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Conditional tail-risk in cryptocurrency markets

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ABSTRACT

In this paper we use $CoVaR$ to estimate the conditional tail-risk in the markets for bitcoin, ether, ripple and litecoin and find that these cryptocurrencies are highly exposed to tail-risk within cryptomarkets, while they are not exposed to tail-risk with respect to other global assets, like the U.S. equity market or gold. Although cryptocurrency returns are highly correlated one with the other, we find that idiosyncratic risk can be significantly reduced and that portfolios of cryptocurrencies offer better risk-adjusted and conditional returns than individual cryptocurrencies. These results indicate that portfolios of cryptocurrencies could offer attractive returns and hedging properties when included in investors' portfolios. However, when we account for liquidity, the share of crypto assets in investors' optimal portfolio is small.

1. Introduction

In this paper we use $CoVaR$ to estimate the conditional tail-risk in the markets for bitcoin, ether, ripple, and litecoin and find that cryptocurrencies are highly exposed to tail-risk within cryptomarkets, while they are not exposed to tail-risk with respect to other global assets, like the U.S. equity market or gold. Although we find that cryptocurrency returns are highly correlated one with the other, we also find that idiosyncratic risk can be significantly reduced and that portfolios of cryptocurrencies offer better risk-adjusted and conditional returns than individual cryptocurrencies. These results indicate that portfolios of cryptocurrencies could offer attractive returns and hedging properties when included in investors' portfolios. However, when we account for liquidity, the share of crypto assets in investors' optimal portfolio is small.

Cryptocurrencies are a growing asset class, with a total market capitalization of 325 billions of U.S. dollars as of April, 2018. In this paper we focus on bitcoin, ether, ripple, and litecoin which are the main cryptocurrencies by market capitalization and volume. Bitcoin was the first cryptocurrency, created in 2009 using a scheme proposed by Nakamoto (2008), and currently accounts for 29% of the total market capitalization and trading volume. Bitcoins started trading in 2010 on the Mt. Gox exchange, now defunct, and are now traded 24/7 every day in several exchanges around the world. Ether is a cryptocurrency whose blockchain is generated by the Ethereum platform and was first proposed at the end of 2013 and started to circulate in July 2015. Ripple is instead based on the Ripple protocol, which is a real-time gross settlement system, currency exchange and remittance network first released in 2012. Litecoin is a peer-to-peer cryptocurrency first released on October 2011 and its technical details are nearly identical to those of bitcoin. The incredible increase in the prices of these cryptocurrencies, since at least the second half of 2016, has attracted the interest of investors who have poured millions of U.S. dollars (as well as other "standard" fiat currencies) in these markets. Fig. 1 shows the incredible rise first, and then sharp drop, in the prices of bitcoin, ether, ripple, and litecoin together with the corresponding

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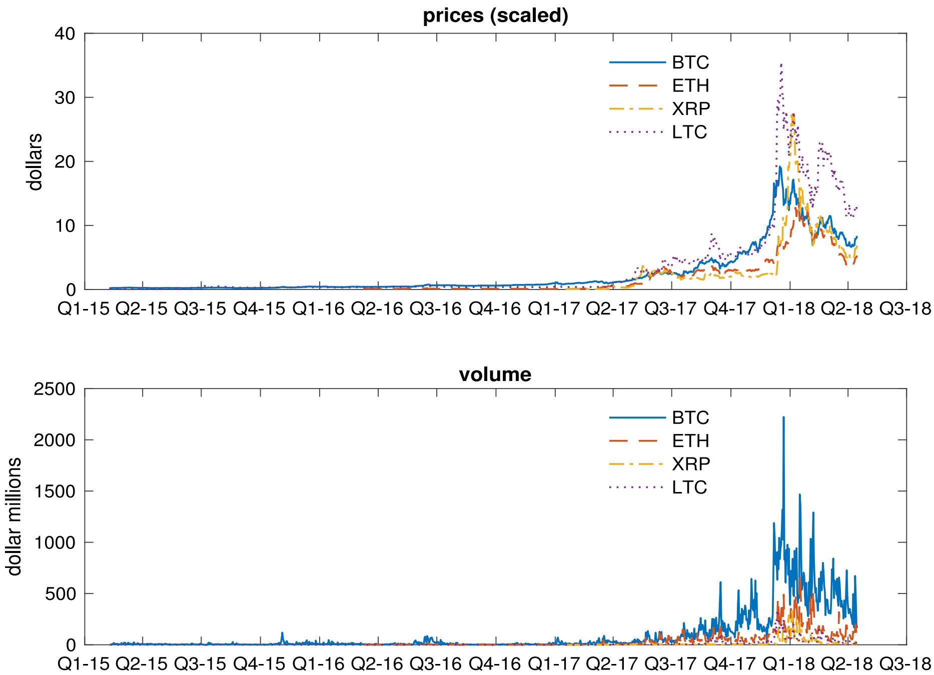

