results

In this section, we analyse the out-of-sample hedging effectiveness (HE) of BTCF as hedging. HE is defined as

$$\text{HE} = 1 - \frac{\rho_h}{\rho_s},$$

a measure of the percentage reduction of portfolio risk attribute, in our case the spot ρ_s, to hedged portfolio risk attribute ρ_h. A higher HE indicates a greater risk reduction and thus the hedge is more effective.

The HE above is a generalisation of how Ederington (1979) evaluate hedging performance. In addition to variance, we include the risk measures which act as loss function while searching for OHR: ES 95% and 99%, VaR 95% and 99% and ERM.

The formulation above gives a point estimate per testing data. However, each of our test data contain only 5 data points, the length is not sufficient to draw meaningful risk measure results. To address this issue, we apply bootstrapping method on the concatenated test data time series as described in the beginning of the result section.

The bootstrapping method is known to be a powerful nonparametric tool for approximating complicated statistics (Efron and Tibshirani, 1994; Davison and Hinkley, 1997). We apply stationary block bootstrapping to the time series introduced by Politis and Romano (1994) in our analysis in order to preserve the temporal structure of the data while sampling. The configuration of stationary bootstrapping procedure in this work is as follows. Assume a time series with N observations $\{X_t\}_{t \in [1,N]}$ is a strong stationary, weakly dependence time series of interest, we form blocks of samples $B = \{X_i, ..., X_{i+j-1}\}$. Index i is a random variable uniformly distributed over $[1, 2, ..., N]$ and j is geometric distributed random variable with parameter p. The block index i and block length j are independent. For any index k which is greater than N, the sample X_k is defined to be $X_{k(\mod N)}$. For each block, we calculate the hedging effectiveness with different risk measures mentioned above. We choose $p = 1/250$, implying the average block length is 250. This average block length is chosen to reasonably calculate ES and VaR. 100 blocks are drawn for each risk minimising objective and spot.

Figure 12 report the bootstrapped HE samples from the concatenated out-of-sample hedge portfolio return. As expected, the BTC involving spots, the BTC, CRIX, BITX and BITW100, are well hedged by the BTCF. The HEs of BTCF to other cryptos and indices are substantially lower than to the BTC involving spots, but the consistency the performances across different risk reduction objectives and HE evaluation remains.

Some HE bootstrapping samples are negative, it means that it is possible that introducing the BTC futures increases risk of the portfolios. This is an unfavorable situation for investors if they want to hedge cryptos with BTC futures. We do not recommend BTC futures being used to cross hedge cryptos.
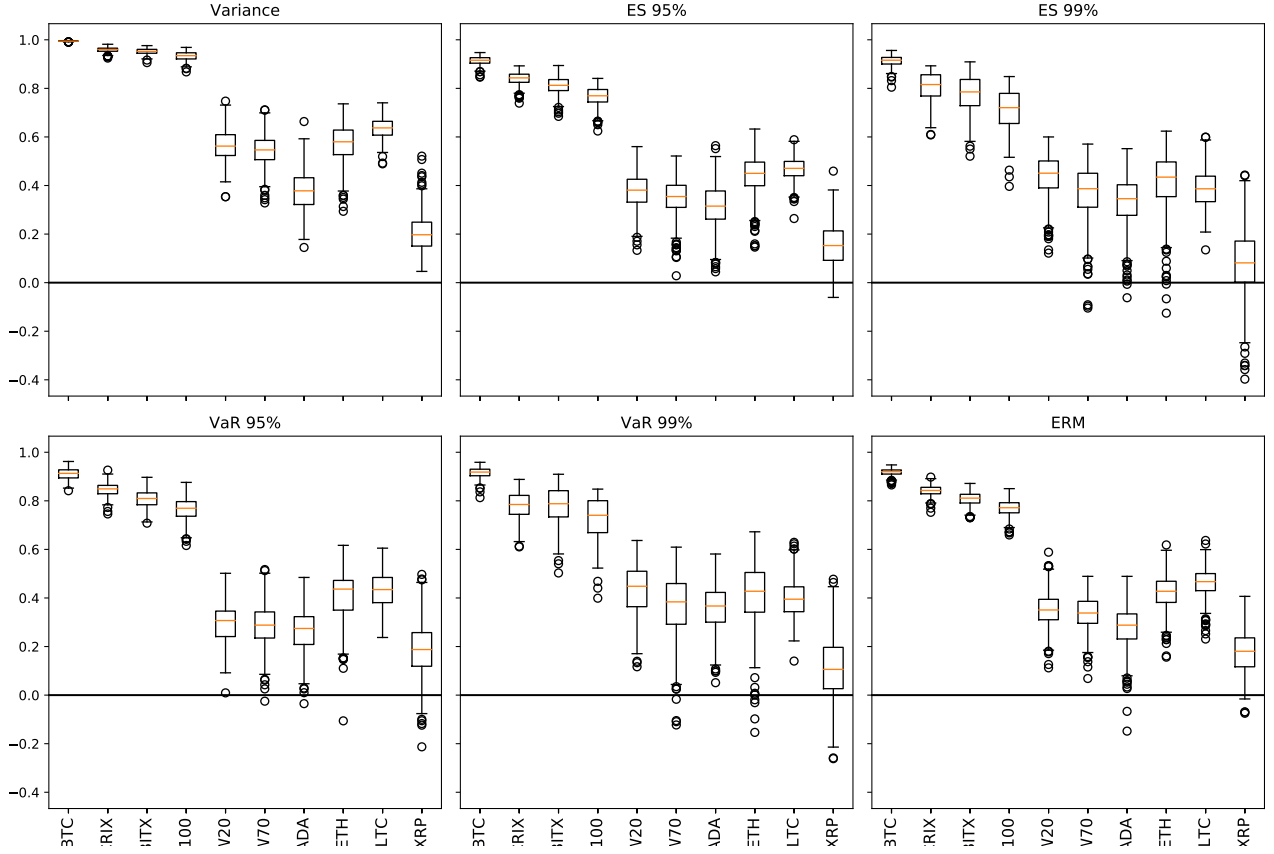
Figure 12: Hedging effectiveness (HE) of portfolios with different risk minimization objectives evaluated by the corresponding risk minimization objectives. The boxplots indicate the the median, upper quartile, lower quartile, minimium and maximum of the bootstrapped HE. The HE of BTC-involved spots are significantly higher than that of BTC-not-involved spots.

