ASSESSING THE STABILIZING ROLE OF STABLECOINS IN CRYPTOMARKETS

Diego Huélamo Longas

Trabajo de investigación 21/014

Master en Banca y Finanzas Cuantitativas

Tutores: Dr. Antonio Díaz
Dr. Carlos Esparcia

Universidad Complutense de Madrid

Universidad del País Vasco

Universidad de Valencia

Universidad de Castilla-La Mancha

www.finanzascuantitativas.com

Máster en Banca y Finanzas Cuantitativas

Trabajo de Fin de Máster

Assessing the stabilizing role of stablecoins in cryptomarkets

Autor:
Diego Huélamo Longás

Directores:
Antonio Díaz Pérez
Carlos Esparcia Sanchís

20 de septiembre de 2021

Abstract

This paper empirically assesses the ability of three putative stablecoins (two dollar-backed, Tether and USD Coin; and one gold-backed, Digix Gold) to reduce the risk of a traditional cryptocurrency portfolio during the COVID-19 pandemic. A monthly rebalance experiment is conducted over an out-of-sample period, so that the effects of including stablecoins in terms of diversification can be clearly assessed. The GO-GARCH model is implemented to obtain dynamic estimates of conditional co-moment arrays up to order four. Then, assuming a CARA utility function and a risk defensive investor profile, an extension of the certainty equivalent with co-skewness and co-kurtosis is conducted for portfolio allocation purposes. Using the Cornish-Fisher expansion of the parametric VaR (i.e., the modified VaR), we evaluate how the introduction of every single stablecoin into a traditional cryptocurrency portfolio affects the downside risk of the combined strategy. Our results reveal that the two dollar-backed tokens have high diversification and hedging capabilities against traditional cryptocurrencies and can even act as safe havens, whereas Digix Gold shows a high diversification potential, but constrained by its high intrinsic volatility. The empirical evidence highlights the importance of considering higher order moments when forming cryptocurrency portfolios and measuring their risk.

Keywords: Stablecoin; Cryptocurrency; Diversification; modified VaR; Portfolio allocation; Higher order moments

Contents

1 Introduction

Since 2008, when a person or group of people under the pseudonym of Satoshi Nakamoto published Bitcoin's white paper (Nakamoto, 2008), the crypto ecosystem has aroused growing interest among an increasingly wide range of agents. So much so that many authors consider cryptocurrencies are a new investment asset class (Glaser et al., 2014; Phillip et al., 2018; Corbet et al., 2018; Gil-Alana et al., 2020; Sifat, 2021). Bitcoin's proposal as a currency with a scarcity paradigm, decentralized, anonymous and robust to manipulations, founded on a revolutionary technology with a potential that goes far beyond finance, the blockchain, has catapulted it to a capitalization of U.S.$ 600 trillion, and reached an all-time high above U.S.$ 63.000 in April 2021. Moreover, since its release, thousands of new cryptocurrencies have emerged with the intention of offering added value or other functionalities beyond pretending to become a commonly accepted medium of exchange, store of value and unit of account. In fact, some central banks have issued or plan to issue their own cryptocurrency (Ostroff, 2020) and even El Salvador has accepted Bitcoin as legal tender (Webber, 2021). Its novel and intangible nature makes it virtually impossible to determine the fair value of these assets, which remains uncertain and sets the breeding ground for speculation (Fry and Cheah, 2016; Huynh et al., 2018; Baur and Dimpfl, 2018; Vidal-Tomás et al., 2019; Kaiser and Stöckl, 2020; Fruehwirt et al., 2021). This prevents them from keeping their value stable and therefore from serving as a new form of money (Yermack, 2015), making difficult for investors to obtain stable returns and constraining their potential as diversifying assets for fixed income, equity or commodities.

The problem of high volatility has led to the emergence, over the last few years, of new cryptoassets designed with some kind of mechanism to limit their price volatility, the so-called stablecoins. Usually, stablecoins are backed by a traditional financial asset (primarily a fiat currency such as the U.S. dollar (USD) or the euro, or a portfolio of them) or a commodity (such as gold or oil, in the cases of PAX Gold and Petro, respectively), or either its supply depends on an algorithm that responds to shifts on demand with the objective of minimizing the volatility (such as Terra and Ampleforth). Currently, financial innovation has even led to the creation of stablecoins backed by other cryptocurrencies -this is the case of Celo Euro, whose price depends on a basket composed of different cryptoassets, such as Bitcoin or Ethereum, among others-.

So far, fiat currency-backed stablecoins, and especially those linked to the USD, have been the most successful, both in terms of popularity and in achieving their ultimate goal of providing a digital currency with a stable value for carrying out transactions. Tether, the most broadly used stablecoin, bases its value on the promise that each token is backed by one USD. Notwithstanding, the lack of transparency of Bitfinex, the issuer of Tether, has been questioned and criticized on numerous occasions in reference to its actual USD reserves (Jemima, 2021). In fact, although from the beginning Tether claimed that all Tethers were backed 1-to-1 by dollars, in April 2019 the general counsel of Bitfinex, Stuart Hoegner, disclosed that 74% of Tether's circulating cash was backed by "cash and cash equivalents", and the remaining 26% in a "less liquid form". More recently, on May 13, 2021, Tether published a breakdown of its reserves which revealed that only 3.87% of them constituted cash. However, the knowledge that Tether is not fully cash-backed, as initially advocated, does not seem to have affected its trading volume too much, as it remains the most widely used medium of exchange for cryptocurrency transactions. Nevertheless, USD Coin, the second largest capitalized fiat currency-backed cryptocurrency after Tether, publishes monthly external audits revealing that there is indeed a 1-to-1 backing per USD since its release in October 2018. This lack of transparency together with the growing popularization of these digital currencies that claim to be fully backed by fiat currency, is leading more and more experts and policymakers to advocate the need to regulate the stablecoins market (Smialek, 2021; Venkataramakrishnan, 2021; Libni and Lipton, 2021).

Gold-backed digital tokens such as Goldcoin or Digix Gold (launched in 2013 and 2014, respectively) are another type of stablecoin that is also gaining popularity lately. In September 2019, Paxos Trust Company launched the first regulated gold-backed cryptocurrency (Chavez-Dreyfuss, 2019), PAX Gold (PAXG), which is, at the time of writing, the largest market capitalization gold-backed digital token on the market. This type of cryptocurrency aims to alleviate the problem of the volatility of traditional cryptocurrencies by linking their value to that of a physical asset (gold), so that they acquire intrinsic value, which traditional cryptocurrencies lack. Moreover, gold has historically been a safe haven asset, so inheriting this characteristic of the precious metal and combining it with the advantages of cryptocurrencies (security, accessibility, etc). This could bring them closer to the goal of functioning as a medium of exchange and constituting a more reliable inflation hedging asset than traditional cryptocurrencies, and with the advantage over gold that it does not require physical storage, maintenance costs and is infinitely divisible (Torres, 2021). Notwithstanding, the literature around this typology of cryptocurrencies is still very scarce, and with the notable exception of Wasiuzzaman and Rahman (2021), most contributions have been made in the context of Islamic finance (Alam et al., 2019; Aloui et al., 2021).

In general, the field of stablecoins has been little studied so far. Some assess its charachteristics and taxonomy, as Bullmann et al. (2019) and Mita et al. (2019), while others focus on its relation with traditional cryptocurrencies and the effects of stablecoins issuances on the crypto market efficiency (Ante et al., 2020, 2021; Kristoufek, 2021). Not much research has yet been done on their capabilities as diversifiers in traditional cryptocurrency portfolios. In this regard, Wang et al. (2020)'s contribution is noteworthy, which investigate the diversifier, hedge and safe-haven capabilities of USD-backed and gold-backed stablecoins against traditional cryptocurrencies using both a DCC- GARCH model and a copula approach. More recently, Wasiuzzaman and Rahman (2021) study the performance of gold-backed cryptocurrencies during the COVID-19 crisis. Our study follow this trend by assessing stablecoins capabilities to reduce the VaR of a traditional cryptocurrency portfolio. Based on a careful and state-of-the-art methodology, we provide empirical evidence to help answer a relevant and novel question for many academics and practitioners: do stablecoins act as safe havens or hedgers against more volatile and traditional cryptocurrencies?

We consider a base portfolio formed by five traditional cryptocurrencies: Bitcoin, Ethereum, Ripple, Cardano and Litecoin; and its diversification by means of the introduction of one of the following three asset-backed cyptocurrencies: Tether, USD Coin and Digix Gold. The first two, as has been already mentioned, are pegged to the USD, while the last one constitutes the most capitalized cryptoasset backed by gold with enough historical data to carry out an investigation of these characteristics. The eight cryptocurrencies chosen are those with the highest capitalization as of May 25, 2021 from among those with the proper characteristics with sufficient historical data in accordance with the sample size required for our study. The traditional cryptocurrencies chosen have been studied in several recent contributions (Bouri et al., 2020; El Montasser et al., 2021; Jia et al., 2021), while recent research on the three asset-backed cryptocurrencies considered can be found in Baur and Hoang (2021a,b) and Kristoufek (2021). Our study goes further the existing literature examining the degree (if any) to which these supposed stablecoins help to reduce the downside risk of a portfolio of cryptocurrencies beyond its second moment, i.e., assessing how the introduction of the stablecoins into the portfolio affects its skewness and kurtosis. To this end, we conduct an out-of-sample experiment during the COVID-19 pandemic, through which the portfolio is reallocated in a monthly basis. The portfolio downside risk is assessed in a dynamic way by estimating the modified VaR (mVaR) proposed in Favre and Galeano (2002), which constitutes an extension with higher moments of the parametric gaussian VaR (gVaR). In order to compute the conditional portfolio density, the co-variance, co-skewness and co-kurtosis matrices are estimated dynamically by making use of the Generalized Orthogonal GARCH (GO-GARCH) model proposed in van der Weide (2002). Then, four portfolios are constructed over the out-of-sample period: one formed by five traditional cryptocurrencies, and three others composed by the latter base portfolio together with one of the three stablecoins. Two portfolio allocation strategies are considered: (1), the maximization of the certainty equivalent (CE) that arises from a CARA utility function of a highly risk-averse investor with preference for positive skewness and low kurtosis; (2), minimum variance (MV) portfolios are formed as a benchmark. Thus, our main contribution consists on assessing the capabilities of stablecoins on the allocation and diversification of traditional cryptocurrency portfolios considering co-moments up to order four both in terms of optimization and risk management. This is also the first paper to apply the GO-GARCH model to portfolios composed exclusively of cryptocurrencies and also the first to apply it to stablecoins.

The preliminary results show that Tether behaves as a diversifier throughout the first months of the pandemic and as a hedger against most traditional cryptocurrencies considered since October 2020, leading it to have a predominant allocation in the CE and MV portfolios across the period under study, assisting to greatly reduce their risk exposure. USD Coin exhibits safe haven properties during the first months of the pandemic, during which uncertainty and turmoil in the markets was very high, while since late 2020 it fulfills a more diversifying role. As such, it receives the largest weight in the portfolios over the entire period and manages to significantly reduce portfolio risk exposure. Regarding Digix Gold, we find an asset with a low positive correlation with traditional cryptocurrencies, which places it as a diversifier, but which is not able to systematically reduce the risk of the portfolios (sometimes even increasing it) due to its high instrinsic volatility.

The results also show that these assets induce a reduction in the portfolio's mVaR greater than the reduction in gVaR. This differential effect is of greater magnitude when we consider high confidence levels, such as 99%, and is explained by a reduction in the conditional kurtosis of the portfolio that is particularly notable in the case of Digix Gold. These results highlight the importance of considering higher order moments when measuring the tail risk of portfolios with cryptocurrencies, as well as the diversifying potential of stablecoins beyond the second moment.

The paper is organized as follows: Section 2 presents a brief summary of the literature related to the measurement of higher order conditional moments and its application in risk measurement, as well as the most recent literature related to stablecoins; Section 3 presents the methodology applied in the estimation of conditional moments, tail risk measures, portfolio allocation strategies and backtesting; Section 4 presents a brief analysis of the assets considered in the study, their basic statistics and their performance over the sample considered; Section 5 presents the main results obtained in the study; finally, Section 6 presents the main conclusions.

2 Literature review

It is a stylized fact that the volatility of most financial series is time-dependent. The autoregressive conditional hetersokedasticity (ARCH) model proposed by Engle (Engle, 1982) and then the Generalized ARCH (GARCH) model by Bollerslev (Bollerslev, 1986) have been broadly used both in the literature and by practitioners, and are the starting point from which a multitude of other models have been developed. The time-dependent nature of asset returns raises the desirability of using dynamic risk assessments, so measures as the Value at Risk (VaR), which constitutes a market and regulatory standard, can benefit from GARCH models since these allow to compute a dynamic quantile on the tail of the distribution conditioned on past information. Notwithstanding, the non-gaussian behavior of most financial time series imply that considering only the dynamics of the second moments could sometimes be not sufficient in risk and portfolio management (Harvey and Siddique, 1999; Peiro, 1999; Ang et al., 2006). In fact, the distribution of financial series tend to be leptokurtic and to display negative skewness. Moreover, skewness and kurtosis usually exhibit time-dependent patterns (Jondeau and Rockinger, 2003), which has inspired the development of methodologies that allow to estimate the dynamics of higher moments. Some examples are the model proposed in Harvey and Siddique (1999) for estimating time-varying conditional skewness, the one introduced in Brooks et al. (2005) for estimating autoregressive conditional kurtosis and the GARCH-type model proposed in León et al. (2005) for estimating autoregressive conditional volatility, skewness and kurtosis.

Risk management is, in particular, an area where the estimation of higher order conditional moments is of great utility, and a wide variety of papers on their applications can be found in the literature. One popular application is the mVaR proposed by Favre and Galeano (2002), which uses the Cornish Fisher expansion (Cornish and Fisher, 1938) to extend a gVaR with terms of skewness and kurtosis. For the case of the Conditional VaR (CVaR), Bali et al. (2008) extend Engle (1982)'s ARCH model to study the role of autoregressive conditional skewness and kurtosis on its estimation, finding that the parameters that capture conditional skewness and kurtosis are statistically significant, and that accounting for higher order moments when estimating VaR improves its performance, namely, on predicting catastrophic market risks.

Beyond the univariate case, most market participants, including institutional investors and big funds, are interested in portfolio allocation and portfolio risk management, which adds the new dimension of accounting for dependencies between assets to the problem (Kosowski et al., 2007; Thapa et al., 2013; Bollerslev et al., 2018). This has motivated the appearence of multivariate conditional heteroscedasticity models such as the BEKK model by Engle and Kroner (1995) or the dynamic conditional correlation GARCH (DCC-GARCH) by Engle (2002). Moreover, considering the fact that investors are not indifferent to skewness and kurtosis, various studies throughout the literature extend conditional co-variance and correlation models to third and fourth order co-moments to assess the optimal investor decision in the context of portfolio allocation (Simaan, 1993; Jondeau and Rockinger, 2006; Martellini and Ziemann, 2010; Boudt et al., 2008, 2015) and risk management (Boudt et al., 2007; Chuang et al., 2014; Cerrato et al., 2017; Fry-McKibbin et al., 2021). The complexity when estimating the third and fourth co-moments increases with respect to that of the co-variance, so that a wide debate and a variety of methodologies for their estimation can be found in the literature. On the one hand, Cornilly and Peterson (2020) propose a methodology to statically estimate these higher order co-moment arrays. Along the same lines are the Structured method (Simaan, 1993) and the Shrinkage method (Ledoit and Wolf, 2003; Martellini and Ziemann, 2010; Boudt et al., 2020). Other studies go further by trying to estimate the dynamics of higher order co-moments by generalizing the idea of conditional heteroscedasticity, as proposed in Jondeau and Rockinger (2003, 2006, 2009) and Jondeau et al. (2018). In this paper, we select the GO-GARCH model (van der Weide, 2002), which is a generalization of the O-GARCH model (Alexander and Chibumba, 1996; Klaassen, 1999; Alexander, 2000, 2001), as it allows obtaining closed analytical expressions for co-skewness and co-kurtosis (see Ghalanos et al., 2015 and Boudt et al., 2019), which is possible thanks to the affine representation of the model, in conjunction with the assumption of hyperbolic distributions.

A wide range of the aforementioned methodologies have been applied for modeling conditional moments when dealing with crypto assets and their connectedness relations, both in univariate and multivariate settings (Ciaian et al., 2018; Elendner et al., 2018; Boako et al., 2019; Borri, 2019; Brauneis and Mestel, 2019). Firstly, Ciaian et al. (2018) estimate an autoregressive distributed lag (ARDL) model with daily data of seventeen cryptocurrencies for the post-subprime crisis period (2013-2016), finding significant interdependencies for the large-cap cryptos. In a fully reversed study, Elendner et al. (2018) perform a Principal Component Analysis (PCA) on the top ten cryptocurrencies by market cap and find weak dependencies, with the first factor explaining only 26% of the variance and needing at least seven factors to explain the 90% of the variance of the system. Boako et al. (2019), derive an R-vine copula approach to study the risk-reward trade-offs as well as the structure of dependence between six cryptocurrencies, revealing a strong correlation that changes over time. Interestingly, Borri (2019) implements the CoVar model to study tail-risk dependences among four main cryptocurrencies and other assets of very different nature, and demonstrates that there exists a significant room for diversification of idiosyncratic risk by combining different cryptocurrencies, in line with the mean-variance analysis carried out by Brauneis and Mestel (2019).

Other studies assess the volatility dynamics of cryptocurrencies using multivariate GARCH-type models (Katsiampa, 2019; Katsiampa et al., 2019; Canh et al., 2019; Brauneis and Mestel, 2019). Firstly, Katsiampa (2019) and Katsiampa et al. (2019) use BEKK models to examine the volatility dynamics and co-movements between pairs of some of the top cryptocurrencies, finding time varying correlations and volatility spillovers between them. The latter results are in tune with those of Canh et al. (2019), who examine structural breaks and interdependencies between seven cryptocurrencies using a DCC-MGARCH model. In addition, Brauneis and Mestel (2019) compare naive crypto portfolios with individual cryptocurrencies in the Markowitz mean-variance framework and find that a strategy that combines different cryptocurrencies outperforms single ones by more than 75% in terms of the Sharpe ratio.