Fig. 1. Cryptocurrencies Prices. *Notes:* The figure plots U.S. dollar prices (top panel) and transaction volume (bottom panel) for bitcoin (BTC), ether (ETH), ripple (XRP), and litecoin (LTC). Prices are scaled as follows: BTC is divided by 1000; ETH is divided by 100; XRP is multiplied by 10; and LTC is divided by 10; volume is in millions of U.S. dollars for all cryptocurrencies and is not computed with re-scaled prices. Data are daily from cryptocompare.com and correspond to the Bitfinex exchange for bitcoin, ether and litecoin, and Bitstamp for ripple. The sample starts on 2/9/2015 for bitcoin; 9/3/2016 for ether; 17/1/2017 for ripple; and 2/8/2015 for litecoin, and ends on 4/15/2018.

volume of transactions in just one of the many exchanges on which they are traded.[2] Casual inspection of Fig. 1 immediately reveals a high degree of co-movement in prices, which is confirmed in the formal analysis of the returns on these assets presented in the next sections. Specifically, in this paper we consider the co-movement between dollar returns on these cryptocurrencies and other global assets both unconditionally, and conditional on the other assets being in a distressed state. We find that cryptocurrency returns are highly correlated, both unconditionally and conditionally, one with the other, but poorly correlated with other global assets, including gold, to which they are often compared to. We measure conditional correlation with $CoVaR$, first proposed by Adrian and Brunnermeier (2016). $CoVaR$ is a risk-measure that allows for the estimation of the exposure of any asset to tail-risk of a second asset, or, more in general, of the market. Results are robust to an extension of the model that includes state variables to account for changes in the global state of the economy. In addition, we show that cryptocurrency portfolios can substantially reduce the idiosyncratic component of cryptocurrency returns, improving the risk-adjusted performance and conditional returns, maintaining the insignificant exposure to tail-risk in other global assets. However, when we account for liquidity in cryptocurrency markets, proxied by transaction costs, we find that the share of crypto assets in the mean–variance optimal portfolio is small.

This paper contributes first to the small but fast growing economic literature on bitcoins and cryptocurrencies. Yermack (2013), Velde and others (2013), and Dwyer (2015) are excellent primers that describe the functioning of the blockchain and cryptocurrencies.[3] Schilling and Uhlig (2018) propose a simple model to study how do bitcoin prices evolve and the implications for monetary policy. Catalini and Gans (2016), Biais et al. (2018), and Ma et al. (2018) analyze, from the prospective of economic theory, how blockchain technology and cryptocurrencies will influence the rate and direction of innovation and the incentives and equilibria behind the ”proof of work” protocols. Gandal et al. (2017) use a unique dataset to investigate suspicious trading activity on the Mt. Gox exchange in 2013 that appears to have inflated bitcoin prices. Liu and Tsyvinski (2018) study the risk and return trade-off of three cryptocurrencies and establish that it is distinct from those of a number of non-crypto assets. Borri and Shakhnov (2018a) study the cross-section of crypto returns across different exchanges, currencies, and markets. Catania et al. (2018) and Osterrieder and Lorenz (2017) study the predictability of the volatility of the main cryptocurrencies and the bitcoin tail behavior. Second, this paper contributes to the literature on vulnerability to tail-risk, providing a novel application of $CoVaR$ in a new and growing market. Huynh et al. (2018) also estimate contagion in cryptocurrency markets, but using a different methodology, shorter time series, and without expanding the analysis to additional global factors. In this paper, we estimate the vulnerability of cryptocurrencies to tail-risk in other