5 Conclusion and Outlook

We study the effectiveness of hedging cryptos and crypto indices with Bitcoin futures. To accomodate different risk appetites and scenarios, a variety of commonly used risk measures are considered to determine the optimal hedge ratio. The risk measures comprise variance, value-at-risk at the confidence levels 95% and 99%, expected shortfall 95% and 99%, and the exponential risk measure with parameter $k = 10$.

At the time of writing, the crypto market is a vibrant and fast-developing market, causing cryptos to have complex and time-changing dependence structures with the Bitcoin futures. As a consequence, the dependence between the cryptos and the futures contract plays an important role in hedging as it determines the distribution of the portfolio returns. We therefore consider various copulae, a flexible statistical tool that separates modelling of the marginals and the dependence structure of multivariate random vectors. To address the potential time-changing dependence, we periodically re-calibrate the copula models and determine the best-fitting copula via AIC.

An extensive out-of-sample backtest suggests that the Bitcoin futures are consistently capable of hedging BTC and BTC-involved indices, i.e., BITX, CRIX, and BITW100, under different risk minimisation objectives and copula models. The mean-square errors (MSEs) and lower semi-variances (LSVs) of the resulting portfolios are indistinguishably at a low level except for the Frank copula. On the other hand, the AIC procedure favours the t-copula because it captures the tail dependence feature of the data. Compared to the unhedged cases, the portfolios' out-of-sample maximum drawdowns are

significantly reduced.

Contrarily, we observe diverse results of the capability of BTC futures to hedge other cryptos and crypto indices that exclude Bitcoin. In general, ES 95% and VaR 95% perform better than their 99% counterparts. In particular, minimising ES 99% leads to relatively high MSEs and LSVs regardless of the copula in use. The ES 99% and VaR 99% even result in out-of-sample maximum drawdowns that are higher than that of the 95% counterparts in some portfolios, for example in the ETH- and LTC-BTCF portfolio. Therefore, we conclude that overly emphasising tail risks by choosing extreme tail risk measures does not lead to a promising hedge in a cross-hedging setting.

The AIC procedure mainly favours the rotated Gumbel and the NIG factor copula in modelling non-BTC relate cryptos and indices. This reflects the idiosyncratic nature of downward movements in the crypto market. Interestingly, the best-fitting copula does not necessary lead to the best performing portfolio in terms of MSE or LSV. For example, this is the case for ADA. We suspect this discrepancy between the optimal copula selection and MSE-LSV results can be attributed to the static linear nature of the hedge, as the sole hedge instrument is a futures contract.

Although copulae are flexible to model complex dependence structures by emphasising a number of important features such as lower tail dependence and radial symmetry, the simple linear hedge is very limited in its flexibility to address this complex dependence. Including liquidly traded derivatives with non-linear payoffs, such as options, might be a possibility to improve the hedge quality for these cryptos and portfolios.

6   Discussion

Cryptohedgers: Our results and conclusion are drawn using a non-parametric way, kernel density estimation, to fit the marginal density of the crypto and futures returns because we intend to leave the modelling of marginal distributions flexible and generic. Copula provides the flexibility to model marginal distributions separately. That means the model assumption and parametrisation for spot and futures can be different. This empowers hedgers to make use of variety of statistical tools to model the marginal distributions according to asset specific features they are interested, to enhance the model predictability, and hence, to improve the hedging effectiveness. For example, one can use various types of GARCH to deal with clustered volatility observed from the spot while using structural time series to deal with seasonality in futures; alternatively, using Hawkes processes to deal with clustered jumps in spots and futures without modelling the spillover or co-jumps in the marginal distribution. Hedgers are allowed to be creative in this regard. In fact, many researchers have enriched the understanding of the crypto market dynamics, see for example Kaiser (2019), Gyamerah and Abaitey (2022), and Mark et al. (2022). Although the hedging effectiveness of combining various statistical tools with copula remain an open question, our analysis shows that hedgers have the freedom to choose the copula (except the Frank copula) to model the dependence structure, whereas t, Plackett, Gaussian Mix independent, rotated Gumbel and NIG copula appear to be conservative choices to start the analysis.

Policy makers: Our results connect to the discussion of minimum capital requirements for crypto market risk exposure. The Basel Committee on Banking Supervision (BCBS) has made proposals and released consultative documents for the prudential treatment of banks' crypto-asset exposures. The Basel chair's stand on placing tough capital rules for crypto assets [4] attracted discussion. The Second Consultation proposes to limit banks' exposures to Group 2 cryptoassets to 1% of the bank's Tier 1 capital, calculated on a "double-gross" basis by adding the long and short

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[4]See https://www.risk.net/regulation/7948536/basel-chair-stands-by-tough-capital-rules-for-crypto-assets

positions without any hedging recognition Net position $=\max\left(\text{Long position}, |\text{Short position}|\right) -$ .65 $\min\left(\text{Long position}, |\text{Short position}|\right)$ (60.66). Respondents to the consultations argued that the proposed methodology of calculating exposure is an extremely restrictive quantitative measure that prohibits banks to manage limit utilisation to crypto assets as the addition of a hedge instrument; a price increase of the underlying cryptoassets could make banks breaching the limit. According to our results, BTC position's market risk measured in various risk measures, even for VaR99% and ES99%, can be effectively reduced by an appropriate size of opposite position in CME BTC futures. While the debates carry on at the time of writing, our results align and can be seen as an extension of the existing researches made by stakeholders, for example, research done by CME [5], and International Swaps and Derivatives Association's report [6].