We also found studies that have gone beyond volatility to study the interdependencies between different cryptocurrencies and other assets when not assuming a gaussian distribution or trying to directly model higher order co-moments (Henriques and Sadorsky, 2018; Pal and Mitra, 2019; Hrytsiuk et al., 2019; Conlon and McGee, 2020; Silahli et al., 2021; Nagy and Benedek, 2021). In Henriques and Sadorsky (2018). The GO-GARCH model is implemented to study whether Bitcoin can replace gold in an investment portfolio, while in Pal and Mitra (2019) the model is estimated to investigate the possibility of hedging Bitcoin with other assets. Hrytsiuk et al. (2019) derive analytical expressions for the VaR of a cryptocurrency portfolio assuming that cryptocurrency returns follow a Cauchy distribution. Another interesting study is Conlon and McGee (2020), which analyse the safe haven properties of Bitcoin using the Cornish Fisher expansion for computing modified versions of VaR and Conditional VaR (CVaR) that account for skewness and kurtosis. More recently, Silahli et al. (2021) combine a historical simulation with a GARCH model with innovations that follow a two sided Weibull distribution proposed in Chen and Gerlach (2013) to compute the VaR of a portfolio of four major cryptocurrencies. They find that the new model outperforms ten other benchmark methods. Also very valuable is the contribution of Nagy and Benedek (2021), who study the effect of co-skewness and co-kurtosis on Sharpe ratios on 72 cryptocurrencies, finding a preference regarding the former and an aversion towards the latter.

Our research covers the fairly recent niche of stablecoins, which has been little explored so far, although there already exist some studies that assess their characteristics, capabilities as diversifiers or safe havens or the role they play in the crypto market (Bullmann et al., 2019; Mita et al., 2019; Wang et al., 2020; Ante et al., 2020, 2021; Kristoufek, 2021; Baur and Hoang, 2021a). Bullmann et al. (2019) and Mita et al. (2019) focus on the stablecoins taxonomy, while Wang et al. (2020) goes more in line with our paper by studying the diversifier, hedge and safe haven capabilities of USD-backed and gold-backed stablecoins against traditional cryptocurrencies, finding that the former perform better than the latter while all of them perform better than its underlying assets. Some others examine how stablecoins relate with traditional crypto assets, as in Ante et al. (2020), who find that stablecoins issuances contribute to the cryptocurrency market efficiency; Ante et al. (2021), who reveal direct links between large stablecoin transactions and the increase in the trading volume of traditional cryptocurrencies; and Kristoufek (2021), who demonstrates that the large stablecoin issuances could be a reflection of the growing investment demand in the crypto market, rather than the other way around, i.e., that the issuances are driving up the prices of traditional cryptocurrencies. Other contributions focus on assessing the extent to which stablecoins deserve their name, as in Baur and Hoang (2021a), which find that in fact they do not always remain stable, although they constitute a strong safe haven against Bitcoin. Our main contribution consists on assessing the potential benefits derived from including stablecoins in a cryptocurrency portfolio, considering conditional co-moments up to order four, and both in the portfolio allocation critera and in the risk measure.

3 Methodology

3.1 The GO-GARCH model

The model chosen for modelling the observed financial series is the GO-GARCH proposed by van der Weide (2002). GO stands for Generalized Orthogonal, and as its name claims it is a generalization of the Orthogonal GARCH model (O-GARCH) proposed in Alexander (2001). The GO-GARCH model lies on the assumption that the vector of returns $\boldsymbol{r}_t$ can be represented as a linear combination of unobserved orthogonal factors $\boldsymbol{f}_t$:

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{A}\boldsymbol{f}_t, \quad t = 1, ..., T \tag{1}$$

where $\boldsymbol{\mu}_t = (\mu_{1,t}, ..., \mu_{N,t})' = \mathbb{E}[\boldsymbol{r}_t|\mathscr{F}_{t-1}]$ represents the mean vector of $\boldsymbol{r}_t$ conditional on the filtration $\mathscr{F}$ at moment $t-1$, i.e., conditional on all information revealed by the realization of the stochastic process $\boldsymbol{r}_t$ until t. The conditional mean of each asset return process is modelled through an AR(1) model:

$$\mu_{i,t} = \phi_0 + \phi_1 r_{i,t-1}, \quad \text{with} \quad i = 1, ..., N \quad \text{and} \quad t = 1, ..., T \tag{2}$$

And the factor vector $\boldsymbol{f}_t$ can be expressed as a vector of unit variance factors $\boldsymbol{z}_t$ scaled by its corresponding diagonal variance matrix $\boldsymbol{H}_t$:

$$\boldsymbol{f}_t = \boldsymbol{H}_t^{1/2}\boldsymbol{z}_t, \quad \text{with} \quad \boldsymbol{H}_t = \begin{pmatrix} \sigma_{1,t} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{N,t} \end{pmatrix}, \quad \text{with} \quad t = 1, ..., T \tag{3}$$

with $\boldsymbol{z}_t$ having zero mean and being independent both among time and among factors, i.e., $\mathbb{E}[z_{i,t}z_{j,t-s}|\mathscr{F}_{t-1}] = 0 \ \forall i \neq j$ and $\forall s > 0$. The mixing matrix $\boldsymbol{A}$ is constant, invertible, and results from the product of the square root of the unconditional co-variance matrix $\boldsymbol{\Sigma}$ and an orthogonal rotation matrix $\boldsymbol{U}$, $\boldsymbol{A} = \boldsymbol{\Sigma}^{1/2}\boldsymbol{U}$. The first two conditional moments of $\boldsymbol{r}_t$ are $\mathbb{E}[\boldsymbol{r}_t|\mathscr{F}_{t-1}] = \boldsymbol{\mu}_t$ since $\boldsymbol{f}_t$ has zero mean and $\mathbb{E}\left[(\boldsymbol{r}_t - \boldsymbol{\mu}_t)(\boldsymbol{r}_t - \boldsymbol{\mu}_t)'|\mathscr{F}_{t-1}\right] = \boldsymbol{A}\boldsymbol{H}_t\boldsymbol{A}' = \boldsymbol{\Sigma}_t$. Note that the dynamics in the conditional co-variance matrix $\boldsymbol{\Sigma}_t$ is addressed via the individual variances of the factors in $\boldsymbol{H}_t$, as the co-variances are unconditional. So, in order to capture the conditional heteroscedasticity, we fit a GARCH(1,1) model to every factor conditional variance:

$$\sigma_{i,t} = \omega_i + \alpha_i f_{i,t-1}^2 + \beta_i\sigma_{i,t-1}^2, \quad \text{with} \ \ i = 1, ..., N \quad \text{and} \quad t = 1, ..., T \tag{4}$$

where $\omega_i = 1 - \alpha_i - \beta_i$ and the constraints $\alpha_i, \beta_i \geq 0$ and $\alpha_i + \beta_i < 1$ have to be met to ensure that the estimated variance is positive and finite, respectively. Note that the first constraint also implies $\omega_i > 0$.

The GO-GARCH model is particularly suitable for this research, as its affine representation allows finding closed form expressions for the conditional co-skewness and co-kurtosis of $\boldsymbol{r}_t$ (see Ghalanos, 2019), which are, respectively:

$$\begin{aligned} \boldsymbol{M}_t^3 &= \mathbb{E}[(\boldsymbol{r}_t - \boldsymbol{\mu}_t)(\boldsymbol{r}_t - \boldsymbol{\mu}_t)' \otimes (\boldsymbol{r}_t - \boldsymbol{\mu}_t)'|\mathscr{F}_{t-1}] = \boldsymbol{A}\boldsymbol{M}_{f,t}^3(\boldsymbol{A}' \otimes \boldsymbol{A}'), \\ \boldsymbol{M}_t^4 &= \mathbb{E}[(\boldsymbol{r}_t - \boldsymbol{\mu}_t)(\boldsymbol{r}_t - \boldsymbol{\mu}_t)' \otimes (\boldsymbol{r}_t - \boldsymbol{\mu}_t)' \otimes (\boldsymbol{r}_t - \boldsymbol{\mu}_t)'|\mathscr{F}_{t-1}] = \boldsymbol{A}\boldsymbol{M}_{f,t}^4(\boldsymbol{A}' \otimes \boldsymbol{A}' \otimes \boldsymbol{A}') \end{aligned} \tag{5}$$

where $\otimes$ represents the Kronecker product and with $\boldsymbol{M}_{f,t}^3$ and $\boldsymbol{M}_{f,t}^4$ being the $N \times N^2$ third and $N \times N^3$ fourth co-moment matrices of $\boldsymbol{f}$, respectively, and given by:

$$\begin{aligned} \boldsymbol{M}_{f,t}^3 &= \mathbb{E}[\boldsymbol{f}_t\boldsymbol{f}_t' \otimes \boldsymbol{f}_t'|\mathscr{F}_{t-1}] = \left[\boldsymbol{M}_{1,f,t}^3, \boldsymbol{M}_{2,f,t}^3, ..., \boldsymbol{M}_{N,f,t}^3\right], \\ \boldsymbol{M}_{f,t}^4 &= \mathbb{E}[\boldsymbol{f}_t\boldsymbol{f}_t' \otimes \boldsymbol{f}_t' \otimes \boldsymbol{f}_t'|\mathscr{F}_{t-1}] = \\ &\quad \left[\boldsymbol{M}_{11,f,t}^4, \boldsymbol{M}_{12,f,t}^4, ..., \boldsymbol{M}_{1N,f,t}^4|...|\boldsymbol{M}_{N1,f,t}^4, \boldsymbol{M}_{N2,f,t}^4, ..., \boldsymbol{M}_{NN,f,t}^4\right] \end{aligned} \tag{6}$$

where $\boldsymbol{M}_{k,f,t}^3$ and $\boldsymbol{M}_{lk,f,t}^4$ for $l, k = 1, ..., N$ are the $N \times N$ submatrices which are made up by the following elements:

$$\begin{aligned} m_{ijk,f,t}^3 &= \mathbb{E}[f_{i,t}f_{j,t}f_{k,t}|\mathscr{F}_{t-1}], \\ m_{ijkl,f,t}^4 &= \mathbb{E}[f_{i,t}f_{j,t}f_{k,t}f_{l,t}|\mathscr{F}_{t-1}] \end{aligned} \tag{7}$$

which in turn are the third and fourth non-standardized conditional co-moments, respectively. Note that since $f_{i,t} = \sigma_{i,t}z_{i,t}$ and given the independency of $z_{i,t}$, then:

$$\begin{aligned} m_{ijk,f,t}^3 &= 0 \quad \text{for} \quad i \neq j \neq k \\ m_{ijkl,f,t}^4 &= \begin{cases} 0 & \text{for} \quad i \neq j \neq k \neq l \\ \sigma_{i,t}^2\sigma_{k,t}^2 & \text{for} \quad i = j, \ k = l \end{cases} \end{aligned} \tag{8}$$

The conditional co-skewness $\boldsymbol{S}_{ijk,t}$ and co-kurtosis $\boldsymbol{K}_{ijkl,t}$ are obtained by standardizing $m_{ijk,f,t}^3$ and $m_{ijkl,f,t}^4$:

$$\boldsymbol{S}_{ijk,t} = \frac{m^3_{ijk,f,t}}{\sigma_{i,t}\sigma_{j,t}\sigma_{k,t}},$$
$$\boldsymbol{K}_{ijkl,t} = \frac{m^4_{ijkl,f,t}}{\sigma_{i,t}\sigma_{j,t}\sigma_{k,t}\sigma_{l,t}} \tag{9}$$

Thus, the conditional co-skewness and co-kurtosis tensors of a portfolio of three assets can be expressed as:

$$\boldsymbol{M}^3_t = [\boldsymbol{S}_{1jk,t}|\boldsymbol{S}_{2jk,t}|\boldsymbol{S}_{3jk,t}] = \left[\begin{array}{ccc|ccc|ccc} S_{111,t} & S_{112,t} & S_{113,t} & S_{211,t} & S_{212,t} & S_{213,t} & S_{311,t} & S_{312,t} & S_{313,t} \\ S_{121,t} & S_{132,t} & S_{133,t} & S_{221,t} & S_{222,t} & S_{223,t} & S_{321,t} & S_{332,t} & S_{323,t} \\ S_{131,t} & S_{132,t} & S_{133,t} & S_{231,t} & S_{232,t} & S_{233,t} & S_{331,t} & S_{332,t} & S_{333,t} \end{array}\right]$$
$$\boldsymbol{M}^4_t = [\boldsymbol{K}_{11kl,t}\boldsymbol{K}_{12kl,t}\boldsymbol{K}_{13k,t}|\boldsymbol{K}_{21kl,t}\boldsymbol{K}_{22kl,t}\boldsymbol{K}_{23k,t}|\boldsymbol{K}_{31kl,t}\boldsymbol{K}_{32kl,t}\boldsymbol{K}_{33k,t}]$$

As it can be seen, the number of elements of the co-moment matrices grows exponentially with the moment order, following a geometric sequence with a common ratio of N, so that we find $N \times N$ elements in the co-variance matrix, $N \times N^2$ in the co-skewness matrix, $N \times N^3$ for co-kurtosis, and so on. Nevertheless, the property of symmetry allows us to compute just $N(N+1)/2$ parameters for the co-variance matrix, $N(N+1)(N+2)/6$ for the co-skewness matrix and $N(N+1)(N+2)(N+3)/24$ for the co-kurtosis matrix.

Lastly, we can consider a portfolio consisting of N assets with weights $\boldsymbol{w}_t = (w_{1,t}, w_{2,t}, ..., w_{N,t})'$, so its returns r_p can be computed as:

$$r_{p,t} = \boldsymbol{w}'_t\boldsymbol{r}_t = \boldsymbol{w}'_t\boldsymbol{\mu}_t + \boldsymbol{w}'_t\boldsymbol{A}\boldsymbol{H}^{1/2}\boldsymbol{z}_t \tag{10}$$

and:

$$\begin{aligned} \sigma^2_{p,t} &= \boldsymbol{w}'_t\boldsymbol{\Sigma}_t\boldsymbol{w}_t \\ s_{p,t} &= \boldsymbol{w}'_t\boldsymbol{M}^3_t(\boldsymbol{w}_t \otimes \boldsymbol{w}_t) \\ k_{p,t} &= \boldsymbol{w}'_t\boldsymbol{M}^4_t(\boldsymbol{w}_t \otimes \boldsymbol{w}_t \otimes \boldsymbol{w}_t) \end{aligned} \tag{11}$$

being portfolio's conditional variance, skewness and kurtosis.

3.2 The portfolio allocation method

We consider an investor who allocates her portfolio by maximizing her CE. Given a lottery L in which a particular individual can participate, the CE is the amount of wealth for which she would feel indifferent between taking it or playing the lottery. That is, given a function $U(W)$ that represents the utility of the individual depending on the uncertain amount of wealth she would end up with after taking the lottery, W, the CE is the amount that satisfies:

$$U(CE) = \mathbb{E}[U(W)] \tag{12}$$

The CE depends both on the expected result of the lottery and on the individual's utility function. In terms of this research, the lottery would be represented as investing on a portfolio whose future performance is uncertain. For the utility function, we follow the work of Jondeau and Rockinger (2006) and opt for a Constant Absolute Risk Aversion (CARA) utility function, which is functional form is as follows:

$$U(W) = -e^{-\lambda W} \tag{13}$$

where λ represents the Arrow-Pratt measure for absolute risk aversion (ARA), defined as:

$$\lambda = -\frac{U''(W)}{U'(W)} \tag{14}$$

with $U'(W) = dU(W)/dW$ and $U''(W) = d^2U(W)/dW^2$. Note that $\lambda > 0$ since $U' > 0$ (i.e., wealth is a good) and $U''(W) < 0$ for risk averse investors. An investor is said to be risk averse if and only if:

$$U(\mathbb{E}[W]) < \mathbb{E}[U(W)] \tag{15}$$

Intuitively, λ represents the quotient between the individual's total wealth and the maximum amount she would be willing to invest in a game that doubles or halves the amount invested with equal probability. So if an individual with a total wealth of 1 million USD is willing to invest U.S.$200,000 in a lottery with 1/2 probability of returning another U.S.$200,000 or either costing her U.S.$100,000, then her absolute risk aversion λ is equal to 5.

Now consider a Taylor expansion on an investor's utility function that depends on the returns of her portfolio, r_p:

$$U(r_p) = U(\mu_p) + U'(\mu_p)(r_p-\mu_p) + \frac{U''(\mu_p)}{2!}(r_p-\mu_p)^2 + \frac{U^{(3)}(\mu_p)}{3!}(r_p-\mu_p)^3 + \frac{U^{(4)}(\mu_p)}{4!}(r_p-\mu_p)^4 + \ldots \tag{16}$$

where $\mu_p = \mathbb{E}[r_p]$ is the portfolio expected return. Computing the expected value and considering (12), we have:

$$\mathbb{E}[U(W)] = U(CE) = U(\mu_p) + \frac{U''(\mu_p)}{2}\mathbb{E}\left[(r_p-\mu_p)^2\right] + \frac{U^{(3)}(\mu_p)}{6}\mathbb{E}\left[(r_p-\mu_p)^3\right] + \frac{U^{(4)}(\mu_p)}{24}\mathbb{E}\left[(r_p-\mu_p)^4\right] \tag{17}$$

And plugging the CARA function in (13) and approximating by taking up to the fourth order term in the Taylor expansion:

$$-e^{-\lambda CE} \approx -e^{-\lambda\mu_p}\left(1 + \frac{\lambda^2}{2}\mathbb{E}\left[(r_p-\mu_p)^2\right] - \frac{\lambda^3}{6}\mathbb{E}\left[(r_p-\mu_p)^3\right] + \frac{\lambda^4}{24}\mathbb{E}\left[(r_p-\mu_p)^4\right]\right) \tag{18}$$

which can also be expressed in terms of the portfolio's returns first four moments:

$$-e^{-\lambda CE} \approx -e^{-\lambda\mu_p}\left(1 + \frac{1}{2}(\lambda\sigma_p)^2 - \frac{s_p}{6}(\lambda\sigma_p)^3 + \frac{k_p}{24}(\lambda\sigma_p)^4\right)$$

since the portfolio's variance, skewness and kurtosis are computed as:

$$\begin{aligned} \sigma_p^2 &= \mathbb{E}\left[(r_p-\mu_p)^2\right] \\ s_p &= \frac{\mathbb{E}\left[(r_p-\mu_p)^3\right]}{\sigma_p^3} \\ k_p &= \frac{\mathbb{E}\left[(r_p-\mu_p)^4\right]}{\sigma_p^4} \end{aligned} \tag{19}$$

Then, taking logarithms and using the approximation[1] $ln(1+x) \approx x - \frac{x^2}{2}$:

$$-\lambda CE \approx -\lambda\mu_p + ln\left(1 + \frac{1}{2}(\lambda\sigma_p)^2 - \frac{s_p}{6}(\lambda\sigma_p)^3 + \frac{k_p}{24}(\lambda\sigma_p)^4\right)$$

$$-\lambda CE \approx -\lambda\mu_p + \frac{1}{2}(\lambda\sigma_p)^2 - \frac{s_p}{6}(\lambda\sigma_p)^3 + \frac{k_p}{24}(\lambda\sigma_p)^4 - \frac{1}{2}\left(\frac{1}{2}(\lambda\sigma_p)^2 - \frac{s_p}{6}(\lambda\sigma_p)^3 + \frac{k_p}{24}(\lambda\sigma_p)^4\right)^2$$

And leaving aside the terms of order greater than four:

$$-\lambda CE \approx -\lambda\mu_p + \frac{1}{2}(\lambda\sigma_p)^2 - \frac{s_p}{6}(\lambda\sigma_p)^3 + \frac{k_p}{24}(\lambda\sigma_p)^4 - \frac{1}{8}(\lambda\sigma_p)^4$$

[1] The Taylor series for $ln(y)$ at a non zero point b is:
$ln(y) = ln(b) + \frac{1}{b}(y-b) + \frac{1}{b^2}\frac{(y-b)^2}{2} + \ldots$
Substitute $y = 1+x$ and evaluate at $b = 1$, so we have the second order approximation $ln(1+x) \approx x - \frac{x^2}{2}$

Finally, simplifying terms we get:

$$CE \approx \mu_p - \frac{1}{2}\lambda\sigma_p^2 + \frac{s_p}{6}\lambda^2\sigma_p^3 - \frac{k_p - 3}{24}\lambda^3\sigma_p^4 \quad (20)$$

which is an approximation for the CE accounting for the first four moments of the portfolio returns. Once we have the explicit function to maximize and the estimates of the co-moments dynamics, the following optimization problem can be solved at different time points t to obtain a portfolio reallocation path:

$$\begin{aligned} \max_{\boldsymbol{w}_t} \quad & \mu_{p,t} - \frac{1}{2}\lambda\sigma_{p,t}^2 + \frac{s_{p,t}}{6}\lambda^2\sigma_{p,t}^3 - \frac{k_{p,t} - 3}{24}\lambda^3\sigma_{p,t}^4 \\ \text{subject to} \quad & \boldsymbol{w}_t \geq 0 \end{aligned} \quad (21)$$

where $\boldsymbol{w}$ stands for the vector of weights, $\mu_{p,t} = \boldsymbol{w}_t'\boldsymbol{\mu}_t$ is the conditional mean of the portfolio's returns derived from (10) and its conditional variance, skewness and kurtosis are computed as in (11). Due to the risky nature of cryptocurrencies, we include no short-selling constraints in all portfolios.