[2] Data for prices and volume are for the Bitfinex exchange for bitcoin, ether and litecoin, and for the Bitstamp exchange for ripple. More details are available in Section 3 and in Appendix A.1.

[3] There exists also a large literature on blockchain technology with a focus on security, anonymity, scalability, and data integrity from researchers in computer science that is outside the scope of our analysis.

assets with the reduced-form risk-measure $CoVaR$, or conditional value-at-risk, first proposed by Adrian and Brunnermeier (2016).[4] $CoVaR$ is a measure of risk conditional upon an adverse shock, where risk is the standard value-at-risk (VaR). VaR measures risk in terms of returns at a given probability: for example, a VaR of −10% at the 5% confidence level indicates that there is a probability of 5% of a return that is lower or equal to −10%. Adrian and Brunnermeier use $CoVaR$ to estimate the systemic risk of financial institutions using a combination of market and balance sheet data. Fong and Wong (2012) adopt a similar approach to estimate bi-lateral systemic risk in the Eurozone using sovereign CDS data and Borri (2018) to study conditional tail-risk in the market for local currency emerging government debt. Note that while $CoVaR$ is widely used, its simplicity comes at a cost. Mainik and Schaanning (2014) show that $CoVaR$, as well as other systemic risk measures like the Marginal Expected Shortfall (MES) and the Systemic Impact Index (SII), is not "dependent consistent" under very general distributional assumptions for the pair of variables. On the contrary, Mainik and Schaanning and Girardi and Ergün (2013) show that conditioning on a variable being "greater or equal", rather than just "equal", to its value-at-risk gives a better response to the dependence between two variables.

The rest of the paper is organized as follows: Section 2 presents the data; Section 3 introduces the model used to estimate the conditional tail-risk for cryptocurrencies and presents the estimation results; Section 4 analyzes the robustness of the main results and introduces a time-varying measure of conditional tail-risk; finally, Section 5 presents our conclusions.