On the other hand, our results support the cryptoassets categorisation criteria proposed by the Basel Committee. In the Second Consultation, Group 2 cryptoassets (Group 1 CCs are digitally tokenised traditional assets) are divided into two subcategories, Group 2a are the CCs that exists a derivative or exchange-traded fund (ETF)/exchange-traded note (ETN) that is traded on a regulated exchange that solely references the cryptoasset; Group 2b are the CCs that fail to meet the requirement. Our results suggest that the existence of derivative that solely references the cryptoasset empowers market participants to hedge their corresponding crypto position, thus it is sensible to treat the aforementioned Group 2a and 2b differently. On the contrary, we show that the hedging effectiveness significantly lower than 1 when the spot is different from what the CME futures is referencing, i.e. the cross hedge setting. That means the risk of holding a CC cannot be perfectly cross hedged by including the CME futures. Even worse, we observe negative HEs in some of the bootstrapped samples. From the great difference in hedging effectiveness between the BTC-BTCF and other cross hedge portfolios, we conclude that the existance of derivative that solely reference the cryptoasset is a sensible choice of crtyptoassets categorisation criteria as it reflects assessibility of market participants to form risk reduction strategy.

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[5]See the CME and KPMG's report on `https://www.cmegroup.com/education/files/basics-of-hedge-effectiveness.pdf`

[6]See the ISDA report "Crypto-asset Risks and Hedging Analysis" on `https://www.isda.org/a/pMWgE/Crypto-asset-Risks-and-Hedging-Analysis.pdf`

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A   Density of linear combination of random variables

Proposition 6 *Let $\boldsymbol{X} = (X_1, ..., X_d)^\top$ be real-valued random variables with corresponding copula density $c_{X_1,...,X_d}$, and continuous marginals $F_{X_1}, ..., F_{X_d}$. Then, the pdf of the linear combination of marginals $Z = n_1 \cdot X_1 + ... + n_d \cdot X_d$ is*

$$f_Z(z) = \left| n_1^{-1} \right| \int_{[0,1]^{d-1}} c_{X_1,...,X_d} \left(F_{X_1}(S(z)), u_2, ..., u_d \right) \cdot f_{X_1}(S(z)) \mathrm{d}u_2...\mathrm{d}u_d \tag{10}$$

$$S(z) = \frac{1}{n_1} \cdot z - \frac{n_2}{n_1} \cdot F_{X_2}^{(-1)}(u_2) - ... - \frac{n_d}{n_1} \cdot F_{X_d}^{(-1)}(u_d).$$

Proof.   Let $Z = n_1 \cdot X_1 + ... + n_d \cdot X_d$ and let $\mathbf{A} = \begin{bmatrix} n_1 & n_2 & \cdots & n_d \\ 0 & 1 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & & 1 \end{bmatrix}$. Then,

$$\begin{bmatrix} Z \\ X_2 \\ \vdots \\ X_d \end{bmatrix} = \boldsymbol{A} \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_d \end{bmatrix}.$$

By transformation of the variables (Härdle and Simar, 2019)

$$\boldsymbol{f}_{Z,X_2,...,X_d}(z, x_2, ..., x_d) = \boldsymbol{f}_{X_1,...,X_d} \left(\boldsymbol{A}^{-1} \begin{bmatrix} z \\ x_2 \\ \vdots \\ x_d \end{bmatrix} \right) \cdot | \det \boldsymbol{A}^{-1} |$$

$$= \left| n_1^{-1} \right| \boldsymbol{f}_{X_1,...,X_d} \left(S(z), x_2, ..., x_d \right).$$

Let $u_i = F_{X_i}(x_i)$ and by chain rule we have

$$\boldsymbol{f}_{X_1,...,X_d}(x_1, ..., x_d) = \frac{\partial^d F_{X_1,...,X_d}(x_1, ..., x_d)}{\partial x_1...\partial x_d}$$

$$= c_{X_1,...,X_d}(u_1, ..., u_d) \cdot \prod_{i=1}^{d} f_{X_i}(x_i).$$

Therefore,

$$\boldsymbol{f}_{Z,X_2,...,X_d}(z, x_2, ..., x_d) =$$

$$\left| n_1^{-1} \right| \cdot c_{X_1,...,X_d} \left(F_{X_1}(S(z)), u_2, ..., u_d \right) \cdot f_{X_1}\{S(z)\} \cdot \prod_{i=2}^{d} f_{X_i}(x_i).$$

The claim (10) is obtained by integrating out $x_2, ...x_d$ by substituting $\mathrm{d}x_i = \frac{1}{f_{X_i}(x_i)} \mathrm{d}u_i$. ∎