In turn, we obtain MV portfolios by solving the following minimization problem:

$$\begin{aligned} \min_{\boldsymbol{w}_t} \quad & \sigma_{p,t}^2 = \boldsymbol{w}_t'\boldsymbol{\Sigma}_t\boldsymbol{w}_t \\ \text{subject to} \quad & \boldsymbol{w}_t \geq 0 \end{aligned} \quad (22)$$

3.3 Downside risk measures and backtesting

In order to assess the potential benefits in terms of downside risk of introducing stablecoins in a crypto portfolio, it is essential to choose a risk measure that allows to capture the statistical properties of the asset returns. As a measure of downside risk we opt for VaR, which represents a quantile of the returns distribution. Intuitevely, the VaR of a portfolio measures the loss which, under a certain confidence level $1-\alpha$, will not be exceeded if the portfolio is held over some period of time. One of the many ways to compute VaR is following a parametric approach that consists on assuming a specific probability distribution for the portfolio returns and then obtaining its corresponding quantile for a chosen confidence level. For instance, the 1 day horizon gVaR for a significance level α (with α usually set to 0.05 or 0.01) can be estimated as follows:

$$\text{gVaR}_t(\alpha) = -\mu_{p,t} - \sigma_{p,t}\Phi^{-1}(\alpha) \quad (23)$$

where Φ^{-1} represents the inverse of the standard gaussian distribution function (i.e. the quantile function).

However, as mentioned before, most financial assets returns and, in particular, cryptocurrency returns, often present negative skewness and excess kurtosis, which implies that assuming a gaussian distribution on the returns can result in an underestimation of downside risk. For this reason, we employ an extension of gVaR that accounts for skewness and excess kurtosis, the mVaR) proposed by Favre and Galeano (2002). The mVaR can be computed as the sum of the gVaR and a term derived from the Cornish-Fisher expansion. The Cornish-Fisher expansion (CF) derives from the Taylor expansion and is computed as follows:

$$CF = z + \frac{1}{6}(z^2 - 1)s_{p,t} + \frac{1}{24}(z^3 - 3z)k_{p,t} - \frac{1}{36}(2z^3 - 5z)s_{p,t}^2 \quad (24)$$

where $z_\alpha = \Phi^{-1}(\alpha)$. So the mVaR can be expressed as:

$$\text{mVaR}_t(\alpha) = -\mu_{p,t} - \sigma_{p,t}\left(z_\alpha + \frac{1}{6}(z_\alpha^2 - 1)s_{p,t} + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)k_{p,t} - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)s_{p,t}^2\right) \quad (25)$$

and rearranging some terms:

$$\text{mVaR}_t(\alpha) = \text{gVaR}_t(\alpha) - \sigma_{p,t}\left(\frac{1}{6}(z_\alpha^2 - 1)s_{p,t} + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)k_{p,t} - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)s_{p,t}^2\right) \quad (26)$$

Both gVaR and mVaR are calculated, so that we can see the role that higher order moments play in the risk of the portfolios, as well as the effect that introducing stablecoins in the portfolios has on the risk. To check the effectiveness of the risk measures considered, we conducted a backtesting based on the dynamic quantile test proposed by Engle and Manganelli (2004). Defining the random variable Hit_t as:

$$Hit_t(\alpha) = \begin{cases} 1-\alpha & \text{if} \quad r_t < -VaR_t(\alpha) \\ -\alpha & \text{if} \quad r_t \geq -VaR_t(\alpha) \end{cases} \tag{27}$$

Note that under an adequate VaR estimation, $P(r_t < -VaR_t(\alpha)|\mathscr{F}_{t-1}) = \alpha \ \forall t$ and thus $\mathbb{E}[Hit_t(\alpha)|\mathscr{F}_{t-1}] = 0 \ \forall t$. So, we test the null hypothesis that Hit_t has zero mean and does not present correlation with any variable that belongs to the information set $\mathscr{F}_t$. To do so, the test considers the following regression:

$$Hit_t(\alpha) = \beta_0 + \sum_{i=1}^{p} \beta_i Hit_{t-i} + \sum_{j=p+1}^{q} \beta_j X_j + \varepsilon_t \tag{28}$$

with X_j being some explanatory variables contained in $\mathscr{F}_t$. So the null hypothesis is:

$$H_0 : \beta_0 = \beta_i = \beta_j = 0, \quad i = 1, ..., p, \quad j = p+1, ..., q$$

And the test statistic is a Wald statistic defined as:

$$\frac{\boldsymbol{Hit}'\boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Hit}}{\alpha(1-\alpha)} \overset{a}{\sim} \chi^2_{(p+q+1)} \tag{29}$$

where $\boldsymbol{Hit} = [Hit_1, ..., Hit_T]'$ and $\boldsymbol{X}$ being the matrix of explanatory variables. We follow Engle and Manganelli (2004) by setting the first four lags of Hit_t and the VaR forecast as explanatory variables, so we can test the presence of serial correlation on the dependent variable and possible linear relations with the VaR forecast.

4 Data sample and summary statistics

The base portfolio include five main cryptocurrencies: Bitcoin, Ethereum, Ripple, Cardanoand Litecoin. Then, four different asset-backed tokens had been considered as potential stablecoins to include in the base portfolio, being: Tether, USD Coin, Digix Gold and Goldcoin. The first two are the higher capitalized tokens backed by US dollars. The selection of gold-backed tokens is not straightforward because most of these assets (and in particular some of the larger-cap ones) emerged very recently (this is the reason why PAX Gold is ruled out), so we do not have a large enough sample of data. We have therefore selected Digix Gold and Goldcoin, which are two of the largest capitalization[2] gold-backed stablecoins in the set that do have a sufficiently large data history.

[2] https://coinmarketcap.com/alexandria/glossary/gold-backed-cryptocurrency

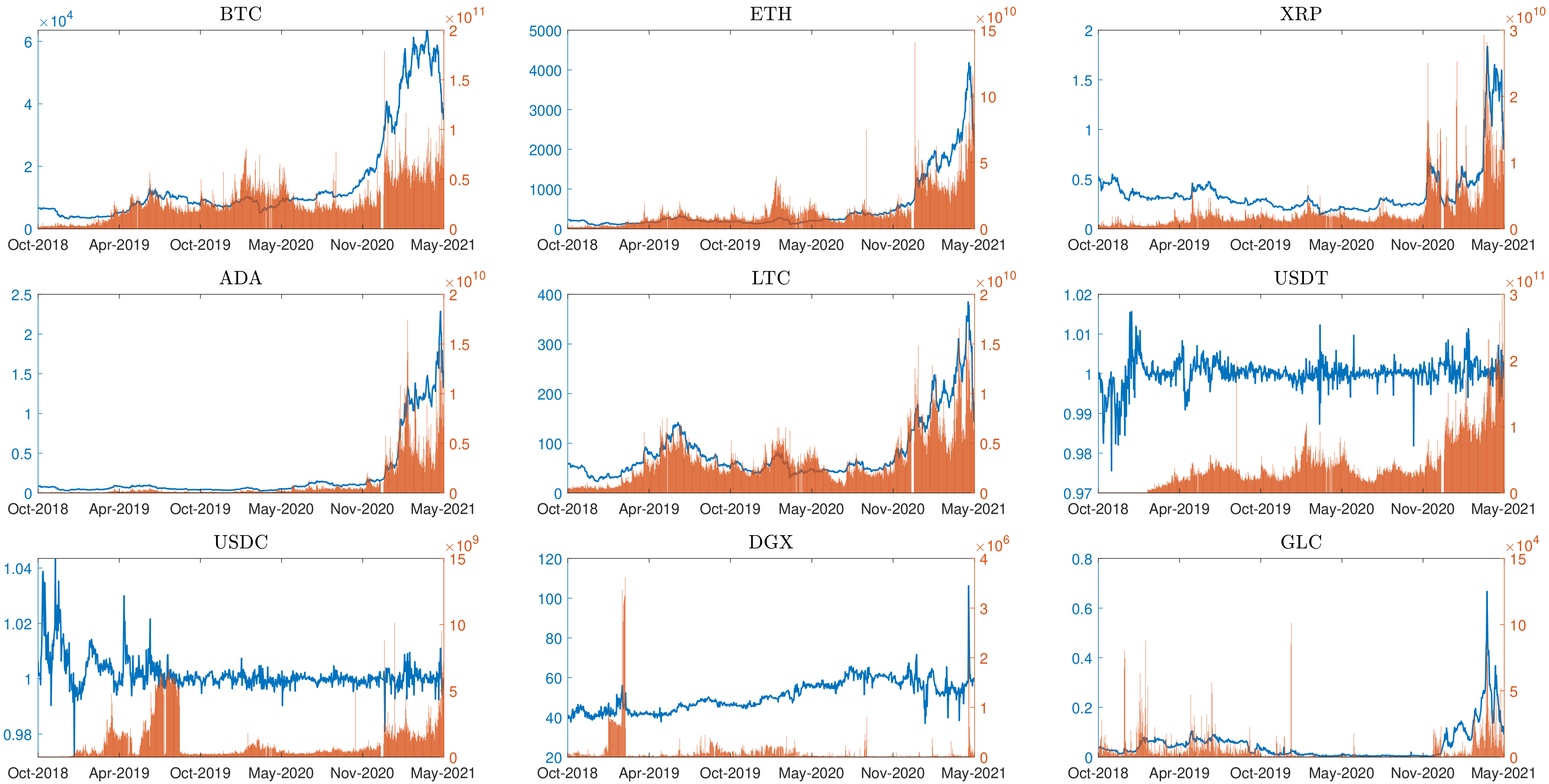

Figure 1: Daily price and trading volume of Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Cardano (ADA), Litecoin (LTC), Tether (USDT), USD Coin (USDC), Digix Gold (DGX) and Goldcoin (GLC). The left axis corresponds to the price and the right axis to the trading volume, both in USD.

The sample ranges from November the 5th of 2018 to May the 25th of 2021, including 953 observations of daily traded prices, of which the first 512 (from 2018/10/05 to 2020/02/29) constitute the in sample period used to calibrate the model, leaving the remaining 451 dates (from 2020/03/01 to 2021/05/25) for the out-of-sample forecast. Figure 1 shows the daily quotation and trading volume during the entire sample period. The sample covers the coronavirus outbreak and the late 2020 and early 2021 bullish rally in traditional cryptocurrencies, as well as part of the subsequent downward correction since May 2021. As reported, the price of traditional cryptocurrencies multiplies since the beginning of the sample, however, that of the potential stablecoins considered shows very different behaviors. In the case of USD-backed cryptocurrencies, we observe no trend and oscillations around parity, with greater stability in the second half of the sample. The ability of these digital tokens to keep their value close to parity with the asset backing them depends directly on the confidence investors have that the backing is trully reliable. If trust is high, then arbitrage will prevent the value of the stablecoin from moving too far away from parity with its peg (Lyons and Viswanath-Natraj, 2020; Jacques Mandeng, 2021). The volatility highs and clusters exhibited by the prices of both USD-backed cryptocurrencies are of a much smaller magnitude than those of any of the other cryptocurrencies under investigation. This makes the study of these cryptocurrencies particularly interesting in the field of the portfolio diversification.

The behavior of the two gold-backed cryptocurrencies is quite different, with large price oscillations and ostensibly lower trading volume than the rest of the assets analyzed. Notwithstanding, it may be interesting to analyze them in order to provide a broader view of cryptocurrencies backed by assets that have historically been used as a safe havens, hedges or diversifiers, such as gold.

	Mean	Std. Dev.	Skewness	Kurtosis	Min	Median	Max	JB stat.	LM stat.(5)
BTC	0.6781	0.7633	-1.20	19.64	-0.434	0.002	0.176	11281.2***	10.347*
ETH	0.9479	1.0100	-1.49	18.99	-0.563	0.002	0.219	10559.2***	20.371***
XRP	0.2394	1.1787	-0.25	20.46	-0.550	-0.000	0.423	12170.0***	10.299*
ADA	1.1265	1.1219	-0.53	11.62	-0.524	0.003	0.269	3009.3	15.464***
LTC	0.4387	1.0775	-0.91	13.44	-0.471	0.000	0.262	4487.2***	18.971***
USDT	0.0011	0.0659	0.16	15.09	-0.025	0.000	0.025	5842.4***	125.302***
USDC	-0.0022	0.0755	0.20	10.89	-0.021	0.000	0.025	2495.0***	88.398***
DGX	0.1411	0.9787	1.41	33.13	-0.355	0.001	0.608	36528.1***	75.022***
GLC	0.4382	3.9803	1.20	16.68	-1.112	-0.003	1.562	7695.7***	11.850**
S&P500	-0.1418	0.2459	0.98	17.78	-0.090	-0.001	0.128	6175.0***	11.850**

Table 1: Descriptive statistics for 9 cryptocurrencies and the S&P 500 index daily log-returns for Oct 5, 2018 to May 25, 2021. The mean and standard deviation are annualized. JB stat. refers to the Jarque-Bera test statistic and LM stat. refers to the Breusch-Godfrey test statistic for fifth-order serial correlation. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 1 shows some relevant statistics to describe the main characteristics of the cryptocurrency returns and the SP500 index returns included as a benchmark. First, any of them have a statistically significant mean since it represents a fraction of the volatility. USD-backed cryptocurrencies have the lowest volatility of all the assets shown in the table, with a volatility more than ten times lower than that of traditional cryptocurrencies. Among the latter, Bitcoin presents the lowest volatility (0.76) and Ripple the highest (1.17). The volatility of the returns of these assets in the period sample is three to four times higher than that of the S&P500. It is striking that one of the gold-backed cryptocurrencies, GLC, is by far the most volatile asset of all. GLC presents a volatility of 3.98, which is between three to four times higher than that of the traditional cryptocurrencies and five times higher than Bitcoin's. This fact leads us directly to discard the inclusion of this cryptocurrency among the set of potential stablecoins to analyze. Despite being considered a stablecoin, the other gold-backed cryptocurrency, Digix Gold, has similar volatility to traditional cryptocurrencies. However, as desirable properties it presents a positive skewness and low correlation with traditional cryptocurrencies (see Figure 2). Interestingly, the asset-backed tokens are the only cryptocurrencies that present positive skewness, with Digix Gold leading the way. Digix Gold also has the highest kurtosis (33.13, an excess of 30.13), and all the other assets present fat tails with sample kurtosis above 10. This, together with the results shown from Jarque-Bera test, brings us to the conclusion that none of the series analyzed follows a gaussian distribution. Lastly, serial correlation is evaluated up to order five using the Breusch-Godfrey test, rejecting the null hypotheses (which is that there is not serial correlation of any order up to five) at 10% significance level, and in most cases also at 5% and 1%.

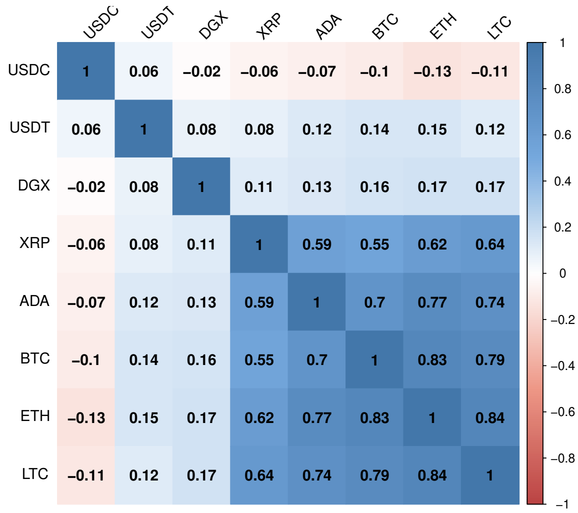

Figure 2: Correlation matrix (Pearson coefficient)

As an starting point in connectedness matters, Figure 2 shows the static correlation matrix for the nine cryptocurrencies finally included in the analysis. It can be seen that traditional cryptocurrencies hold strong linear correlation with each other, above 0.55, while asset-backed cryptocurrencies present low correlation both with each other and with traditional cryptocurrencies. Litecoin shows the stronger linear correlation with most other assets, particularly with Ethereum and Bitcoin, with which it presents a Pearson correlation coefficient of 0.84 and 0.79, respectively. Conversely, USD Coin is the cryptocurrency with a lowest linear correlation coefficient, in fact being negative with all of the other assets except of Tether. However, it may surprise the low correlation between these two cryptocurrencies, since they are both pegged to the same asset, the USD. This could be due to the fact that the USD acts as a numeraire, so any movement we may observe in the quotation of these two cryptocurrencies constitutes a deviation with respect to the parity with the USD. It is reasonable to think that such deviations from parity with the underlying asset are due to idiosyncratic causes of the cryptocurrency under study, so it is natural that these two assets show hardly any linear correlation when we use the asset backing them as a numeraire. These and other dependence findings are discussed in greater depth in later sections

5 Empirical analysis

In this section conduct the empirical experiment and report on the main results and findings. First, we show the parameter estimates of the Normal Inverse Gaussian (NIG) distribution and the calibration of the GO-GARCH models over the rolling window. Then, we examine the estimates of the conditional correlations and the weight distribution of the portfolios over the out-of-sample period. The, we analyze the results obtained in terms of risk exposure when introducing stablecoins into traditional cryptocurrency portfolios. Finally, backtesting results are presented.