2. Data

In this paper we use $CoVaR$ to measure the conditional exposure to tail-risk of four of the most widely used cryptocurrencies: bitcoin, ether, ripple, and litecoin. We first collect daily cryptocurrency prices from cryptocompare.com using a Python script to scrap the data. Note that cryptocurrencies are traded on several exchanges across the globe that operate every day 24/7, including Saturdays, Sundays, and holidays. We focus on the dollar prices of bitcoin (BTC), ether (ETH), and litecoin (LTC) on the Bitfinex exchange, and of ripple (XRP) on the Bitstamp exchange, in order to obtain the longest reliable time series for all three currencies.[5] Bitcoin, ether, ripple, and litecoin are the main cryptocurrencies by market capitalization: as of April 2018, bitcoin had a market capitalization of approximately 140 billion U.S. dollars, while ether, ripple and litecoin of 50, 26, and 7 billion U.S. dollars respectively (see Appendix A.1 fort further details). Specifically, we obtain closing, high, and low daily prices, together with daily volume expressed both in dollars and cryptocurrency. In addition, we obtain from Datastream daily dollar prices for the Gold Bullion, the CBOE volatility index (VIX), the S&P400 commodity chemicals index, and the S&P500 composite equity index. We use data on these additional assets both to estimate cross markets conditional exposure to tail-risk (Section 3), and time-varying measures of conditional exposure to tail-risk (Section 4). Note that as the crypto exchanges operate 24/7, there is not a proper "closing price". Therefore, the convention is that the closing price at day t is equal to the opening price at day $t+1$. In order to avoid any data overlap, we collect crypto prices setting the closing time to 4PM Eastern Time as for the other series. Data for bitcoin start on 2/9/15; for ether on 9/3/2016; for litecoin on 2/8/2015; and only on 1/17/2017 for ripple. Therefore, our sample is constrained by the short length of the available time-series and we choose to consider only the period in which data of all three cryptocurrencies are available, i.e., starting on 1/17/2017 and ending on 4/15/2018. Table 1 reports descriptive statistics on the log daily returns on these assets. Note that even though the sample is common for the cryptocurrencies and the global assets, the number of observations for the cryptocurrencies is larger because, contrary to the other assets we consider, they are traded also on non-business days. Three facts are of particular relevance. First, cryptocurrencies have large and volatile returns. The mean returns on bitcoin, ether, ripple, and litecoin are, respectively, 49bp, 87bp, 102bp, and 77bp per day with volatilities of 528bp, 697bp, 1113bp, and 816bp. Despite the large volatilities, these returns are statistically significant: as back of the envelope estimate, recall that $\sqrt{453} \approx 21$ and that the uncertainty around the mean is measured as $\sigma/\sqrt{T}$. Therefore, for our sample, all mean returns are at least two standard deviations above zero. Note that the volatility in *daily* returns on cryptocurrencies is closer to the *annual* volatility for the U.S. stock market returns. However, cryptocurrency Sharpe ratios are large and around 10%, thus comparable to the Sharpe ratio on the U.S. stock market. Second, risks and returns on cryptocurrencies are very different from those on gold, or on the commodity index, even though they are often compared to these assets according to the idea that governments cannot control their supplies, as the they cannot produce, for example, more gold. The mean return on gold is only 3bp per day, with a volatility of 64bp, while the mean return and volatility on the commodity index are, respectively, equal to 2bp and 129bp. In fact, cryptocurrencies, at least in terms of risk-adjusted returns, are closer to the equity index, or to the volatility index in terms of unconditional volatility. Also in terms of value-at-risk, cryptocurrencies are riskier than most of the other assets. Specifically, value-at-risk estimates are large and negative and in the range of −10% per day. Only the VIX index has a similar value of −12.47%, while all the other assets have value-at-risk estimates never smaller than −2% per day. Third, cryptocurrencies are positively correlated one with the other, with correlations ranging from 0.53 to 0.26, but poorly correlated with all the other assets (see Table 2). On the contrary, the U.S. stock market, the volatility index, and the commodity index are highly correlated one with the other, while gold is poorly correlated with every asset. The latter fact explains why investors consider gold as good *hedge* and is in line with recent findings in Wong et al. (2018).

[4] There exist several alternative measures of systemic risk and exposure to tail-risk. Many of them rely on CDS data. For example, Acharya et al. (2012) focus on high-frequency marginal expected shortfall; Acharya et al. (2017) and Brownlees and Engle (2016) develop SRISK, which measures capital shortfall conditional on market stress; Billio et al. (2012) builds a risk-measure based on Granger causality across institutions; Nucera et al. (2016) construct a systemic risk measures that summarize the information provided by alternative risk rankings using principal components.

[5] Cryptocurrencies are traded on multiple exchanges where investors can trade crypto for fiat currencies, or crypto for crypto currencies. Borri and Shakhnov (2018b) study price differences between the dollar prices of bitcoins across different exchanges across the globe where investors trade different fiat currencies for bitcoin. Note that Bloomberg also provides the prices for these cryptocurrencies, but for a shorter sample. We verify that the prices obtained from cryptocompare.com are the same to those in Bloomberg over the same sample. We do not include in the analysis Bitcoin Cash, which in April 2018 is the fourth cryptocurrency by market capitalization, because of the shorter available sample.