B Summary Statistics of Assets

	Mean %	Std %	Skew	Kurt	MD %	MD date	ρ	τ
Hedging Instrument								
BTCF	0.3906	4.6312	-0.5060	4.4204	-26.9920	2020-03-12	1.0000	1.0000
Individual Cryptos								
BTC	0.3915	4.4023	-0.5857	4.6565	-25.9965	2020-03-12	0.9975	0.9507
ETH	0.6819	6.0103	-0.2557	5.2646	-32.0144	2020-03-12	0.7712	0.5988
ADA	0.9467	6.6990	0.1661	2.3086	-26.8528	2020-03-12	0.6296	0.4825
LTC	0.3227	6.4781	-0.9935	5.3011	-37.5913	2021-05-19	0.8080	0.6113
XRP	0.2987	7.9843	0.5542	12.4882	-52.7652	2020-12-23	0.4510	0.4939
Crypto Indices with BTC Constituent								
BITX	0.4308	4.5676	-0.8842	4.7222	-27.0220	2020-03-12	0.9769	0.8738
CRIX	0.4602	4.5420	-0.7952	4.7549	-27.1385	2020-03-12	0.9799	0.8769
BITW100	0.4683	4.6174	-0.9864	4.9381	-27.2694	2020-03-12	0.9674	0.8537
Crypto Indices without BTC Constituent								
BITW20	0.6249	5.5021	-1.1518	5.2203	-31.0092	2020-03-12	0.7674	0.5883
BITW70	0.6353	5.8155	-1.1171	5.1926	-32.3453	2021-05-19	0.7525	0.5459

Table 5: Summary statistics of assets' daily returns during the out-of-sample period, from 2019-10-21 to 2021-05-27. The first four columns are the first four moments of assets' daily returns. The fifth and sixth columns are the maximum drawdown (MD) and the date of the MD. The last two columns are Pearson's ρs and Kendall's τs between the assets and BTCF.

C Summary Statistics of Hedged Portfolios

	Mean %	Std %	Skew	Kurt	MD %	MD date	Variance
Individual Cryptos							
BTC	0.0215	0.3221	-1.0119	3.1929	-1.4393	2020-11-30	0.0000
ETH	0.2823	3.8741	0.9469	7.1064	-17.7421	2021-05-19	0.0015
ADA	0.5617	5.2722	1.3634	4.4818	-13.8687	2021-01-08	0.0028
LTC	-0.0871	3.9052	-0.3617	7.6239	-28.3029	2021-05-19	0.0018
XRP	-0.0123	7.1537	1.1451	20.0236	-52.5236	2020-12-23	0.0043
Crypto Indices with BTC Constituent							
BITX	0.0561	0.9954	-0.4204	13.2487	-7.7567	2021-05-19	0.0001
CRIX	0.0812	0.9183	-0.0027	14.3136	-7.1025	2021-05-19	0.0001
BITW100	0.0855	1.1986	-1.7440	22.2644	-11.3866	2021-05-19	0.0001
Crypto Indices without BTC Constituent							
BITW20	0.2429	3.5846	-0.3063	4.1622	-21.4680	2021-05-19	0.0013
BITW70	0.2706	3.8838	-0.6490	4.6312	-23.9984	2021-05-19	0.0015

Table 6: Summary statistics of out-of-sample daily returns of hedged portfolios that minimize variance.

	Mean %	Std %	Skew	Kurt	MD %	MD date	VaR 5%
Individual Cryptos							
BTC	0.0253	0.3294	-0.9725	3.4373	-1.5347	2020-11-30	0.0063
ETH	0.3084	3.8944	1.0243	7.4297	-19.1750	2021-05-19	0.0514
ADA	0.5726	5.2204	1.2981	4.2544	-14.6974	2021-05-19	0.0769
LTC	-0.0742	3.9145	-0.3836	7.5384	-28.3672	2021-05-19	0.0622
XRP	0.0208	7.1520	1.1269	19.8930	-52.5667	2020-12-23	0.0683
Crypto Indices with BTC Constituent							
BITX	0.0562	0.9930	-0.3117	12.4780	-7.5639	2021-05-19	0.0128
CRIX	0.0863	0.9151	0.0718	13.7915	-6.9744	2021-05-19	0.0092
BITW100	0.0846	1.1980	-1.6592	21.3725	-11.2582	2021-05-19	0.0164
Crypto Indices without BTC Constituent							
BITW20	0.2728	3.5940	-0.3721	4.4896	-22.0733	2021-05-19	0.0546
BITW70	0.2847	3.9133	-0.6580	4.7874	-24.6513	2021-05-19	0.0626

Table 7: Summary statistics of out-of-sample daily returns of hedged portfolios that minimize VaR 5%.

	Mean %	Std %	Skew	Kurt	MD %	MD date	VaR 1%
Individual Cryptos							
BTC	0.0176	0.3270	-1.0405	3.3742	-1.5689	2020-11-30	0.0134
ETH	0.2977	3.9132	0.9547	7.2414	-18.6061	2021-05-19	0.1026
ADA	0.5562	5.3466	1.1362	3.9334	-15.4795	2021-05-19	0.1106
LTC	-0.0852	4.1503	-0.7234	7.3208	-29.0915	2021-05-19	0.1030
XRP	0.0352	7.1658	1.1582	19.8506	-52.5727	2020-12-23	0.1387
Crypto Indices with BTC Constituent							
BITX	0.0593	1.0178	-0.5331	13.3100	-8.0299	2021-05-19	0.0247
CRIX	0.0738	0.9695	-0.4729	13.6500	-7.0185	2021-05-19	0.0245
BITW100	0.0823	1.2338	-1.9365	23.1938	-11.8752	2021-05-19	0.0347
Crypto Indices without BTC Constituent							
BITW20	0.2499	3.6210	-0.3866	4.3396	-21.6634	2021-05-19	0.0988
BITW70	0.2788	3.9257	-0.7635	5.1288	-24.5294	2021-05-19	0.1147

Table 8: Summary statistics of out-of-sample daily returns of hedged portfolios that minimize VaR 1%.