5.1 Parameter calibration

We estimate a model for each combination of assets considered in the formation of portfolios, being: the set of five traditional cryptocurrencies, which will form the base portfolio whose risk we aim to reduce, and then the set of these with each of the potential stablecoins separately. We calibrate a total of four GO-GARCH models, since we consider three potential stablecoins: Tether, USD Coin and Digix Gold. We follow Barndorff-Nielsen (1997a,b) and Zakamouline and Koekebakker (2009) by assuming that the model innovations follow a NIG distribution with free skew (ρ) and shape (ν) parameters.

First, we make use of the decomposition $\boldsymbol{A} = \boldsymbol{\Sigma}^{1/2}\boldsymbol{U}$ for the estimation of the mixing matrix $\boldsymbol{A}$, so we start by estimating the unconditional co-variance matrix $\boldsymbol{\Sigma}$. For this purpose, we estimate the conditional mean $\boldsymbol{\mu}_t$ of the AR(1) process in (2) and thereby obtain an estimate of $\boldsymbol{\Sigma}$ from the OLS residuals $\hat{\boldsymbol{\epsilon}}_t = \boldsymbol{r}_t - \hat{\boldsymbol{\mu}}_t$.

Second, we estimate the orthogonal matrix $\boldsymbol{U}$ using the FastICA method proposed in Hyvärinen and Oja (2000), which allows decomposing multivariate mixed signals $\boldsymbol{x} = [x_1, ..., x_n]'$ into independent non-Gaussian factors $\boldsymbol{s} = [s_1, ..., s_n]'$, so that $\boldsymbol{x} = \boldsymbol{B}\boldsymbol{s}$, where $\boldsymbol{B}$ is a linear mixing matrix. The FastICA algorithm is applied to the whitened data $\hat{\boldsymbol{\Sigma}}^{-1/2}\hat{\boldsymbol{\epsilon}}_t$, so that we obtain an estimate of $\boldsymbol{U}$ and of $\boldsymbol{f}_t$ (for further details on ICA and FastICA see Broda and Paolella, 2009; Zhang and Chan, 2009 and Ghalanos, 2019).

Third, we estimate the GARCH(1,1) model parameters of the conditional variance of the orthogonal factors $\boldsymbol{f}_t$ estimated in the previous step. Given the assumption of independence of these factors, the conditional log-likelihood function of the GO-GARCH model can be expressed as the sum of the individual conditional log-likelihoods plus an additional term for the mixing matrix $\boldsymbol{A}$:

$$L(\hat{\boldsymbol{\epsilon}}_t|\boldsymbol{\theta}, \boldsymbol{A}) = T\log\left|\boldsymbol{A}^{-1}\right| + \sum_{i=1}^{N}\sum_{t=1}^{T}\log\left(\text{NIG}(f_{i,t}|\theta_i)\right)$$

where $\boldsymbol{\theta}$ represents the vector of unknown parameters to be estimated and $\text{NIG}(f_{i,t}|\theta_i)$ represents the density function of the NIG distribution.

Fourth, we obtain an estimate of the conditional co-variance matrix $\boldsymbol{\Sigma}_t$ using the decomposition $\boldsymbol{\Sigma}_t = \boldsymbol{A}\boldsymbol{H}_t\boldsymbol{A}'$, given the estimates of the mixing matrix $\boldsymbol{A}$ and of the diagonal matrix of variances of the factors $\boldsymbol{H}_t$ obtained in the first and the third steps, respectively. Finally, the conditional third and fourth co-moment arrays, $\boldsymbol{M}_t^3$ and $\boldsymbol{M}_t^4$, are computed following the procedure described in Section 3.1.

Table 2 reports the estimation results for the GARCH and ρ and ν parameters of the NIG distribution, as well as the LM statistic from the Breusch-Godfrey test for testing the presence of autocorrelation on second moments for every orthogonal factor of each GO-GARCH calibration. For simplicity, the parameter estimates of the AR(1) model for the conditional mean $\boldsymbol{\mu}_t$ and the mixing matrix $\boldsymbol{A}$ estimates have been omitted from the table. The estimates in the table correspond to the first calibration, and the re-estimations done in a monthly basis (every 30 observations) by a rolling window procedure over the out-of-sample period are shown in Figure 3.

Consistent with what is usually observed in financial series, we find that factor conditional volatility can be explained mainly by a first-order autoregressive component (captured by the β parameter) and to a lesser extent by innovations (captured by the α parameter). Also, we find that ρ and ν are statistically significant in most cases, and the LM test on the squared innovations at different lags shows that the model adequately captures conditional heteroscedasticity. Note that the factors are not equal across systems, i.e., the parameter estimates for f_1 in the system containing Tether are not equal to those of f_1 in the system containing USD Coin. However, by sharing the same base of variables (the returns of traditional cryptocurrencies), the estimates between factors of different systems are similar. From Figure 3, certain underlying factors can be identified that capture a particular set of the information contained in the system, as they always present similar estimates. For example, f_5 in the traditional cryptocurrency system presents parameter estimates throughout the out-of-sample

Traditional	ω	α	β	ρ	ν	LM Lag 3	LM Lag 5	LM Lag 7
f_1	0.0225	0.1314	0.8675	0.1807	0.3841	1.029	4.506	5.327
	1.3959	2.7900***	18.3663***	2.6953***	3.6708***	(0.3105)	(0.1334)	(0.1934)
f_2	0.3340	0.4130	0.3591	0.2930	0.3545	0.1399	0.2477	0.4015
	3.0777***	2.6955***	2.5790***	4.5538***	3.9616***	(0.7084)	(0.9538)	(0.9864)
f_3	0.0449	0.1288	0.8337	-0.3103	1.4606	0.0994	0.3117	0.3758
	2.0629**	3.0831***	18.2525***	-4.1859***	2.7922***	(0.7525)	(0.9371)	(0.9882)
f_4	0.0946	0.1101	0.7969	0.3294	0.6053	0.0190	0.2832	0.4991
	2.2055**	2.3178**	11.3133***	5.1061***	3.5265***	(0.4432)	(0.9447)	(0.9785)
f_5	0.0415	0.0708	0.8927	0.4043	1.0995	0.0051	0.1693	0.4511
	1.4225	2.0971**	16.8577***	5.7680***	3.3359***	(0.9427)	(0.9726)	(0.9826)

USDT	ω	α	β	ρ	ν	LM Lag 3	LM Lag 5	LM Lag 7
f_1	0.0886	0.1050	0.8079	-0.3309	0.6021	0.0172	0.2776	0.4692
	2.2453**	2.3494**	12.4408***	-5.1312***	3.5311***	(0.8957)	(0.9462)	(0.9811)
f_2	0.0436	0.0628	0.8973	0.3911	1.0190	0.0319	0.1998	0.4505
	1.4361	2.0182**	17.1347***	5.5758***	3.3315***	(0.8583)	(0.9881)	(0.9826)
f_3	0.0556	0.1443	0.8083	0.3079	1.5538	0.0085	0.4123	0.5181
	2.2418**	3.1431***	16.2571***	4.0829***	2.7514***	(0.9267)	(0.9192)	(0.9767)
f_4	0.0181	0.1342	0.8647	-0.2232	0.3810	0.7561	1.8221	2.2489
	1.3022	2.8837***	17.4965***	-3.4471***	3.7666***	(0.3845)	(0.5119)	(0.6647)
f_5	0.0105	0.1358	0.8568	-0.2109	1.3211	0.2034	0.2795	0.4290
	1.8378*	3.9209***	30.7166***	-2.5827***	3.2855***	(0.6520)	(0.9457)	(0.9844)
f_6	0.3065	0.3738	0.4087	0.2942	0.3546	0.1741	0.2464	0.3976
	2.8770***	2.5926***	2.8627***	4.5379***	3.9922***	(0.6765)	(0.9542)	(0.9867)

USDC	ω	α	β	ρ	ν	LM Lag 3	LM Lag 5	LM Lag 7
f_1	0.0372	0.0595	0.9068	0.4153	1.1674	0.0021	0.1588	0.4317
	1.3926	2.0904**	19.2966***	5.8961***	3.3221***	(0.9633)	(0.9749)	(0.9842)
f_2	0.0441	0.1235	0.8389	0.3040	1.4509	0.1883	0.4397	0.4949
	2.0811**	3.0798***	19.1226***	4.1016***	2.7990***	(0.6643)	(0.9013)	(0.9788)
f_3	0.0219	0.1365	0.8624	0.1912	0.4041	1.028	4.575	5.412
	1.4210	2.8610***	18.0257***	2.8523***	3.6975***	(0.3106)	(0.1287)	(0.1861)
f_4	0.0137	0.1775	0.8208	-0.0143	0.9345	0.7344	0.9641	2.2888
	1.5585	2.7167***	14.6085***	-0.1851	3.3008***	(0.3915)	(0.7436)	(0.6563)
f_5	0.1053	0.1121	0.7800	0.2844	0.6849	0.0328	0.2438	0.3748
	2.0916**	2.2135**	9.4767***	4.1261***	3.3791***	(0.8562)	(0.9548)	(0.9883)
f_6	0.3502	0.4631	0.3106	-0.2803	0.3789	0.1031	0.2437	0.3940
	3.2675***	2.7851***	2.2693**	-4.2627***	3.9693***	(0.7481)	(0.9548)	(0.9870)

DGX	ω	α	β	ρ	ν	LM Lag 3	LM Lag 5	LM Lag 7
f_1	0.0247	0.1275	0.8496	0.0468	0.9639	0.0119	0.2510	0.4016
	1.7662*	2.7212***	17.6293***	0.6017	3.3238***	(0.9131)	(0.9530)	(0.9864)
f_2	0.0983	0.1094	0.7925	0.3284	0.6193	0.0358	0.2277	0.3577
	2.1665**	2.225089**	10.5014***	5.0727***	3.4933***	(0.8498)	0.9588)	(0.9894)
f_3	0.0245	0.1356	0.8633	0.1937	0.4023	1.217	40931	5.856
	1.4049	2.6871**	17.5495***	2.8696***	3.6700***	(0.2699)	(0.1066)	(0.1512)
f_4	0.0468	0.1256	0.8341	0.3068	1.4993	0.1200	0.3158	0.3794
	2.0623**	3.0901***	18.2066***	4.0936***	2.7740***	(0.729)	(0.936)	(0.988)
f_5	0.0418	0.0690	0.8937	-0.3979	1.0961	0.1878	0.1828	0.4687
	1.4293	2.1190**	17.1462***	-5.6628***	3.3540***	(0.8910)	(0.9695)	(0.9811)
f_6	0.0126	0.0357	0.9509	0.2905	0.3745	0.0672	0.1571	0.3667
	1.0037	2.2318**	43.1549***	4.5624***	3.9654***	(0.7955)	(0.9753)	(0.9888)

Table 2: Estimation results for GO-GARCH model and LM statistic from the Breusch-Godfrey autocorrelation test in the second moments for different lags over the in-sample period. Traditional indicates the estimate of the model considering only the five traditional cryptocurrencies, while Tether (USDT), USD Coin (USDC) and Digix Gold (DGX) indicate the estimates of the models considering the five traditional cryptocurrencies plus the corresponding asset-backed cryptocurrency. Breusch-Godfrey p-values reported in parenthesis and *, ** and *** reveal significance at the 10%, 5% and 1% levels, respectively.

period similar to those of f_5 in the systems containing Tether and Digix Gold, and also to those of f_3 in the system containing USD Coin. This is especially notable in the α and β estimates, as this factor stands out for presenting higher α estimates than the rest (and lower β estimates), which implies that the stochastic process following its volatility has lower inertia and is more influenced by innovations. This factor also stands out for having more unstable and higher estimates of the ω parameter than the rest at certain times. Thus, as it would occur with a principal component analysis (PCA), overlapping systems can be decomposed into a set of factors where some of which will capture common information in both systems.

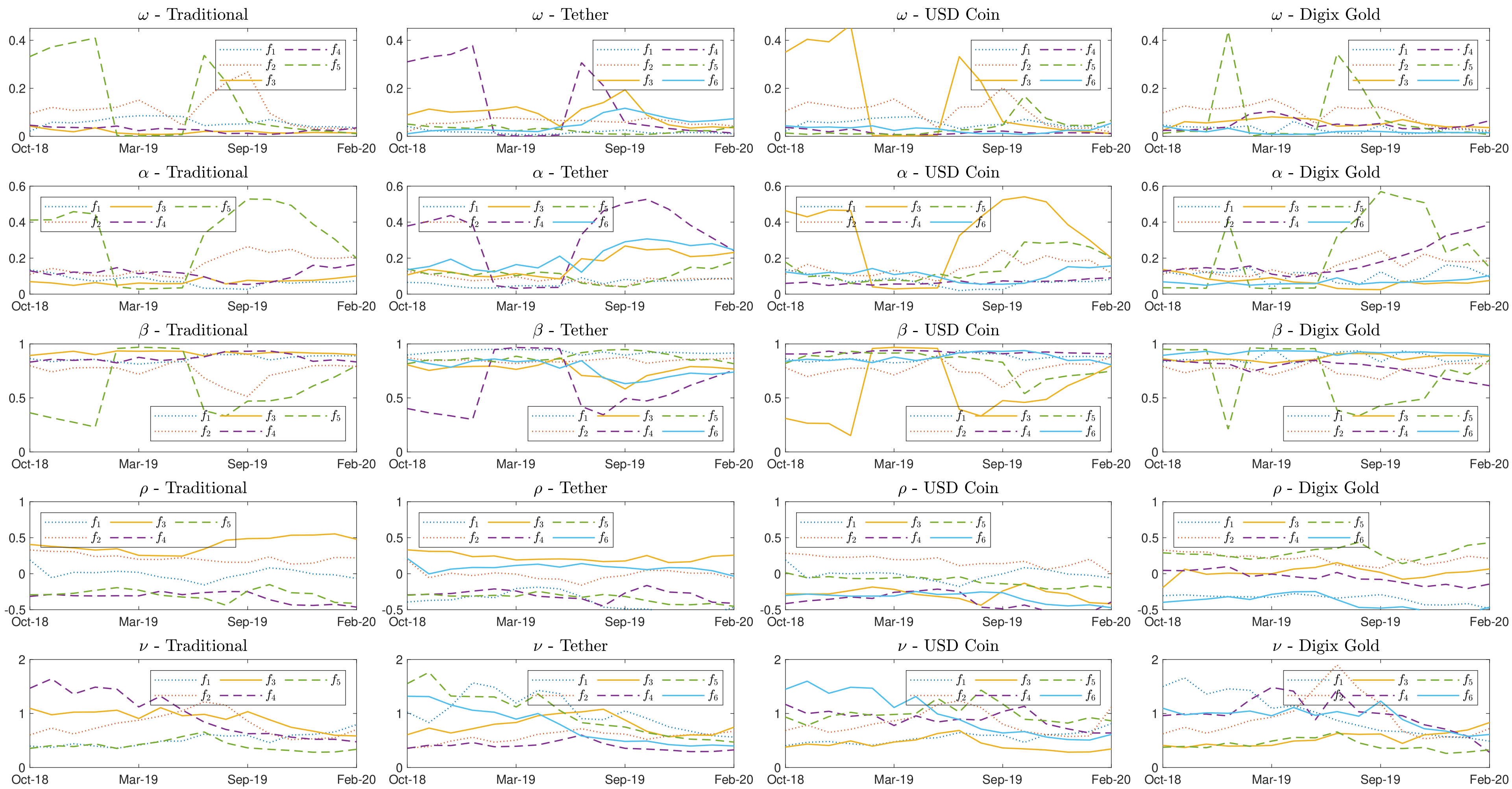

Figure 3: Calibrated parameters of the GO-GARCH models. Re-estimation is carried on every 30 observations over the out-of-sample period, which contains 451 observations, obtaining a time series of 16 observations with regard of each parameter

5.2 Conditional correlations

In this section, we examine the diversifying role of the considered stablecoins by means of a dynamic dependence analysis. We evaluate whether the considered stablecoins act as hedges, safe-haven assets or simply diversifiers, depending on the time point evaluated. Following Baur and McDermott (2010)'s definition, we consider that an asset is a diversifier when it presents a non-perfect positive correlation with another asset, while a hedger would be one that presents a null or negative correlation with another asset. Finally, a safe haven would be an asset that has zero or negative correlation with another asset in times of market stress or turmoil.

The descriptive analysis presented in Section 4 shows that these stablecoins keep a low sample correlation with traditional cryptocurrencies, which places them as potential diversifiers, and in some cases even negative, which could grant them the property of safe havens or hedges. To further explore this issue, we analyze the dynamics of the conditional connectedness between stablecoins and each of the traditional cryptocurrencies in Figure 4.

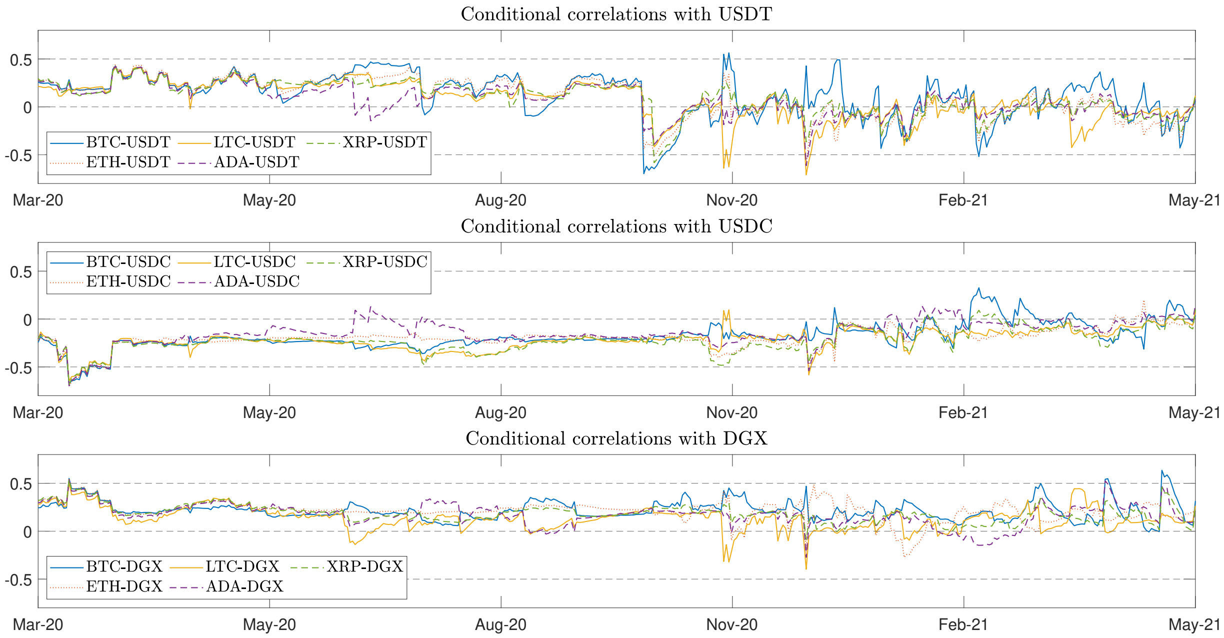

Figure 4: Conditional correlations between traditional cryptocurrencies (Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Cardano (ADA), Litecoin (LTC)) and stablecoins (Tether (USDT), USD Coin (USDC), Digix Gold (DGX))

First, we find that Tether keeps a positive but low correlation, almost always below 0.5 with all traditional cryptocurrencies, throughout the first few months of pandemic. From October 2020 onwards, the conditional correlations between Tether and traditional cryptocurrencies are markedly reduced and remain oscillating around zero. In Table 3 we find that Tether keeps an average conditional correlation below 15% with all traditional cryptocurrencies, although we find peaks of correlations around 0.4 with most cryptocurrencies (up to 0.56 in the case of Bitcoin) and lows between -0.6 and -0.7, finding, therefore, a high dispersion. Given these results, it seems reasonable to classify Tether as a diversifying asset during the period under consideration. Then, Tether act as a diversifier during the first months of the pandemic and as a hedger since October 2020.

Second, we find the conditional correlations between traditional cryptocurrencies and USD Coin, which are shown to be lower than those of Tether, especially until the end of 2020. In fact, in Table 3 we find that USD Coin keeps a negative average conditional correlation with all cryptocurrencies. The maxima only reach correlations of 0.33 in the case of Bitcoin, and are lower than 0.2 in all other cases. The dispersion is also somewhat lower than what we find in the correlations with Tether, although they are not low relative to the average correlations. This would place USD Coin in a first instance as an asset with greater potential as a safe haven or hedging asset than Tether. In fact, the second plot of Figure 4 reveals that conditional correlations with USD Coin are lower during the first months of the pandemic, during which uncertainty and turmoil in the markets was very high, thus acting as a safe haven.

Third, Digix Gold conditional correlations with traditional cryptocurrencies are considerably higher than those of USD-backed stablecoins. We find averages between 13% for Ripple and 22% for Bitcoin, with dispersions similar to those of USD Coin, which places Digix Gold as a diversifier over the period considered. Negative correlations are observed less frequently and in smaller magnitude than in the case of Tether (and thus also against USD Coin), so Digix Gold demonstrates less potential than USD-backed ones in reducing the risk of a cryptocurrency portfolio.

Correlation with USDT	BTC	ETH	XRP	ADA	LTC
Mean	0.1217	0.0951	0.0732	0.0729	0.0923
Std. dev.	0.2267	0.2101	0.1909	0.1559	0.1749
Max	0.5635	0.4404	0.4123	0.4243	0.4159
Min	-0.6974	-0.6044	-0.7090	-0.6152	-0.5844
Correlation with USDC	**BTC**	**ETH**	**XRP**	**ADA**	**LTC**
Mean	-0.1793	-0.1954	-0.2203	-0.1415	-0.2234
Std. dev.	0.1406	0.1086	0.1098	0.1282	0.1216
Max	0.3261	0.1982	0.0959	0.1471	0.1008
Min	-0.6778	-0.7027	-0.6449	-0.6994	-0.6873
Correlation with DGX	**BTC**	**ETH**	**XRP**	**ADA**	**LTC**
Mean	0.2181	0.2096	0.1325	0.1740	0.1859
Std. dev.	0.0995	0.1043	0.1184	0.1155	0.0904
Max	0.6360	0.5499	0.5049	0.5348	0.5375
Min	-0.0072	-0.2729	-0.3976	-0.2751	-0.0869

Table 3: Mean, standard deviation, maximum and minimum of conditional correlations traditional cryptocurrencies (Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Cardano (ADA), Litecoin (LTC)) and stablecoins (Tether (USDT), USD Coin (USDC), Digix Gold (DGX))

5.3 Time-varying portfolio weights

We build eight portfolios with no short-selling constraints. We first build a portfolio composed only by traditional cryptocurrencies under the CE maximization criterion explained in Section 3.2. Following the notions by Balder and Schweizer (2017) and León Valle et al. (2019), who link the order of Kappa ratios and Lower Partial Moments LPMs to individuals' risk aversion, we assume that the investor has a defensive attitude towards risk and assign a λ value of 10 in a context of market turmoil such as the COVID-19 pandemic. Then, adding separately each of the three stablecoins considered in the study, another three portfolios are formed, and the last four follow the same structure but their composition is determined under the MV criterion.

Figure 5 and Table 4 show the evolution and summary statistics of the portfolio composition over the out-of-sample period, where subplots on the left report the different maximum CE portfolios, while the right ones display the MV strategies. Both portfolio allocation strategies allow analyzing different aspects of portfolio formation. CE maximization considers the risk-return binomial and incorporates the CARA utility function of a risk-averse investor. Variance minimization only considers the risk side of the risk-return binomial, so a more relevant role of stablecoins in the resulting portfolios is expected.

First, we examine the results of the CE optimization approach. The benchmark analysis of the traditional cryptocurrency portfolio shows the predominant weight during most of the sample period of Bitcoin. Its average weight is almost two-thirds of the total portfolio. The weights of Ripple and

Ethereum are very unstable, with periods in which they dominate the rest of the assets and long periods in which they remain close to zero, with their average values being around 14% and 13%, respectively. Cardano presents an average weight of around 8% but only because it receives the entire portfolio allocation in a particular rebalancing in early summer 2020. Litecoin presents a residual weight, with an average weight lower than 1%.

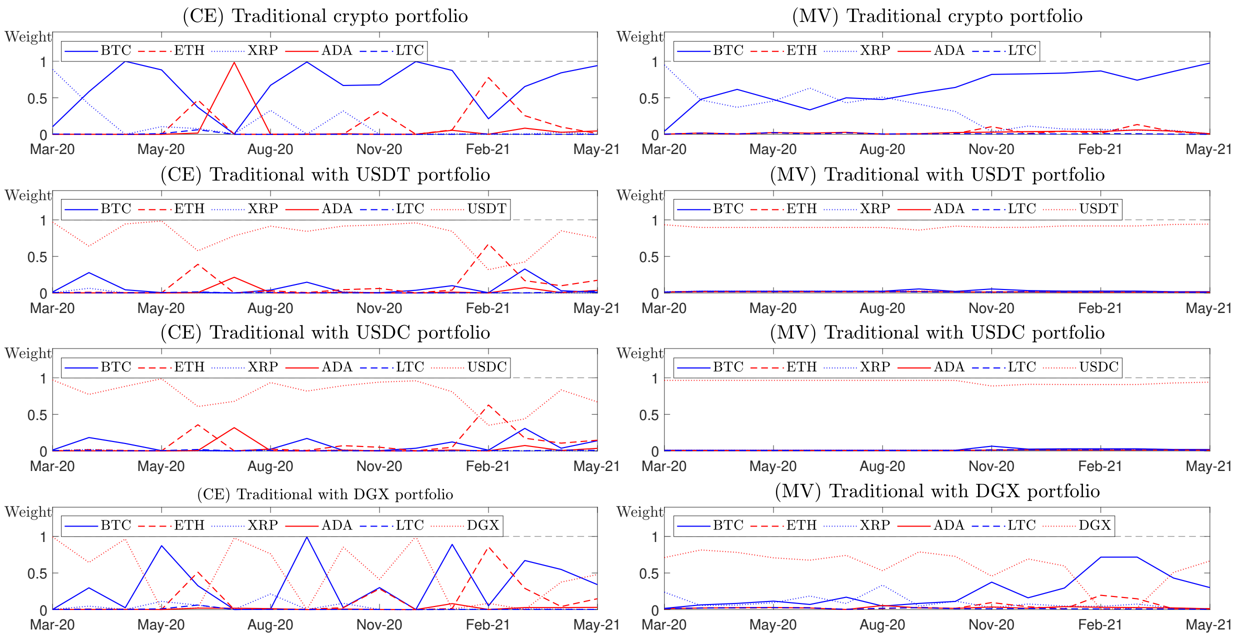

Figure 5: Dynamics of portfolio composition over the out-of-sample period, where the vertical axis represents the relative weight of each asset over the total portfolio, so that a weight of one would imply total allocation to a single asset and zero would imply its exclusion. The graphs in the left column correspond to the CE portfolios and those on the right to the MV portfolios. The first row shows the dynamics of the composition of the base portfolio, composed only of the five traditional cryptocurrencies. The second, third and fourth rows correspond to the dynamics of the portfolios including Tether, USD Coin and Digix Gold, respectively.

The behavior of portfolio composition with the inclusion to the traditional cryptocurrency portfolio of any of the USD-backed cryptocurrencies shows relevant implications. In both cases, stablecoin has a predominant weight in the portfolio, with average weights of 79% and 78%, respectively for Tether and USD Coin, displacing Bitcoin, which goes from having an average weight of over 65% in the traditional portfolio to one of around 7%. This reflects the potential of these two cryptocurrencies to reduce the risk of a traditional cryptocurrency portfolio, given that the CE maximization considers not only the expected return, but also the risk in terms of second, third and fourth moments.

In the case of the CE portfolio that includes the gold-backed cryptocurrency, we find a less stable composition, with Bitcoin and Digix Gold sharing most of the weight, representing, on average, around 33% and 47% of the total portfolio, respectively. As we have already seen in Section 4, Digix Gold is a cryptoasset whose returns exhibit a volatility that is similar to that of the other traditional cryptocurrencies, but with the attractiveness of having a lower correlation with them. It is the latter that could be attributed for it taking a dominant position in the portfolio for much of the period, while its high instability would be preventing it from holding a more stable weight. In fact, we find that its volatility represents a great proportion of its mean. The weights oscillate between the entire range of values allowed by the no short sales constraints in the CE portfolio and are slightly narrower in the case of the MV portfolio, specifically between 0.0047 and 0.8149. The bulk of the portfolio composition alternates almost at every rebalance between Digix Gold and Bitcoin, which represent around 47% and 33% of the total portfolio, respectively. Ethereum and Litecoin are the only traditional cryptocurrencies whose weight hardly varies with the introduction of any of the considered stablecoins.

		Traditional		Trad. with USDT		Trad. with USDC		Trad. with DGX	
		CE	MV	CE	MV	CE	MV	CE	MV
BTC	Mean	0.6542	0.6287	0.0665	0.0273	0.0733	0.0242	0.3345	0.2348
	St. Dev.	0.3234	0.2424	0.1008	0.0117	0.0898	0.0120	0.3566	0.2243
	Min	0.00521	0.04332	0.00072	0.01302	0.00082	0.01761	0.00001	0.01575
	Q25	0.5299	0.4779	0.0068	0.0237	0.0070	0.0176	0.0203	0.0805
	Q75	0.8959	0.8297	0.0577	0.0260	0.1272	0.0283	0.5790	0.3191
	Max	0.9995	0.9748	0.3278	0.0556	0.3085	0.0653	0.9926	0.7171
ETH	Mean	0.1258	0.0276	0.1070	0.01679	0.1033	0.0160	0.1372	0.0423
	St. Dev.	0.2242	0.0381	0.1820	0.0031	0.1688	0.0021	0.2431	0.0554
	Min	0.00015	0.00187	0.00094	0.01117	0.00103	0.01106	0.00001	0.00181
	Q25	0.0014	0.0057	0.0056	0.0156	0.0062	0.0156	0.0030	0.0120
	Q75	0.1394	0.0241	0.1165	0.0186	0.1167	0.0169	0.1822	0.0326
	Max	0.7774	0.1343	0.6705	0.0236	0.6287	0.0215	0.8582	0.1956
XRP	Mean	0.1365	0.3097	0.0069	0.0188	0.0038	0.0177	0.0341	0.09440
	St. Dev.	0.2429	0.2680	0.0159	0.0058	0.0055	0.0046	0.0591	0.0875
	Min	0.00005	0.00879	0.00032	0.00539	0.00032	0.00464	0.00000	0.00814
	Q25	0.0010	0.0652	0.0008	0.0165	0.0008	0.0182	0.0008	0.0459
	Q75	0.1594	0.4598	0.0031	0.0239	0.0027	0.0202	0.0499	0.1002
	Max	0.8874	0.9487	0.0649	0.0245	0.0205	0.0219	0.2131	0.3350
ADA	Mean	0.0771	0.0248	0.0233	0.0149	0.0300	0.0142	0.0145	0.0244
	St. Dev.	0.2432	0.0168	0.0544	0.0033	0.0792	0.0025	0.0209	0.0126
	Min	0.00010	0.00213	0.00049	0.01098	0.00050	0.01030	0.00001	0.00134
	Q25	0.0008	0.0090	0.0011	0.0111	0.0013	0.0119	0.0011	0.0174
	Q75	0.0329	0.0378	0.0105	0.0181	0.0116	0.0159	0.0217	0.0293
	Max	0.9843	0.0608	0.2150	0.0203	0.3184	0.0188	0.0812	0.0554
LTC	Mean	0.0060	0.0090	0.0059	0.0154	0.0051	0.0150	0.0059	0.0146
	St. Dev.	0.0154	0.0063	0.0068	0.0034	0.0050	0.0025	0.0150	0.0078
	Min	0.00009	0.00199	0.00047	0.00799	0.00049	0.00780	0.00000	0.00304
	Q25	0.0008	0.0054	0.0021	0.0136	0.0021	0.0152	0.0013	0.0088
	Q75	0.0028	0.0096	0.0068	0.0188	0.0068	0.0156	0.0029	0.0215
	Max	0.0631	0.0236	0.0267	0.0188	0.0196	0.0205	0.0615	0.0277
USDT	Mean			0.7901	0.9065				
	St. Dev.			0.2008	0.0202				
	Min			0.31847	0.85981				
	Q25			0.7239	0.8960				
	Q75			0.9336	0.9164				
	Max			0.9842	0.9410				
USDC	Mean					0.7843	0.9125		
	St. Dev.					0.1902	0.0124		
	Min					0.35071	0.88785		
	Q25					0.6761	0.9081		
	Q75					0.9366	0.9148		
	Max					0.9875	0.9403		
DGX	Mean							0.4735	0.5892
	St. Dev.							0.4129	0.2464
	Min							0.00005	0.00472
	Q25							0.0173	0.5248
	Q75							0.8815	0.7306
	Max							0.9999	0.8149

Table 4: Basic statistics on the relative weights of the various cryptocurrencies comprising the CE and MV portfolios through the out-of-sample period. A weight equal to one would imply total allocation to a single asset and zero would imply its exclusion. St. Dev. represents the standard deviation of the relative weight and Q25 and Q75 the 0.25 and 0.75 quantiles, respectively.

Second, as expected, the MV portfolios show more stable compositions over time, as the standard deviations of the weights are significantly lower compared with the CE strategy. Until August 2020, the portfolio composed solely of traditional cryptocurrencies is based almost exclusively on two assets: Bitcoin and Ripple. These maintain similar proportions until that time, after which Bitcoin begins to accumulate a successively increasing proportion of the portfolio, while Ripple's converges to values close to zero. At first glance, it may come as a surprise that the MV portfolio gives such a significant weight to Ripple, being the traditional cryptocurrency with the highest volatility among those considered (see Table 1). Conversely, Ripple exhibits the least degree of dependence with the rest of the traditional cryptocurrencies, forming precisely with Bitcoin the lowest pairwise correlation (see Figure 2). Adding to this the fact that Bitcoin presents the lowest sample volatility among the set of traditional cryptocurrencies, we find the reason why Ripple and Bitcoin share most of the weight during the whole period. The rest of the cryptocurrencies have a residual weight, with Ethereum holding the highest proportion among them.

For MV portfolios that include any of the USD-backed cryptocurrencies, we find that these account for almost the entire portfolio allocation, as one would initially expect, given that its returns exhibit present a low volatility and low correlation with the traditional cryptocurrency set (see Table 1, Figure 2 and Figure 4), and the allocation remains stable over the period under study. It is striking that Tether and USD Coin have such similar average weights in both portfolios (both EC and DC), despite the fact that USD Coin has better safe haven properties than Tether, which acts primarily as a diversifier (albeit a very powerful one). In fact, Tether has a slightly higher weighting than USD Coin in the CE portfolio, while the opposite is true in the MV portfolio. From this we can deduce that Tether could be bringing higher returns to the portfolio in terms of first, third and fourth moments, as these are not taken into account in the variance minimization strategy.

Finally, in the case of the MV portfolio with Digix Gold, we find that this cryptocurrency maintains an average weight of 58% throughout the period considered, remaining above 60% for much of 2020. However, the most remarkable aspect of Digix Gold's weightings is its very high volatility. In fact, it even disappears from the portfolio during February 2021. The instability in portfolio composition introduced by this cryptocurrency limits its properties as a diversifier. It is these properties, however, that allow it to obtain such a significant average weight in both portfolios and are also what make its weight higher in the MV portfolio than in the CE portfolio, since Digix Gold generates lower returns than traditional cryptocurrencies despite having a similar volatility (as shown in Table 1).

From the evolution of the composition of the portfolios considered can be deduced that depending on whether the investor's objective is focused on finding the best balance between risk and expected return, considering higher order moments, or seeks to minimize volatility as the sole objective, the composition of the portfolio will not only be different, as might be expected, but will also be more unstable in the first case. USD-backed cryptocurrencies allow to greatly reduce the volatility of the portfolio at the cost of reducing the expected return. Traditional cryptocurrencies have the potential to generate very high returns that are intrinsically linked to high volatility, making them of virtually zero interest in a portfolio that ignores the expected return to focus on minimizing risk, provided there is a systematically less volatile alternative, as is the case with USD-backed cryptocurrencies. This logic is evident in the composition of the MV portfolios, which provide almost the entire weight to Tether and USD Coin. However, these stablecoins do not yield returns comparable to traditional cryptocurrencies, so in the case of CE portfolios the latter become more important, and their high volatility results in more abrupt rebalancing dynamics.