	Mean %	Std %	Skew	Kurt	MD %	MD date	ES 5%
Individual Cryptos							
BTC	0.0204	0.3234	-1.0150	3.4423	-1.5629	2020-11-30	0.0101
ETH	0.3082	3.8890	1.0119	7.4077	-18.7819	2021-05-19	0.0782
ADA	0.5525	5.2673	1.2557	4.2423	-14.9647	2021-05-19	0.0984
LTC	-0.0808	3.9829	-0.4957	7.2302	-28.4608	2021-05-19	0.0962
XRP	0.0176	7.1533	1.1411	19.9176	-52.5698	2020-12-23	0.1354
Crypto Indices with BTC Constituent							
BITX	0.0591	1.0065	-0.3453	12.1335	-7.6211	2021-05-19	0.0215
CRIX	0.0777	0.9207	0.0164	13.5608	-6.9894	2021-05-19	0.0173
BITW100	0.0848	1.2125	-1.6397	19.7472	-11.1357	2021-05-19	0.0274
Crypto Indices without BTC Constituent							
BITW20	0.2608	3.6115	-0.3555	4.2016	-21.5430	2021-05-19	0.0804
BITW70	0.2785	3.9157	-0.6949	4.8047	-24.3474	2021-05-19	0.0908

Table 9: Summary statistics of out-of-sample daily returns of hedged portfolios that minimize ES 5%.

	Mean %	Std %	Skew	Kurt	MD %	MD date	ES 1%
Individual Cryptos							
BTC	0.0148	0.3476	-0.8354	3.3054	-1.6225	2020-11-30	0.0234
ETH	0.3080	3.8954	0.9840	7.4947	-18.7625	2021-05-19	0.1299
ADA	0.5016	5.4040	1.1008	3.9607	-15.4481	2021-05-19	0.1463
LTC	-0.1029	4.1581	-0.7757	7.4375	-29.1727	2021-05-19	0.1647
XRP	-0.0200	7.2887	1.1121	18.8732	-52.5700	2020-12-23	0.2516
Crypto Indices with BTC Constituent							
BITX	0.0598	1.0312	-0.4410	11.5863	-7.7424	2021-05-19	0.0411
CRIX	0.0835	0.9461	-0.0361	12.4047	-7.0203	2021-05-19	0.0350
BITW100	0.0781	1.2640	-1.9645	21.8836	-11.9263	2021-05-19	0.0593
Crypto Indices without BTC Constituent							
BITW20	0.2538	3.6323	-0.4086	4.4462	-21.9866	2021-05-19	0.1282
BITW70	0.2660	3.9320	-0.7598	5.0050	-24.4764	2021-05-19	0.1535

Table 10: Summary statistics of out-of-sample daily returns of hedged portfolios that minimize ES 1%.

	Mean %	Std %	Skew	Kurt	MD %	MD date	ERM k=10
Individual Cryptos							
BTC	0.0223	0.3221	-1.0008	3.4153	-1.5242	2020-11-30	0.0057
ETH	0.3117	3.8679	1.0345	7.5751	-18.8729	2021-05-19	0.0491
ADA	0.5722	5.3590	1.4203	4.6970	-14.3885	2021-01-08	0.0700
LTC	-0.0512	3.8812	-0.2929	7.7022	-28.0879	2021-05-19	0.0616
XRP	0.0155	7.1579	1.1244	19.8583	-52.5689	2020-12-23	0.0787
Crypto Indices with BTC Constituent							
BITX	0.0590	1.0078	-0.4427	13.0839	-7.8581	2021-05-19	0.0127
CRIX	0.0840	0.9087	0.0488	14.5501	-7.0530	2021-05-19	0.0100
BITW100	0.0853	1.2032	-1.6522	20.5562	-11.1846	2021-05-19	0.0153
Crypto Indices without BTC Constituent							
BITW20	0.2564	3.6009	-0.3446	4.2152	-21.5920	2021-05-19	0.0503
BITW70	0.2818	3.9074	-0.6952	4.8745	-24.5250	2021-05-19	0.0557

Table 11: Summary statistics of out-of-sample daily returns of hedged portfolios that minimize ERM $k = 10$.

C.1 Supplementary Material: Intraday Hedging

This supplementary material extends the study in the main body to the intraday rebalancing setting. Studying the intraday hedge is familiar to academia, e.g. Harris et al. (2010), Dungey et al. (2013), Tse and Williams (2013), and Sheu and Lai (2014). Numerous pieces of work on the crypto market are associated with or motivated by the presence of intraday traders as well, e.g. Petukhina et al. (2021), Meshcheryakov et al. (2020), Alexander et al. (2022), Zhang et al. (2022), and Katsiampa et al. (2022).

We have in view to robustify the results from the main body. The methodology in this supplementary material is similar to the main body, except we

1. form two hedging portfolios, BTC-BTCF and ETH-BTCF,

2. simulate trades using Deribit hourly data, and

3. rebalance every four hours.

C.1.1 Data

The intraday analysis is built upon a dataset of date range from 2020-06-01 00:00 UTC to 2020-08-01 00:00 UTC. All the price data are sampled hourly.

The Deribit contract BTCUSD25SEP20 represents the BTCF; the Deribit BTC and ETH index represent the spot of BTC and ETH respectively. We take the hourly closing mid-price of the BTCUSD25SEP20 as the futures price and the last value of the BTC and ETH index in every hourly bucket as the spot prices. Since the date range of the data is fully covered by the lifetime of BTCUSD25SEP20, this study does not require rolling procedure to roll over futures contract near expiry.