5.4 Downside risk results

In Figure 6 we present the returns, gVaR and mVaR at 96% and 99% confidence levels of the base portfolio, which is the one composed only of the five traditional cryptocurrencies considered in the study and whose risk we want to reduce by introducing stablecoins. We note that the returns are very similar when comparing the CE portfolio with the MV portfolio since both portfolios are dominated primarily by Bitcoin. In terms of risk, we find that mVaR is equal to or higher than gVaR when the confidence level is 99%, and the difference between the two measures expands at times of high volatility, while for a level of 96% both measures yield almost identical results throughout the entire period. This gives us an idea of the importance of considering higher order moments when measuring the risk of portfolios with cryptocurrencies, as we see that with the gVaR we might be underestimating the risk by an increasing magnitude with the confidence level and especially at times of turmoil.

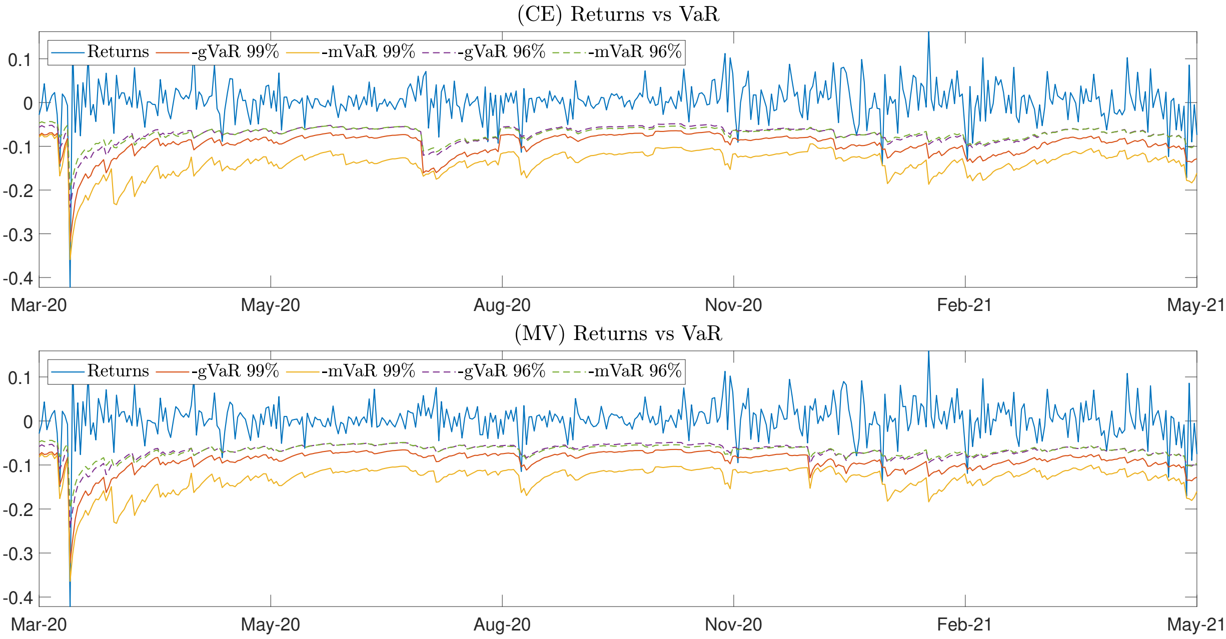

Figure 6: Returns and VaR measures of the base CE and MV portfolios, comprised solely of the five traditional cryptocurrencies. Both mVaR and gVaR are plotted with a negative sign to easily identify times when these risk measures are exceeded.

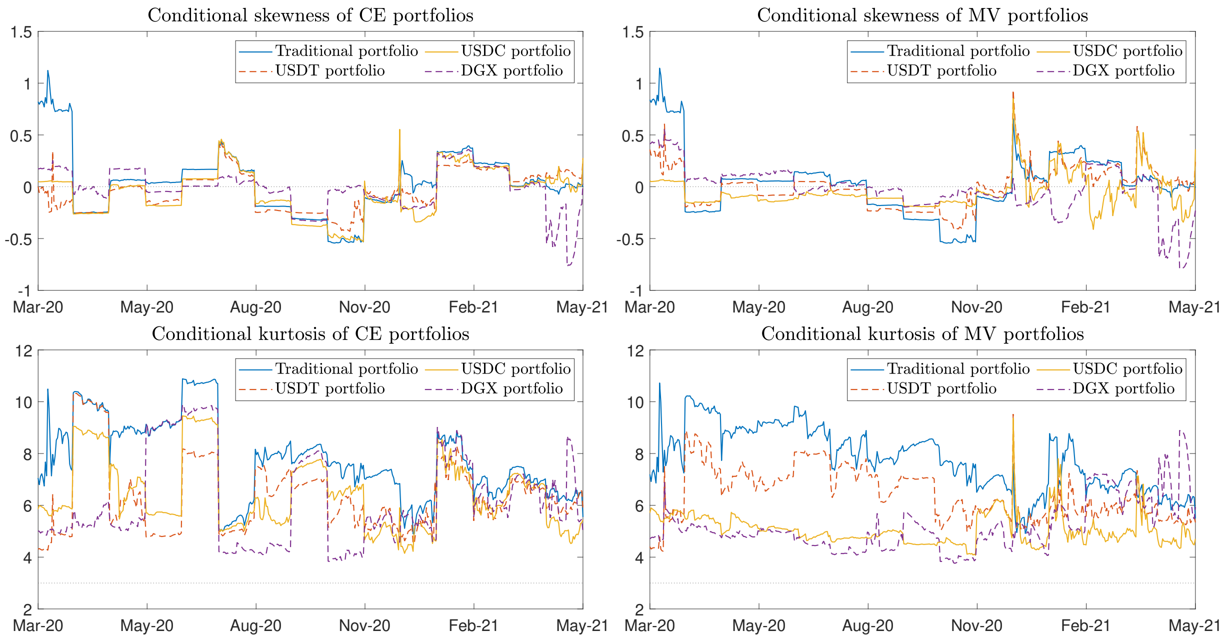

Figure 7: Conditional skewness and kurtosis of the different portfolios analyzed. Conditional skewness and kurtosis are calculated according to (11).

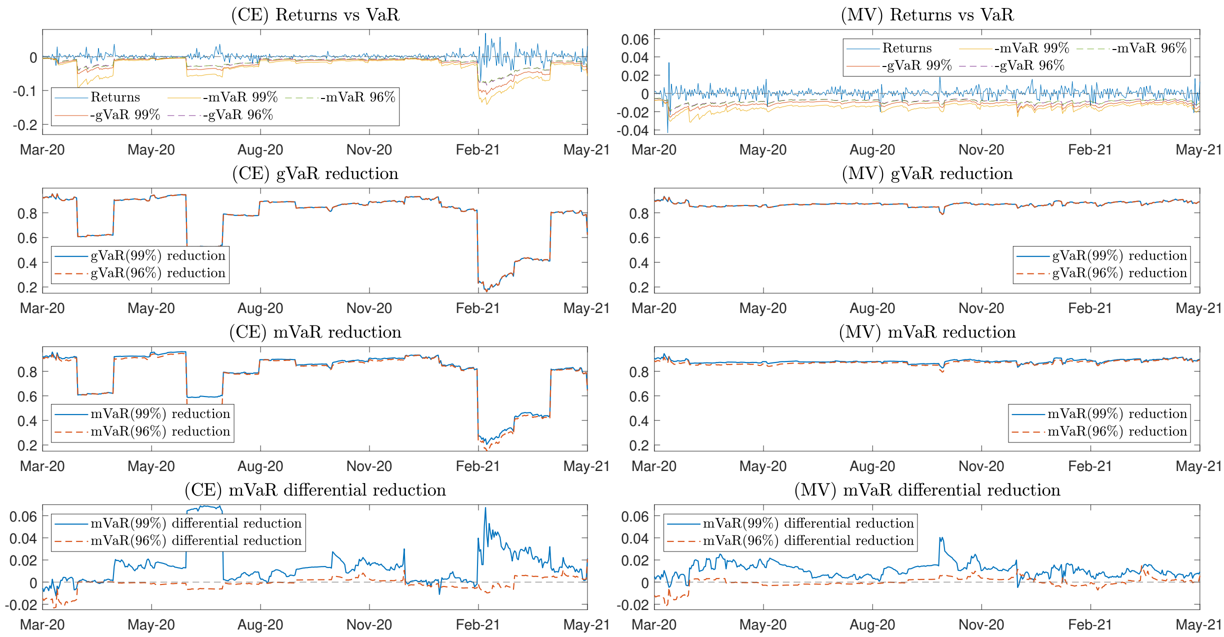

Figure 8: Effects on VaR of introducing Tether (USDT) into the portfolio. In the second row, gVaR$(100-\alpha\%)$ reduction indicates the relative reduction of gVaR when comparing the portfolio that includes Tether against the portfolio of traditional cryptocurrencies, i.e., $\frac{\text{gVaR}_{\text{USDT}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}-1$, and equivalently for mVaR$(100-\alpha\%)$ reduction shown in the third row. In the fourth row, the differential reduction represents the difference between the mVaR and gVaR relative reductions, i.e., $\frac{\text{mVaR}_{\text{USDT}}(100-\alpha\%)}{\text{mVaR}_{\text{trad}}(100-\alpha\%)}-\frac{\text{gVaR}_{\text{USDT}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}$, so positive (negative) values indicate that the introduction of Tether in the portfolio generates a higher (lower) relative reduction or increase in mVaR than in gVaR.

In figures 8 and 9, we find that introducing Tether and USD Coin into the traditional cryptocurrency portfolio results in both cases in a very significant reduction of risk, especially in the MV portfolio, as this provides a higher weighting to USD-backed cryptocurrencies compared to the CE portfolio. Table 5 shows some basic statistics on the impact on risk that the introduction of these stablecoins has on portfolios. The average reduction in gVaR in the CE portfolio is around 76% in both the Tether and USD Coin portfolios, with little difference between a 96% and 99% significance level. In the case of the MV portfolio, Tether manages to reduce gVaR by 87% on average for both confidence levels, while USD Coin achieves an average reduction of 89% for a 96% confidence level and 91% for a 99% confidence level. Note that the minimum reduction observed in the gVaR of the CE portfolio is around 16% in the case of Tether and 24% in the case of USD Coin, while in the MV portfolio they are around 79% and 80%, respectively. In addition, the maximum reduction they achieve in the gVaR of the CE portfolio is around 95% for Tether and 97% for USD Coin, while in the MV portfolio it is 93% for Tether and 97% and 93% for USD Coin, respectively at the 99% and 96% confidence levels. This is a very remarkable risk reduction that we could reasonably attribute to the conjunction of a very low intrinsic volatility of these stablecoins with a diversifying and powerful hedging profile versus traditional cryptocurrencies, as we have seen in previous sections. The higher risk reduction observed in the MV portfolio might be attributed to the fact that the weight of the stablecoin is higher than in the CE portfolio, in accordance with what is observed in Figure 5.

Beyond the effect these cryptocurrencies have on the second moment of the portfolio, we are interested in how they affect higher order moments and especially for high confidence levels, where we see that the consideration of co-skewness and co-kurtosis substantially increase the tail risk. In this sense, not only do we find that these gold-backed tokens manage to reduce mVaR by a similar magnitude to that observed in the case of gVaR, but in fact we see that on average they reduce it to a greater extent. The differential reduction of mVaR versus gVaR that we can observe in the fourth row of figures 8 and 9 and whose statistics we can see in Table 5, show that, on average, the introduction of Tether in the CE portfolio allows to reduce mVaR by 1.5% more than gVaR when we consider a

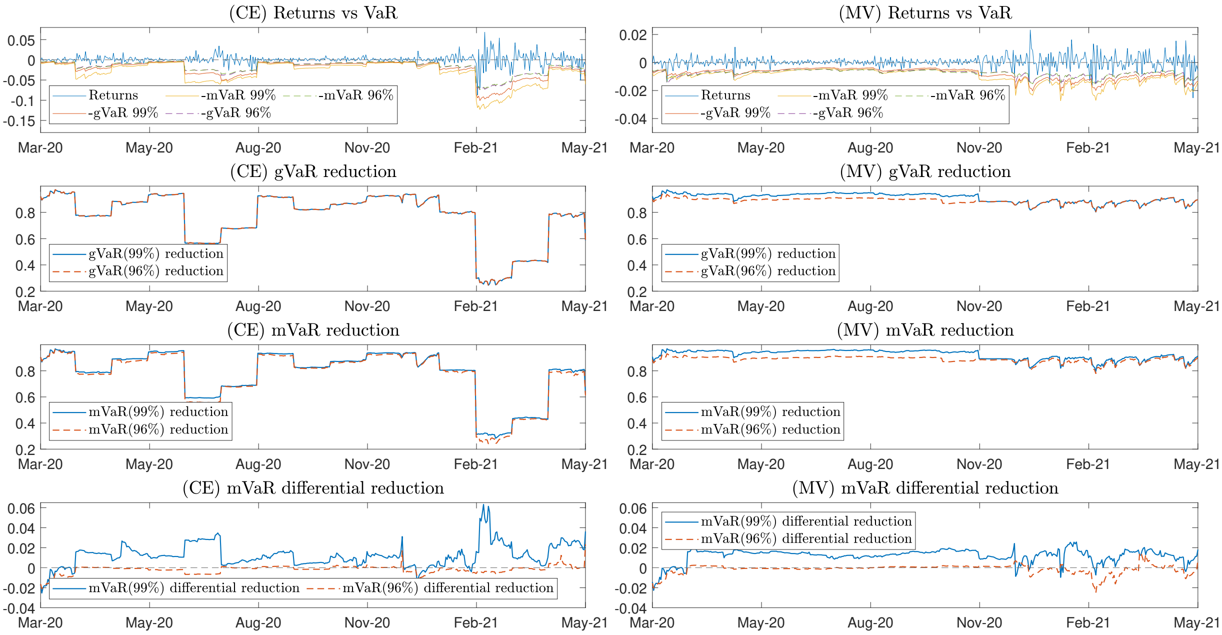

Figure 9: Effects on VaR of introducing USD Coin (USDC) into the portfolio. In the second row, gVaR$(100-\alpha\%)$ reduction indicates the relative reduction of gVaR when comparing the portfolio that includes USD Coin against the portfolio of traditional cryptocurrencies, i.e., $\frac{\text{gVaR}_{\text{USDC}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}-1$, and equivalently for mVaR$(100-\alpha\%)$ reduction shown in the third row. In the fourth row, the differential reduction represents the difference between the mVaR and gVaR relative reductions, i.e., $\frac{\text{mVaR}_{\text{USDC}}(100-\alpha\%)}{\text{mVaR}_{\text{trad}}(100-\alpha\%)}-\frac{\text{gVaR}_{\text{USDC}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}$, so positive (negative) values indicate that the introduction of USD Coin in the portfolio generates a higher (lower) relative reduction or increase in mVaR than in gVaR.

99% confidence level, and by about 1.1% when we consider a 96% level. In the case of USD Coin, these numbers are 1.2% and -0.2%, respectively at the 99% and 96% confidence level. These results reveal that these stablecoins not only reduce portfolio volatility, but also provide benefits in terms of higher order moments. We can delve a bit deeper into this by attending to Figure 7, which shows the conditional skewness and kurtosis of all the portfolios considered. We see that Tether and USD Coin do not manage to systematically increase skewness, which would be desirable for a risk-averse investor, while they do allow for a significant reduction in excess kurtosis, which would explain the differential reduction in mVaR versus gVaR. Contrary, in the case of the MV portfolio with Tether we find a higher reduction in gVaR versus mVaR, albeit to a smaller extent, which is consistent with the fact that this portfolio only considers the second moment versus the CE portfolio, which considers the first four moments in its allocation algorithm. However, USD Coin does induce a superior reduction in the mVaR of the MV portfolio when we consider a 99% significance level.

Another interesting issue is the difference we found between the results at different confidence levels. We see that in a generalized way the reduction produced in the mVaR at a 99% confidence level is higher than the corresponding one at a 96% level, while in the case of the gVaR the choice of the significance level does not seem to be related to the magnitude of the risk reduction. This, as we commented in Figure 6, where we observed that gVaR and mVaR maintain practically identical levels at a 96% confidence level while at 99% the difference is totally visible, is related to the construction of the mVaR. The higher the level of significance, the greater the relative weight of the third and fourth moments over the total computation of this risk measure. This highlights, on the one hand, the importance of considering higher order moments when measuring tail risk in cryptocurrency portfolios, and, on the other hand, the attractiveness of these types of stablecoins in reducing such risk.

Regarding Digix Gold, we find more ambiguous results that can be found in Figure 10 and in Table 5. On the one hand, in the graphs we observe that the effect of gold-backed cryptocurrency is very unstable throughout the sample, with standard deviation of the reduction in gVaR around 45% in both the CE and MV portfolios. On average, it manages to reduce the gVaR of the CE portfolio by almost 8%, and that of the MV portfolio by 14%. On the other hand, the high intrinsic volatility of this cryptocurrency does not allow us to achieve a systematic reduction in portfolio risk. In fact, this stablecoin raises the risk of the portfolio at specific times, increasing the gVaR and mVaR of the traditional portfolio by up to 365% and 528%, respectively. However, the interesting thing about this cryptocurrency is that it induces a differential reduction of mVaR with respect to gVaR notably higher than that observed with USD-backed stablecoins, reducing mVaR by 27% more compared to gVaR when we consider a 99% confidence level. Interestingly, when Digix Gold increases the risk of the portfolio, the mVaR increases less than the gVaR, which leads us to deduce that the benefits of this cryptocurrency are sustained when it comes to higher order moments, and in particular when it comes to reducing the kurtosis of the portfolio, as we can see in Figure 7. In fact, we can see that the portfolios with Digix Gold are, in general, the ones with the lowest kurtosis, especially in the case of the MV portfolio during 2020.

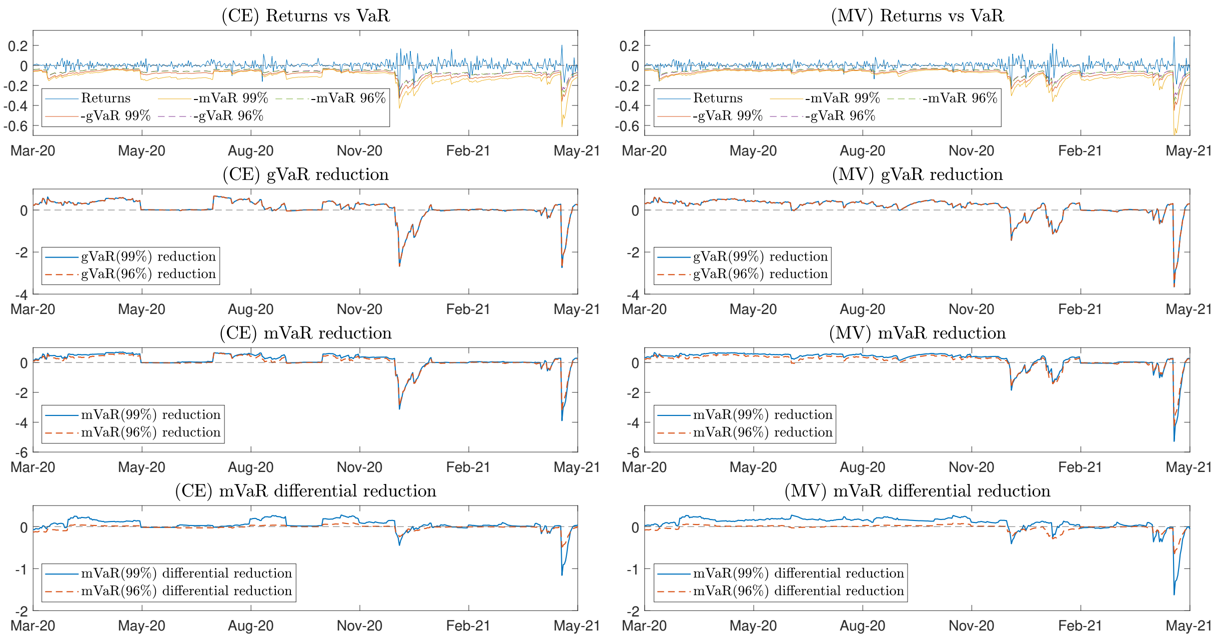

Figure 10: Effects on VaR of introducing Digix Gold (DGX) into the portfolio. In the second row, gVaR($100-\alpha\%$) reduction indicates the relative reduction of gVaR when comparing the portfolio that includes Digix Gold against the portfolio of traditional cryptocurrencies, i.e., $\frac{\text{gVaR}_{\text{DGX}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}-1$, and equivalently for mVaR($100-\alpha\%$) reduction shown in the third row. In the fourth row, the differential reduction represents the difference between the mVaR and gVaR relative reductions, i.e., $\frac{\text{mVaR}_{\text{DGX}}(100-\alpha\%)}{\text{mVaR}_{\text{trad}}(100-\alpha\%)}-\frac{\text{gVaR}_{\text{DGX}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}$, so positive (negative) values indicate that the introduction of Digix Gold in the portfolio generates a higher (lower) relative reduction or increase in mVaR than in gVaR.

Finally, in Figure 11 the gVaR and mVaR of the three potential stablecoins considered are shown together, so that it is easier to compare the results. Between the two USD-backed cryptocurrencies we do not find major differences in terms of the risk reduction they allow to obtain in the CE portfolios. Notwithstanding, in the MV portfolios USD Coin allows a slightly but systematically higher reduction in gVaR and mVaR until October 2020. This responds to the fact that USD Coin acts a as a safe have during this period while Tether performs as a diversifier. In terms of mVaR reduction relative to gVaR reduction, we do not find significant differences between the two stablecoins. With respect to Digix Gold, we find that this cryptocurrency, when it reduces risk rather than increasing it, does so to a lesser extent than the previous two stablecoins. However, its differential effect on mVaR with respect to gVaR is much higher than that of Tether and USD Coin, both when we consider increasing risk and reducing it.

	CE portfolio				MV portfolio			
with USDT	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
gVaR(99%) reduction	0.75878	0.20395	0.16062	0.95411	0.87015	0.01742	0.78627	0.93316
gVaR(96%) reduction	0.75874	0.20390	0.16062	0.95339	0.87005	0.01722	0.78628	0.93029
mVaR(99%) reduction	0.77390	0.19401	0.20444	0.95980	0.75730	0.01473	0.82673	0.94359
mVaR(96%) reduction	0.88104	0.20381	0.15097	0.94748	0.86973	0.01594	0.79228	0.92041
differential (99%)	0.01511	0.01751	-0.01243	0.06899	-0.00144	0.00629	-0.00482	0.04045
differential (96%)	0.01088	0.00577	-0.02339	0.02085	-0.00032	0.00471	-0.02203	0.01490
with USDC	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
gVaR(99%) reduction	0.76621	0.19221	0.24496	0.97221	0.91122	0.03422	0.80316	0.97186
gVaR(96%) reduction	0.76622	0.19222	0.24496	0.97299	0.88950	0.02051	0.80316	0.93852
mVaR(99%) reduction	0.77819	0.18640	0.28306	0.96878	0.92311	0.03582	0.79586	0.96927
mVaR(96%) reduction	0.76434	0.19252	0.24036	0.96731	0.88810	0.02213	0.77804	0.93133
differential (99%)	0.01198	0.01146	-0.02530	0.06325	0.01189	0.00689	-0.02261	0.02571
differential (96%)	-0.00187	0.00411	-0.02121	0.02331	-0.00140	0.00491	-0.02512	0.01521
with DGX	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
gVaR(99%) reduction	0.07947	0.45223	-2.73782	0.66770	0.14117	0.44818	-3.65938	0.60865
gVaR(96%) reduction	0.07941	0.45218	-2.73780	0.66770	0.14110	0.44813	-3.65936	0.60908
mVaR(99%) reduction	0.12419	0.56241	-3.89687	0.70818	0.22333	0.61631	-5.28361	0.67136
mVaR(96%) reduction	0.06172	0.49999	-3.27553	0.64488	0.12045	0.52273	-4.34238	0.55148
differential (99%)	0.04472	0.14250	-1.15905	0.27534	0.08215	0.18891	-1.62425	0.27227
differential (96%)	-0.01769	0.06600	-0.53773	0.09257	-0.02064	0.08459	-0.68301	0.08152

Table 5: Summary statistics on the impact on the risk of CE and MV portfolios when introducing stablecoins. Note that here gVaR$(100-\alpha\%)$ reduction indicates the relative reduction of gVaR when comparing the portfolio that includes the stablecoin against the base portfolio, i.e., $\frac{\text{gVaR}_{\text{stable}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}-1$, and equivalently for mVaR$(100-\alpha\%)$ reduction. Also, differential$(100-\alpha\%)$ represents the difference between the mVaR and gVaR relative reductions, i.e., $\frac{\text{mVaR}_{\text{stable}}(100-\alpha\%)}{\text{mVaR}_{\text{trad}}(100-\alpha\%)} - \frac{\text{gVaR}_{\text{stable}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}$.

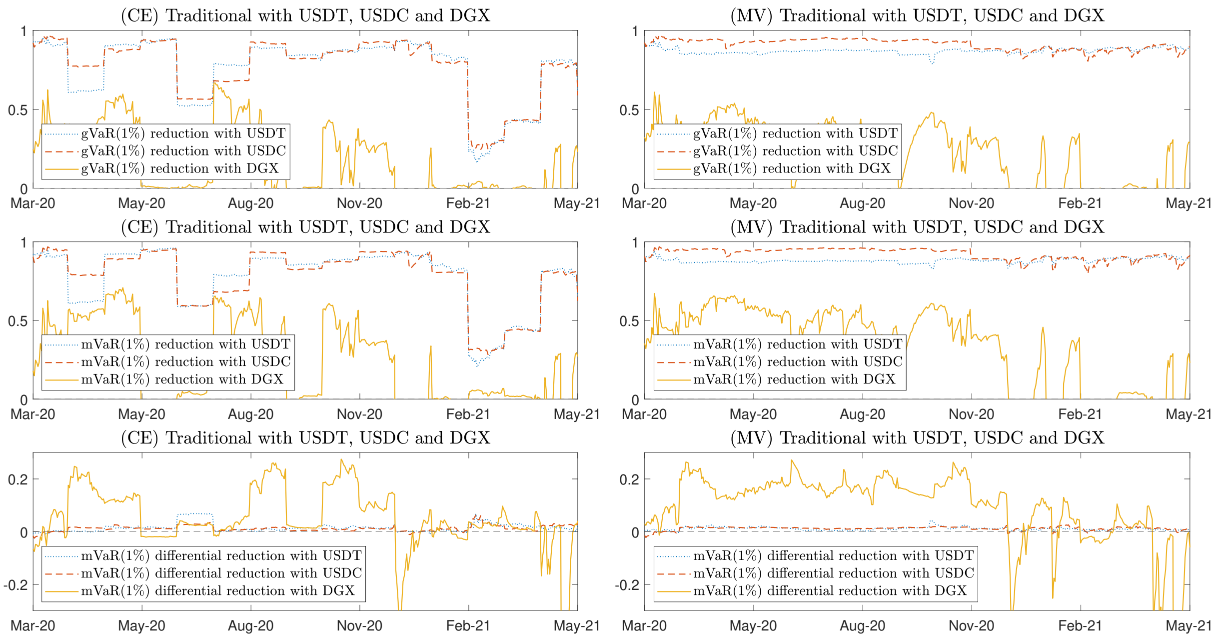

Figure 11: Effects on VaR of introducing Tether (USDT), USD Coin (USDC) and Digix Gold (DGX). In the second row, gVaR$(100-\alpha\%)$ reduction indicates the relative reduction of gVaR when comparing the portfolio that includes a stablecoin against the portfolio of traditional cryptocurrencies, i.e., $\frac{\text{gVaR}_{\text{stable}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}-1$, and equivalently for mVaR$(100-\alpha\%)$ reduction shown in the third row. In the fourth row, the differential reduction represents the difference between the mVaR and gVaR relative reductions, i.e., $\frac{\text{mVaR}_{\text{stable}}(100-\alpha\%)}{\text{mVaR}_{\text{trad}}(100-\alpha\%)} - \frac{\text{gVaR}_{\text{stable}}(100-\alpha\%)}{\text{gVaR}_{\text{trad}}(100-\alpha\%)}$, so positive (negative) values indicate that the introduction of the stablecoin in the portfolio generates a higher (lower) relative reduction or increase in mVaR than in gVaR.

5.5 Backtesting

To complete the empirical analysis, backtesting is conducted to check the validity of the risk models implemented. In particular, Kupiec (1995)'s unconditional coverage (UC) test, Christoffersen (1998)'s conditional coverage (CC) test and Engle and Manganelli (2004)'s Dynamic Quantile (DQ) Test, described in section Section 3.3, are performed. Table 6 lists the backtesting VaR performances for the different portfolios considered. First, we note that for a 96% confidence level no model exceeds the number of expected excesses (18) except in the case of the MV portfolio with USD Coin, which shows a total of 20. In most portfolios, the same number of excesses is observed with the mVaR as with the gVaR at a 96% confidence level (as would be expected considering that the differences between gVaR and mVaR at 96% confidence are small). As we have seen above, the effect of higher order moments on mVaR is greater at higher confidence levels, and this becomes evident when we look at the number of excesses observed for 99% confidence, for which the gVaR exceeds the number of expected excesses (4) in all the portfolios considered except for the CE portfolio with Digix Gold, which equals the expected number of excesses. We also find that the introduction of stablecoins in the base portfolio leads to an increase in the number of excesses in most cases, with Digix Gold, interestingly, penalizing the least in this regard. Note that in contrast to a confidence level of 96%, at 99% a lower number of excesses over the mVaR than over the gVaR is observed in all cases, which highlights the relevance of higher order moments in the risk of the portfolios under study. In fact, we observe that the number of expected excesses is exceeded in seven of the eight portfolios considered with the gVaR at 99% confidence level, while with the mVaR it is exceeded in only two portfolios.

Regarding the UC test, in most cases we cannot reject the null hypothesis for a significance level of less than 10%, and in no case can we reject the null hypothesis (which is that the observed proportion of excesses over the total observations is equal to that specified for the VaR significance level) for a significance level of 1%. These results allow us to conclude that the VaR models give rise to excess ratios appropriate to the confidence level considered. In the case of the CC test, the null hypothesis that there is no first-order serial correlation in the observed proportion of excesses is tested. The results show that we cannot reject the null hypothesis for significance levels below 10% in any case except for the gVaR of the MV portfolio with USD Coin, in which case the likelihood ratio statistic is not significant at levels below 5%.

We complete the backtesting by conducting the DQ test with a specification for the regression equation with one lag of the endogenous variable and four lags of the VaR as explanatory variables, according to Engle and Manganelli (2004). In the CE portfolios, we reject the null hypothesis for a 1% significance level in the gVaR and mVaR of the traditional portfolio and the Tether portfolio. For the rest of the models applied to the CE portfolios, we cannot reject the null hypothesis for significance levels below 5%. For the case of the MV portfolios we only cannot reject the null hypothesis for significance levels below 10% in the gVaR and mVaR models of the Digix Gold portfolio, while in most cases we reject it for 5% or 1% levels. These results, together with those of the CC and UC tests, lead us to conclude that the proposed models give rise to an adequate proportion of excesses, which does not exhibit first order autocorrelation, but in some cases may depend on past information.

6 Main conclusions

This paper investigates the diversifying potential of three putative stablecoins, two USD-backed (Tether and USD Coin) and one gold-backed (Digix Gold), regarding traditional cryptocurrency portfolios during the COVID-19 pandemic. We conduct an out-of-sample pandemic experiment that consists on forming optimal portfolios of traditional cryptocurrencies and studying how the introduction of a stablecoin into the portfolio affects the tail risk of the combined strategy. For portfolio allocation purposes, we employ two different criteria: (1) we conduct the classical MV problem as a benchmark; (2) we form portfolios by maximizing a functional form for the CE that incorporates conditional portfolio skewness and kurtosis in addition to expected return and conditional variance. Portfolio conditional moments are obtained analytically from conditional co-moment estimates obtained using

Portfolio	Model	Exceedances 1%	Exceedances 4%	LR_{UC} 1%	LR_{UC} 4%	LR_{CC} 1%	LR_{CC} 4%	DQ 1%	DQ 4%
CE									
Traditional	gVaR	7	11	1.1997	3.2783*	1.4214	3.8309	42.9778***	21.6749***
	mVaR	1	11	4.0192**	3.2783*	4.0237	3.8309	18.3322***	21.2561***
USDT	gVaR	8	16	2.2333	0.2401	2.5236	1.4229	23.5146***	20.3556***
	mVaR	7	15	1.1997	0.5511	1.4214	1.5882	17.4655***	22.1622***
USDC	gVaR	4	15	0.0582	0.5511	0.1302	1.5882	0.7280	2.1920
	mVaR	2	15	1.7702	0.5511	1.7881	1.5882	1.4751	2.2018
DGX	gVaR	5	11	0.0541	3.2783*	0.1667	4.5428	8.0133	11.1270*
	mVaR	2	11	1.7702	3.2783*	1.7881	4.5428	1.4545	10.7191*
MV									
Traditional	gVaR	8	11	2.2333	3.2783*	2.5236	3.8309	70.9154***	20.6719***
	mVaR	1	11	4.0192**	3.2783*	4.0237	3.8309	20.5815***	19.58542***
USDT	gVaR	7	17	1.1997	0.0589	1.4214	0.2433	15.8291**	20.2074***
	mVaR	5	15	0.0541	0.5511	0.1667	1.5882	23.7380***	23.8724***
USDC	gVaR	10	20	5.0383**	0.2236	5.4939*	2.0891	29.8094***	16.7664**
	mVaR	4	17	0.0582	0.0589	0.1302	1.3972	26.6643***	18.7460***
DGX	gVaR	6	14	0.4572	1.0001	0.6197	1.5792	1.1566	14.18108**
	mVaR	3	14	0.5722	1.0001	0.6126	1.5792	0.5589	10.69039*

Table 6: Backtesting gVaR and mVaR for all cryptocurrency portfolios considered. Traditional indicates the estimate of the model considering only the 5 traditional cryptocurrencies, while Tether (USDT), USD Coin (USDC) and Digix Gold (DGX) indicate the estimates of the models considering the 5 traditional cryptocurrencies plus the corresponding asset-backed cryptocurrency. 4 and 18 exceedances are expected at 1% and 4% significance levels, respectively. LR_{UC} denotes Kupiec (1995)'s unconditional coverage test statistic, which is a chi-squared distribution with 1 degree of freedom. LR_{CC} denotes Christoffersen (1998)'s conditional coverage test statistic, which is a chi-squared distribution with 2 degree of freedom. DQ denotes Engle and Manganelli (2004)'s Dynamic Quantile test specified with 4 lags of the endogenous variable Hit and one lag of the VaR as explanatory variables. *, ** and *** reveal significance at the 10%, 5% and 1% levels, respectively.

the GO-GARCH model. To measure the downside risk of the portfolios, we implement the parametric gVaR and the mVaR, which extends the gVaR by means of the Cornish-Fisher expansion to consider not only the skewness but the kurtosis of the distribution.

From our preliminary analysis of the conditional correlation between stablecoins and traditional cryptocurrencies, we report on the different behaviors exhibited by the various structures of dependence, depending not only on the pairwise stablecoin but on the point in time under study. We follow Baur and McDermott (2010) by defining an asset as a diversifier when it presents a non-perfect positive correlation with another asset, as a hedger when it presents a null or negative correlation with another asset, and as a safe haven when it presents zero or negative correlation with another asset in times of market stress or turmoil. The analysis shows that Tether performs as a diversifier during the first months of the pandemic, during which uncertainty and turmoil in the markets was very high, and as a hedger since late 2020. In contrast, correlations with USD Coin show a more stable and inverse behavior during most of the period considered, suggesting its role as a safe haven asset. In the case of Digix Gold, we find a diversifying asset with a low positive correlation with traditional cryptocurrencies throughout the out-of-sample period. This low conditional correlation with traditional cryptocurrencies synergizes with the low intrinsic volatility of USD-backed tokens, which explains why they obtain average weightings close to 80% in CE portfolios and around 90% in MV portfolios. Conversely, Digix Gold's diversification potential gives it a significant position in the portfolio, with an average weighting of around 48% in the EC portfolio and 59% in the case of the MV portfolio; however, its high intrinsic volatility limits this potential and leads to a more unstable portfolio composition, drastically so in the case of the EC portfolio.

From the risk impact analysis we find that including USD-pegged stablecoins into the base cryptocurrency portfolio results in a significant and systematic risk mitigation of the combined strategy throughout the entire sample. In contrast, considering Digix Gold conducts to a greater instability in risk reduction, even increasing it with respect to the base portfolio at certain times, which undoubtedly obeys to the high intrinsic volatility of this gold-backed currency, and which places it outside the domain of stablecoins, acting as a mere diversifier. Moreover, the empirical results highlight the importance of considering higher order moments when measuring the tail risk of cryptocurrencies, otherwise leading to an underestimation of the actual risk exposure, as mVaR exceeds gVaR by an increasing magnitude with confidence level. In this sense, the introduction of any of the considered stablecoins (especially Digix Gold) leads to a reduction in the conditional kurtosis of the CE and MV portfolios during most of the sample period, while they do not induce significant changes in the conditional skewness, allowing mVaR to be reduced to a greater extent than gVaR.