C.1.2 Procedure

Starting from oldest data:

1. Calibrate a copula by a training data of 336 datapoints, equivalent to 14 days data

2. Draw samples $(\tilde{r}_s, \tilde{r}_f)$ from the calibrated copula

3. Numerically search for $h^* = \arg\max \phi(\tilde{r}_s - h\tilde{r}_f)$ according to a risk measure ϕ

4. Apply h^* to testing data to yield r_h; the testing data is the consecutive 4 data points to training data, i.e. the 4 hours data consecutive to the last training data

5. Repeat the procedure for the next 4 datapoints

6. Concatenate r_hs the and sort chronologically to form a full length out-of-sample hedging portfolio returns

The procedure is further repeated for all the combinations of risk measures and copulae. The full-length out-of-sample returns represent the corresponding performance of a particular risk measure-copula combination. They are used in computation mean square error (MSE) and lower-semi-variance (LSV) shown in the following section.

The AIC selection step is performed between step 1 and step 2 of the procedure above. The resulting out-of-sample returns are a mix of results from the copula that has the lowest AIC on the
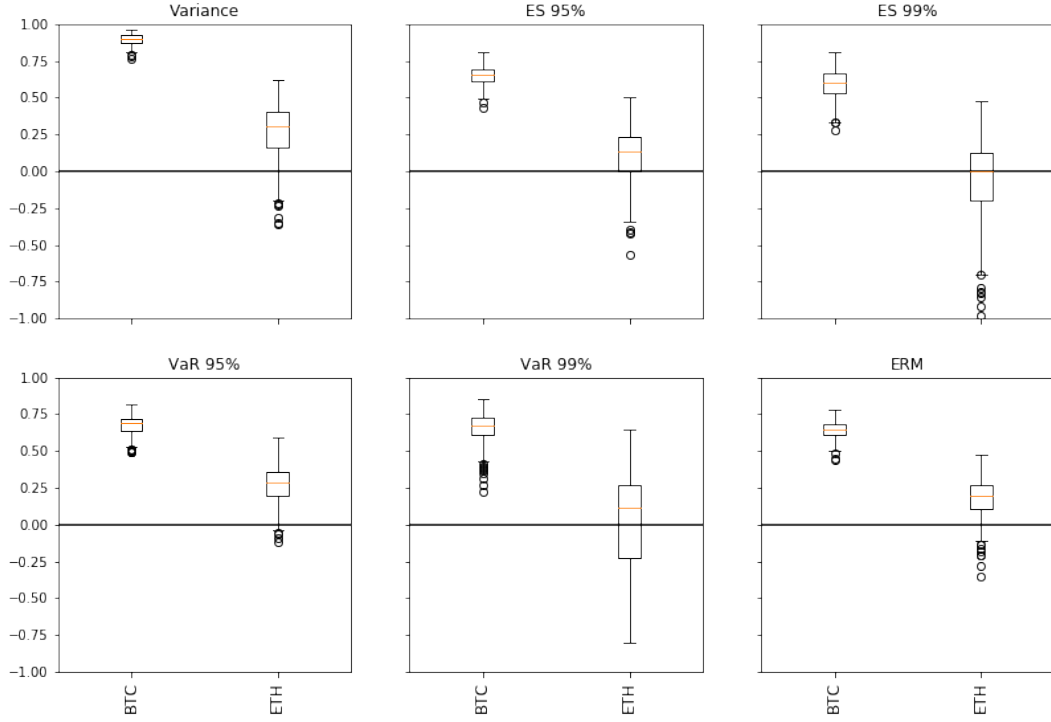
Figure 13: Intraday HEs of BTC-BTCF and ETH-BTCF portfolio. The HEs of BTC-BTCF portfolios are significantly higher than 0, which suggests involving the BTCF in the portfolio can effectively reduce market risk. The HEs of ETH-BTCF portfolios are lower than that of BTC-BTCF portfolios, and sometimes go below 0. We nullify the hedging ability of BTCF in this intraday ETH-BTCF setting.

training data. We keep a record of how many times a copula is choosen by this step. To yield robust HE measures, we apply stationary bootstrapping to the full-length AIC selected OOS returns with the following parameters: $p = 1/4, T = 300, N = 1000$.

C.1.3 Results

Bootstrapped OOS HEs: The analysis begins with the boxplot in figure 13 of the bootstrapped OOS HEs. In general, most of the daily rebalancing results of BTC-BTCF carry over to the intraday rebalancing schedule; The intraday rebalancing ETH-BTCF is different from its daily rebalancing counterpart. Note that the exact values of HEs from the two rebalancing schedules should not be directly compared for two reasons: 1. The data are from different date ranges; 2. Various factors contribute to the difference between results from different sampling frequencies, e.g. Epps effect, microstructure noise, and asynchronous trading. However, we compare the patterns and conclusions to get a general understanding of the hedging issue for future use.