This paper can be extended in several ways. On the one hand, there is a wide range of possibilities when dealing with portfolio allocation and risk measurement with different and very diverse methodologies that already exist in the literature. It would be interesting to use Expected Shortfall (ES) and modified Expected Shortfall (mES) as complementary measures to gVaR and mVaR, or to approach risk measurement using copulas or Extreme Value Theory (EVT). On the other hand, a logical extension of this paper would be to broaden the variety of assets analyzed, especially with regard to stablecoins. In this sense, it would be interesting to consider tokens backed by fiat currencies other than the USD and stablecoins of a different nature (for example, those whose stability is based on an algorithm and not on the backing of another asset).

References

Alam, N., Gupta, L. and Zameni, A. (2019), Cryptocurrency and islamic finance, in 'Fintech and Islamic Finance', Springer, pp. 99–118.

Alexander, C. (2000), 'Orthogonal methods for generating large positive semi-definite covariance matrices'.

Alexander, C. (2001), 'Orthogonal garch', Mastering risk pp. 21–38.

Alexander, C. and Chibumba, A. (1996), 'Multivariate orthogonal factor garch models', Discussion Papers in Mathematics. Universitv of Sussex .

Aloui, C., ben Hamida, H. and Yarovaya, L. (2021), 'Are islamic gold-backed cryptocurrencies different?', Finance Research Letters 39, 101615.

Ang, A., Chen, J. and Xing, Y. (2006), 'Downside risk', The review of financial studies 19(4), 1191–1239.

Ante, L., Fiedler, I. and Strehle, E. (2020), 'The influence of stablecoin issuances on cryptocurrency markets', Finance Research Letters p. 101867.

Ante, L., Fiedler, I. and Strehle, E. (2021), 'The impact of transparent money flows: Effects of stablecoin transfers on the returns and trading volume of bitcoin', Technological Forecasting and Social Change 170, 120851.

Balder, S. and Schweizer, N. (2017), 'Risk aversion vs. the omega ratio: Consistency results', Finance research letters 21, 78–84.

Bali, T. G., Mo, H. and Tang, Y. (2008), 'The role of autoregressive conditional skewness and kurtosis in the estimation of conditional var', Journal of Banking & Finance 32(2), 269–282.

Barndorff-Nielsen, O. E. (1997a), 'Normal inverse gaussian distributions and stochastic volatility modelling', Scandinavian Journal of statistics 24(1), 1–13.

Barndorff-Nielsen, O. E. (1997b), 'Processes of normal inverse gaussian type', Finance and stochastics 2(1), 41–68.

Baur, D. G. and Dimpfl, T. (2018), 'Asymmetric volatility in cryptocurrencies', Economics Letters 173, 148–151.

Baur, D. G. and Hoang, L. T. (2021a), 'A crypto safe haven against bitcoin', Finance Research Letters 38, 101431.

Baur, D. G. and Hoang, L. T. (2021b), 'How stable are stablecoins?', The European Journal of Finance pp. 1–17.

Baur, D. G. and McDermott, T. K. (2010), 'Is gold a safe haven? international evidence', Journal of Banking & Finance 34(8), 1886–1898.

Boako, G., Tiwari, A. K. and Roubaud, D. (2019), 'Vine copula-based dependence and portfolio value-at-risk analysis of the cryptocurrency market', International Economics 158, 77–90.

Bollerslev, T. (1986), 'Generalized autoregressive conditional heteroskedasticity', Journal of econometrics 31(3), 307–327.

Bollerslev, T., Patton, A. J. and Quaedvlieg, R. (2018), 'Modeling and forecasting (un) reliable realized covariances for more reliable financial decisions', Journal of Econometrics 207(1), 71–91.

Borri, N. (2019), 'Conditional tail-risk in cryptocurrency markets', Journal of Empirical Finance 50, 1–19.

Boudt, K., Cornilly, D. and Verdonck, T. (2020), 'A coskewness shrinkage approach for estimating the skewness of linear combinations of random variables', Journal of Financial Econometrics 18(1), 1–23.

Boudt, K., Galanos, A., Payseur, S. and Zivot, E. (2019), Multivariate garch models for large-scale applications: A survey, in 'Handbook of statistics', Vol. 41, Elsevier, pp. 193–242.

Boudt, K., Lu, W. and Peeters, B. (2015), 'Higher order comoments of multifactor models and asset allocation', Finance Research Letters 13, 225–233.

Boudt, K., Peterson, B. and Croux, C. (2007), 'Estimation and decomposition of downside risk for portfolios with non-normal returns', DTEW-KBI_0730 pp. 1–30.

Boudt, K., Peterson, B. G. and Carl, P. (2008), 'Hedge fund portfolio selection with modified expected shortfall', WIT Transactions on Information and Communication Technologies 41, 99–107.

Bouri, E., Shahzad, S. J. H. and Roubaud, D. (2020), 'Cryptocurrencies as hedges and safe-havens for us equity sectors', The Quarterly Review of Economics and Finance 75, 294–307.

Brauneis, A. and Mestel, R. (2019), 'Cryptocurrency-portfolios in a mean-variance framework', Finance Research Letters 28, 259–264.

Broda, S. A. and Paolella, M. S. (2009), 'Chicago: A fast and accurate method for portfolio risk calculation', Journal of Financial Econometrics 7(4), 412–436.

Brooks, C., Burke, S. P., Heravi, S. and Persand, G. (2005), 'Autoregressive conditional kurtosis', Journal of Financial Econometrics 3(3), 399–421.

Bullmann, D., Klemm, J. and Pinna, A. (2019), 'In search for stability in crypto-assets: are stablecoins the solution?', ECB Occasional Paper (230).

Canh, N. P., Wongchoti, U., Thanh, S. D. and Thong, N. T. (2019), 'Systematic risk in cryptocurrency market: Evidence from dcc-mgarch model', Finance Research Letters 29, 90–100.

Cerrato, M., Crosby, J., Kim, M. and Zhao, Y. (2017), 'Relation between higher order comoments and dependence structure of equity portfolio', Journal of Empirical Finance 40, 101–120.

Chavez-Dreyfuss, G. (2019), 'Paxos gets u.s. regulator nod for gold-backed token, dollar-backed stablecoin', Reuters .
URL: https://www.reuters.com/article/us-crypto-currencies-paxos-idUSKCN1VQ26P

Chen, Q. and Gerlach, R. H. (2013), 'The two-sided weibull distribution and forecasting financial tail risk', International Journal of Forecasting 29(4), 527–540.

Christoffersen, P. F. (1998), 'Evaluating interval forecasts', International Economic Review 39(4), 841–862.
URL: http://www.jstor.org/stable/2527341

Chuang, C.-C., Wang, Y.-H., Yeh, T.-J. and Chuang, S.-L. (2014), 'Backtesting var in consideration of the higher moments of the distribution for minimum-variance hedging portfolios', Economic Modelling 42, 15–19.

Ciaian, P., Rajcaniova, M. et al. (2018), 'Virtual relationships: Short-and long-run evidence from bitcoin and altcoin markets', Journal of International Financial Markets, Institutions and Money 52, 173–195.

Conlon, T. and McGee, R. (2020), 'Safe haven or risky hazard? bitcoin during the covid-19 bear market', Finance Research Letters 35, 101607.

Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L. (2018), 'Exploring the dynamic relationships between cryptocurrencies and other financial assets', Economics Letters 165, 28–34.

Cornilly, D. and Peterson, B. G. (2020), Performanceanalytics estimation of higher order moments, Technical report, Mimeo.

Cornish, E. A. and Fisher, R. A. (1938), 'Moments and cumulants in the specification of distributions', Revue de l'Institut International de Statistique / Review of the International Statistical Institute 5(4), 307–320.
URL: http://www.jstor.org/stable/1400905

El Montasser, G., Charfeddine, L. and Benhamed, A. (2021), 'Covid-19, cryptocurrencies bubbles and digital market efficiency: Sensitivity and similarity analysis', Finance Research Letters p. 102362.

Elendner, H., Trimborn, S., Ong, B. and Lee, T. M. (2018), The cross-section of crypto-currencies as financial assets: Investing in crypto-currencies beyond bitcoin, in 'Handbook of Blockchain, Digital Finance, and Inclusion, Volume 1', Elsevier, pp. 145–173.

Engle, R. (2002), 'Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models', Journal of Business & Economic Statistics 20(3), 339–350.

Engle, R. F. (1982), 'Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation', Econometrica: Journal of the econometric society pp. 987–1007.

Engle, R. F. and Kroner, K. F. (1995), 'Multivariate simultaneous generalized arch', Econometric theory pp. 122–150.

Engle, R. F. and Manganelli, S. (2004), 'Caviar: Conditional autoregressive value at risk by regression quantiles', Journal of business & economic statistics 22(4), 367–381.

Favre, L. and Galeano, J.-A. (2002), 'Mean-modified value-at-risk optimization with hedge funds', The journal of alternative investments 5(2), 21–25.

Fruehwirt, W., Hochfilzer, L., Weydemann, L. and Roberts, S. (2021), 'Cumulation, crash, coherency: A cryptocurrency bubble wavelet analysis', Finance Research Letters 40, 101668.

Fry, J. and Cheah, E.-T. (2016), 'Negative bubbles and shocks in cryptocurrency markets', International Review of Financial Analysis 47, 343–352.

Fry-McKibbin, R., Greenwood-Nimmo, M., Hsiao, C. Y.-L. and Qi, L. (2021), 'Higher-order comoment contagion among g20 equity markets during the covid-19 pandemic', Finance Research Letters p. 102150.

Ghalanos, A. (2019), 'The rmgarch models: Background and properties.(version 1.3-0)'.

Ghalanos, A., Rossi, E. and Urga, G. (2015), 'Independent factor autoregressive conditional density model', Econometric Reviews 34(5), 594–616.

Gil-Alana, L. A., Abakah, E. J. A. and Rojo, M. F. R. (2020), 'Cryptocurrencies and stock market indices. are they related?', Research in International Business and Finance 51, 101063.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C. and Siering, M. (2014), 'Bitcoin-asset or currency? revealing users' hidden intentions', Revealing Users' Hidden Intentions (April 15, 2014). ECIS .

Harvey, C. R. and Siddique, A. (1999), 'Autoregressive conditional skewness', Journal of financial and quantitative analysis pp. 465–487.

Henriques, I. and Sadorsky, P. (2018), 'Can bitcoin replace gold in an investment portfolio?', Journal of Risk and Financial Management 11(3), 48.

Hrytsiuk, P., Babych, T. and Bachyshyna, L. (2019), Cryptocurrency portfolio optimization using value-at-risk measure, in '6th International Conference on Strategies, Models and Technologies of Economic Systems Management (SMTESM 2019)', Atlantis Press, pp. 385–389.

Huynh, T. L. D., Nguyen, S. P. and Duong, D. (2018), Contagion risk measured by return among cryptocurrencies, in 'International econometric conference of Vietnam', Springer, pp. 987–998.

Hyvärinen, A. and Oja, E. (2000), 'Independent component analysis: algorithms and applications', Neural networks 13(4-5), 411–430.

Jacques Mandeng, O. (2021), 'Stable coins' rise has echoes of bretton woods', Financial Times .
URL: https://www.ft.com/content/4bb77dd2-ad49-4f26-990a-cf6513b54057

Jemima, K. (2021), 'Tether says its reserves are backed by cash to the tune of... 2.9%'.
URL: https://www.ft.com/content/529eb4e6-796a-4e81-8064-5967bbe3b4d9

Jia, Y., Liu, Y. and Yan, S. (2021), 'Higher moments, extreme returns, and cross–section of cryptocurrency returns', Finance Research Letters 39, 101536.

Jondeau, E., Jurczenko, E. and Rockinger, M. (2018), 'Moment component analysis: An illustration with international stock markets', Journal of Business & Economic Statistics 36(4), 576–598.

Jondeau, E. and Rockinger, M. (2003), 'Conditional volatility, skewness, and kurtosis: existence, persistence, and comovements', Journal of Economic dynamics and Control 27(10), 1699–1737.

Jondeau, E. and Rockinger, M. (2006), 'Optimal portfolio allocation under higher moments', European Financial Management 12(1), 29–55.

Jondeau, E. and Rockinger, M. (2009), 'The impact of shocks on higher moments', Journal of Financial Econometrics 7(2), 77–105.

Kaiser, L. and Stöckl, S. (2020), 'Cryptocurrencies: Herding and the transfer currency', Finance Research Letters 33, 101214.

Katsiampa, P. (2019), 'Volatility co-movement between bitcoin and ether', Finance Research Letters 30, 221–227.

Katsiampa, P., Corbet, S. and Lucey, B. (2019), 'Volatility spillover effects in leading cryptocurrencies: A bekk-mgarch analysis', Finance Research Letters 29, 68–74.

Klaassen, F. (1999), 'Have exchange rates become more closely tied? evidence from a new multivariate garch model', Tilburg University, CentER Discussion Paper Series (1999-10).

Kosowski, R., Naik, N. Y. and Teo, M. (2007), 'Do hedge funds deliver alpha? a bayesian and bootstrap analysis', Journal of Financial Economics 84(1), 229–264.

Kristoufek, L. (2021), 'Tethered, or untethered? on the interplay between stablecoins and major cryptoassets', Finance Research Letters p. 101991.

Kupiec, P. (1995), 'Techniques for verifying the accuracy of risk measurement models', The J. of Derivatives 3(2).

Ledoit, O. and Wolf, M. (2003), 'Improved estimation of the covariance matrix of stock returns with an application to portfolio selection', Journal of empirical finance 10(5), 603–621.

León, Á., Rubio, G. and Serna, G. (2005), 'Autoregresive conditional volatility, skewness and kurtosis', The Quarterly Review of Economics and Finance 45(4-5), 599–618.

León Valle, Á. M., Navarro, L. and Nieto, B. (2019), 'Screening rules and portfolio performance'.

Libni, E. and Lipton, E. (2021), 'Crypto banking and decentralized finance, explained', The New York Times .
URL: https://www.nytimes.com/2021/09/05/us/politics/cryptocurrency-explainer.html

Lyons, R. K. and Viswanath-Natraj, G. (2020), What keeps stablecoins stable?, Technical report, National Bureau of Economic Research.

Martellini, L. and Ziemann, V. (2010), 'Improved estimates of higher-order comoments and implications for portfolio selection', The Review of Financial Studies 23(4), 1467–1502.

Mita, M., Ito, K., Ohsawa, S. and Tanaka, H. (2019), What is stablecoin?: A survey on price stabilization mechanisms for decentralized payment systems, in '2019 8th International Congress on Advanced Applied Informatics (IIAI-AAI)', IEEE, pp. 60–66.

Nagy, B. Z. and Benedek, B. (2021), 'Higher co-moments and adjusted sharpe ratios for cryptocurrencies', Finance Research Letters 39, 101543.

Nakamoto, S. (2008), 'Bitcoin: A peer-to-peer electronic cash system'.
URL: https://bitcoin.org/bitcoin.pdf

Ostroff, C. (2020), 'Why central banks want to create their own digital currencies like bitcoin', The Wall Street Journal .
URL: https://www.wsj.com/articles/why-central-banks-want-to-create-their-own-digital-currencies-like-bitcoin-11603291131

Pal, D. and Mitra, S. K. (2019), 'Hedging bitcoin with other financial assets', Finance Research Letters 30, 30–36.

Peiro, A. (1999), 'Skewness in financial returns', Journal of Banking & Finance 23(6), 847–862.

Phillip, A., Chan, J. S. and Peiris, S. (2018), 'A new look at cryptocurrencies', Economics Letters 163, 6–9.

Sifat, I. (2021), 'On cryptocurrencies as an independent asset class: Long-horizon and covid-19 pandemic era decoupling from global sentiments', Finance Research Letters p. 102013.

Silahli, B., Dingec, K. D., Cifter, A. and Aydin, N. (2021), 'Portfolio value-at-risk with two-sided Weibull distribution: Evidence from cryptocurrency markets', Finance Research Letters 38(C).
URL: https://ideas.repec.org/a/eee/finlet/v38y2021ics1544612319312024.html

Simaan, Y. (1993), 'Portfolio selection and asset pricing—three-parameter framework', Management Science 39(5), 568–577.

Smialek, J. (2021), 'As stablecoins explode in popularity, regulators prepare a response.', The New York Times .
URL: https://www.nytimes.com/2021/07/19/business/stablecoins-regulation.html

Thapa, C., Paudyal, K. and Neupane, S. (2013), 'Access to information and international portfolio allocation', Journal of Banking & Finance 37(7), 2255–2267.

Torres, C. (2021), 'The crypto market needs to lean back on gold to fight extreme volatility', Financial Times .
URL: https://www.nasdaq.com/articles/the-crypto-market-needs-to-lean-back-on-gold-to-fight-extreme-volatility-2021-08-12

van der Weide, R. (2002), 'Go-garch: a multivariate generalized orthogonal garch model', Journal of Applied Econometrics 17(5), 549–564.

Venkataramakrishnan, S. (2021), 'Stablecoin strife: crypto assets face calls for tougher oversight', Financial Times .
URL: https://www.ft.com/content/e4081366-b061-4b17-bdbe-e975fcf6288d

Vidal-Tomás, D., Ibáñez, A. M. and Farinós, J. E. (2019), 'Herding in the cryptocurrency market: Cssd and csad approaches', Finance Research Letters 30, 181–186.

Wang, G.-J., Ma, X.-y. and Wu, H.-y. (2020), 'Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests?', Research in International Business and Finance 54, 101225.

Wasiuzzaman, S. and Rahman, H. S. W. H. A. (2021), 'Performance of gold-backed cryptocurrencies during the covid-19 crisis', Finance Research Letters p. 101958.

Webber, J. (2021), 'El salvador becomes first country to adpot bitcoin as legal tender', Financial Times .
URL: https://www.ft.com/content/7b5b1cc4-50bb-437f-aa16-f106d2dbc1c7

Yermack, D. (2015), Is bitcoin a real currency? an economic appraisal, in 'Handbook of digital currency', Elsevier, pp. 31–43.

Zakamouline, V. and Koekebakker, S. (2009), 'Portfolio performance evaluation with generalized sharpe ratios: Beyond the mean and variance', Journal of Banking & Finance 33(7), 1242–1254.

Zhang, K. and Chan, L. (2009), 'Efficient factor garch models and factor-dcc models', Quantitative Finance 9(1), 71–91.