The main difference between the intraday rebalancing and daily rebalancing ETH-BTCF portfolio is negative HEs appear in the intraday results in all the risk measures we consider. The negative HEs suggests that BTCF should not be used to hedge against ETH in an intraday setting. Consider also the fact that BTCF is written on BTC instead of ETH, hedgers have no ground to assume they can take advantage of the intraday dependency structure between ETH and BTCF for hedging. Therefore, we mainly focus on the BTC-BTCF portfolios and mentioning the results of the ETH-BTCF portfolio
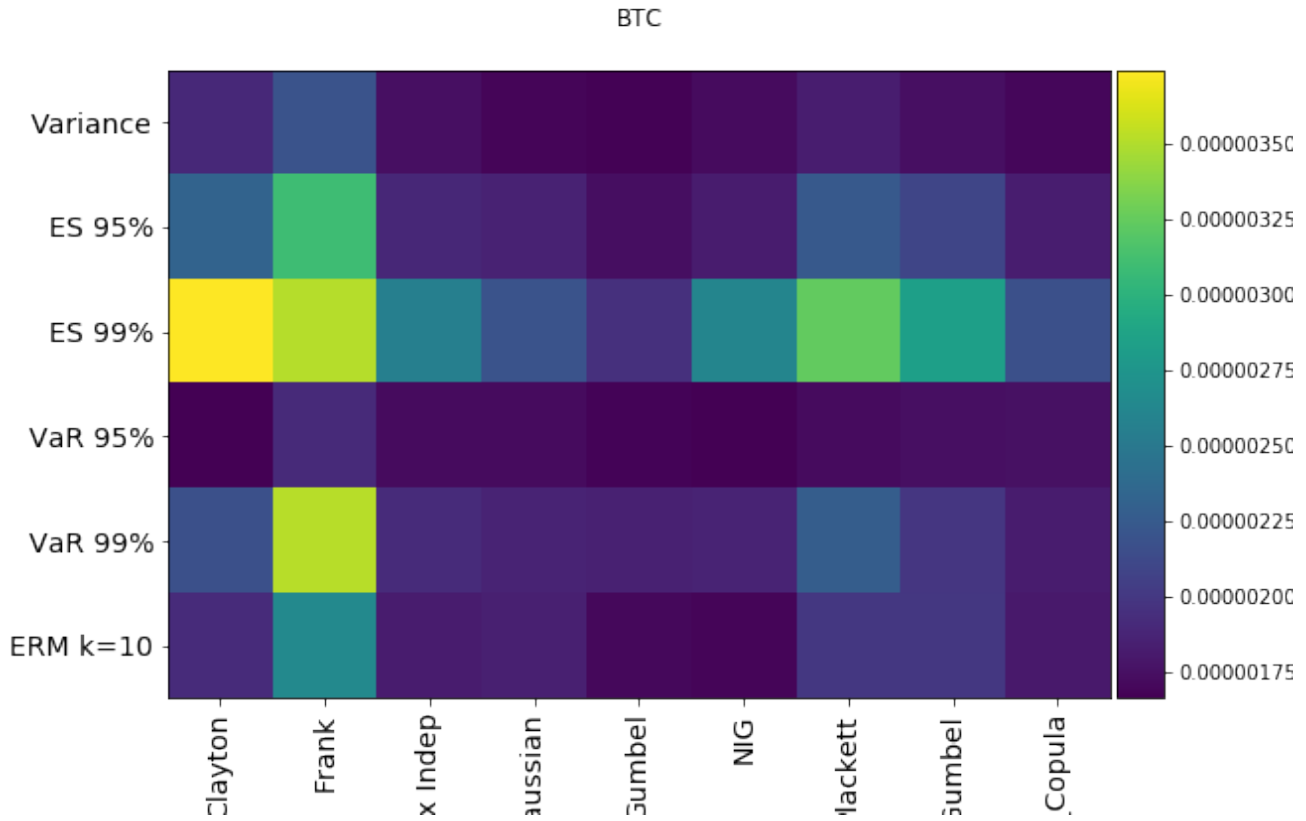
Figure 14: Intraday out-of-sample MSEs of the BTC-BTCF portfolio constructed by combinations of copula and ris minimization objectives. The Frank copula is again inferior. Minimising ES99% results in higher MSEs disregard of which copula is in use.

is needed.

BTC-BTCF HEs: The HEs of BTC-BTCF are significantly higher than zero across different risk measures, suggesting that adding BTCF to a BTC portfolio can effectively reduce the risk measured by selected measures. Among risk measures, HE of variance is the highest for the BTC-BTCF portfolio, ranging from 72% to 98%; HE of other risk measures ranges from 25% to 80%. This result suggests that reducing variance is a well-achievable objective in the intraday setting. This finding is consistent with the conclusions of the daily rebalancing schedule. On the other hand, the HEs of ES99% and VaR99% are relatively more dispersed and skewed to the left. Both risk measures consider only 1% of the data from the left for deciding the hedge ratio and computing the HEs. Considering only a few data points naturally leads to a less reliable hedge ratio and lower consistency HEs. Evidence also shows that ES99% VaR99% minimising portfolios have higher MSE and LSV. This result is again consistent with the daily rebalancing setting.

BTC-BTCF MSE and LSV: Figures 14 and 15 report the OOS MSE and LSV of the BTC-BTCF when different copula and risk measures are in use. The MSE and LSV are in a similar magnitude with a few exceptions, a similar pattern to the daily rebalancing setting.

Across various copulae, the BTC-BTCF portfolio that minimises VaR95% provides the lowest MSE and LSV. Portfolios that minimise variance and ERM k=10 result in similar magnitudes of MSEs and LSVs, which are higher than VaR95% but not by much, especially when Gumbel and NIG copulae are in use to model the dependency. ES99% generates the highest MSEs and LSVs, disregarding which copula is in use. Notice that the portfolios that minimise ES99% and VaR99% are generally riskier
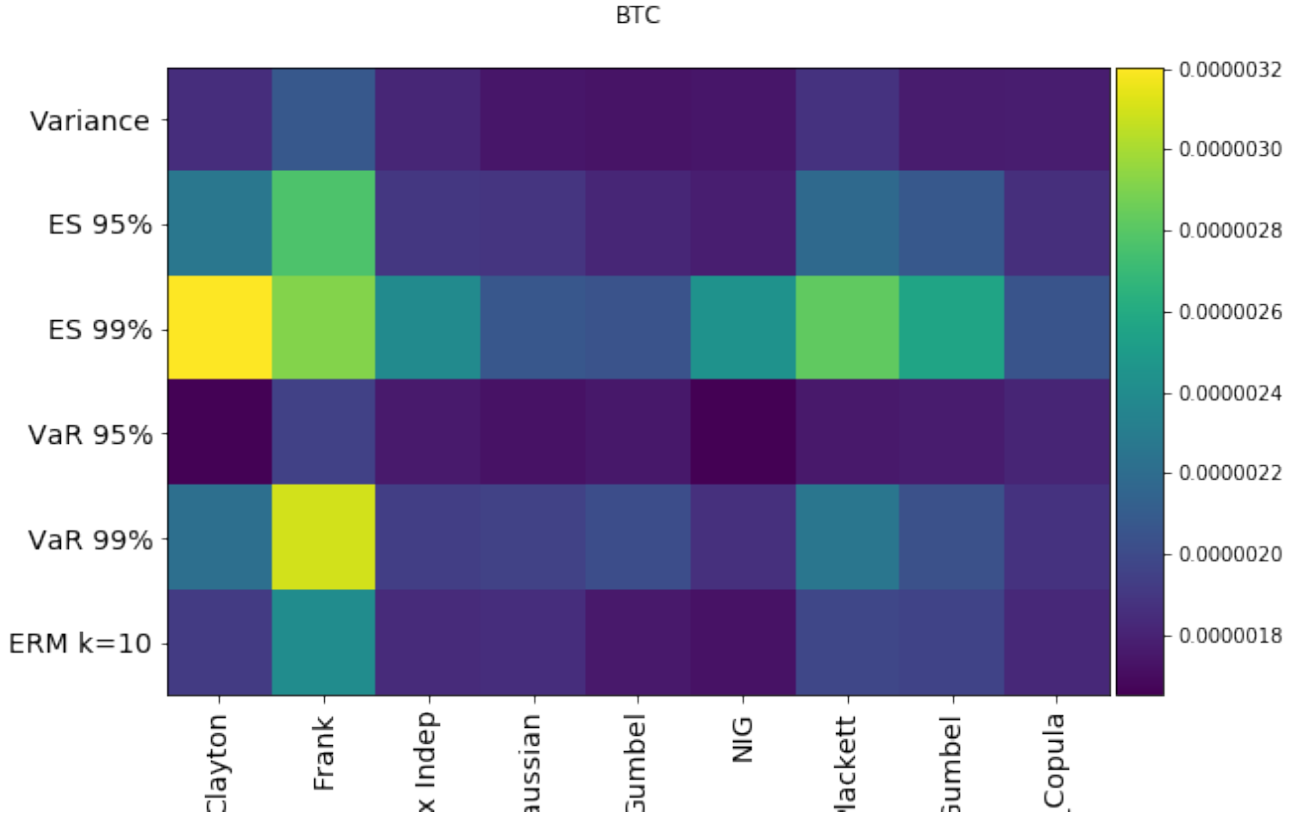
Figure 15: Intraday out-of-sample LSVs of the BTC-BTCF portfolio constructed by combinations of copula and ris minimization objectives. The Frank copula is again inferior. Minimising ES99% results in higher MSEs disregard of which copula is in use.

than their 95% counterparts in terms of MSEs and LSVs.

Across various risk measures, Gumbel and NIG copulae are performing very well in the resulting portfolios' MSE and LSV, except for ES99%. The Frank copula is underperforming, disregarding which risk measures are in use. These results are consistent with the daily rebalancing setting and results in other literature. Notice that Gumbel and NIG are the only copulae that can model upper tail dependence among the copulae we examine. This suggests that the upper tail dependence is an essential feature of the dependency structure for hedging. The conclusion is further supported by comparing the Gumbel and the rotated Gumbel copula. The rotated Gumbel copula is the 180-degree rotated version of the Gumbel copula, sharing all the features of the Gumbel copula but switching from modelling the lower tail dependence to upper tail dependence. The rotated Gumbel copula results in portfolios with higher MSEs and LSVs consistently across risk measures.

AIC selection results: From table 12, we can see the AIC procedure favours the same set of copulae in the intraday setting for both BTC-BTCF and ETH0BTCF portfolios. They are t-, Plackett, Gaussian Mix Independent, rotated Gumbel and NIG. Similar to the result in the daily rebalancing schedule, most of the time, 60% in this case, the AIC procedure chooses t-Copula to model the dependence structure of BTC-BTCF in the intraday setting. For the rest of the time, the NIG copula is mainly chosen, accounting for around 26% of the time. Rotated Gumbel, Gaussian Mix Independent, and Plackett are spontaneously chosen. On the other hand, the intraday ETH-BTCF's AIC selection result is very different from that of the daily rebalancing. There are three copulae: t-, Gaussian Mix Independent, and NIG copula, that are closely chosen, instead of a single copula, rotated Gumbel

Spot/ Copula	t	Plackett	GMI	rotGumbel	NIG
BTC	60.00	1.11	3.33	8.89	26.67
ETH	35.14	0	24.32	15.68	24.86

Table 12: Intraday copula selection results (shortened). The values are the percentage counts of a copula chosen by the AIC procedure during the out-of-sample period. The table shows only the frequently chosen copula, i.e. t, Plackett, Gaussian Mix Independent (GMI), rotated Gumbel (rotGumbel), and Normal Inverse Gaussian factor copula (NIG).

copula, dominating the list in the daily rebalancing setting. In the intraday setting, the three copulae are chosen 35.1%, 24.9%, and 24.3% of the time, respectively.