Table 1
Descriptive statistics.

asset	$Mean(\%)$	$Std(\%)$	SR	$Skew$	$Kurt$	$VaR_q(\%)$	T
BTC	0.49	5.28	0.09	−0.11	5.13	−8.38	453
ETH	0.87	6.97	0.13	0.17	4.92	−9.45	453
XRP	1.02	11.13	0.09	2.26	23.82	−12.26	453
LTC	0.77	8.16	0.09	1.44	11.17	−9.94	453
GOLD	0.03	0.64	0.05	0.01	3.43	−1.04	323
VIX	−0.10	8.79	−0.01	−2.52	22.82	−12.47	323
COMM	0.02	1.29	0.02	0.20	6.62	−2.00	323
MKT	0.05	0.70	0.07	−1.52	11.53	−1.10	323

Notes: The table reports mean, standard deviation, Sharpe-ratio, skewness, kurtosis, value-at-risk (VaR), and number of observations for the log daily returns on bitcoin (BTC), ether (ETH), ripple (XRP), litecoin (LTC), gold (GOLD), the CBOE volatility index (VIX), the S&P commodity index (COMM) and the S&P500 index (MKT). Mean, standard deviation, and VaR are in percentages. The Sharpe ratio is computed as daily mean over daily standard deviation. For the value-at-risk, the confidence level is $q = 5\%$. We multiply returns on the VIX index by -1 so that negative returns correspond to an increase in the value of the index and, thus, to *bad times*. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

Table 2
Correlation matrix.

asset	BTC	ETH	XRP	LTC	$GOLD$	VIX	$COMM$	MKT
BTC	1.00	0.51	0.26	0.53	0.04	0.06	0.03	0.06
ETH	0.51	1.00	0.27	0.49	0.10	0.07	0.06	0.05
XRP	0.26	0.27	1.00	0.34	0.02	0.03	−0.00	0.04
LTC	0.53	0.49	0.34	1.00	0.03	0.06	0.04	0.06
GOLD	0.04	0.10	0.02	0.03	1.00	−0.08	−0.08	−0.09
VIX	0.06	0.07	0.03	0.06	−0.08	1.00	0.47	0.78
COMM	0.03	0.06	−0.00	0.04	−0.08	0.47	1.00	0.59
MKT	0.06	0.05	0.04	0.06	−0.09	0.78	0.59	1.00

Notes: The table reports sample correlation coefficients of the log returns between different pairs of assets. The assets are the three cryptocurrencies (i.e., bitcoin (BTC), ether (ETH), ripple (XRP), and litecoin (LTC)), gold, the CBOE volatility index (VIX), a commodity index (COMM), and the S&P 500 (MKT). We multiply returns on the VIX index by -1 so that negative returns correspond to an increase in the value of the index and, thus, to *bad times*. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

Investors are not simply interested in unconditional correlations, but rather they look at correlations in different states of the world. For example, investors might be interested in the returns on their bitcoin investment at times in which the U.S. stock market is in distress (i.e., at times when the investors' overall portfolio is likely to drop in value). We start with some simple measures of dependence, and in the next section we present a model to exactly measure the conditional tail-risk of cryptocurrencies, i.e., the exposure of each cryptocurrency to tail-risk events in the other cryptocurrencies as well as in other global assets. Figs. 2 and 3 present the differences between the upper and lower portions of "quantile dependence" plots for standardized residuals of bitcoin and, respectively, the remaining cryptocurrencies (Fig. 2) and the other global assets (Fig. 3), for $q \in [0.025, 0.975]$, along with 90% (pointwise) i.i.d. bootstrap confidence intervals for this difference (Patton, 2009, 2012). Standardized residuals are constructed using an AR(2) model for the conditional means, and the GJR-GARCH model of Glosten et al. (1993) for the conditional volatilities. Lower quantile dependence is given by $\lambda_L^q = Pr(U_1 \leq q, U_2 \leq q)/q$, for $q \in (0, 0.5]$, and the upper quantile dependence is given by $\lambda_U^q = Pr(U_1 > q, U_2 > q)/(1-q)$, for $q \in [0.5, 1)$. As discussed in Patton (2012), confidence intervals are narrower in the middle of the distribution, and wider near the tails. While Fig. 2 shows that, for cryptocurrencies, observations in the lower tail are more dependent than observations in the upper tail, Fig. 3 shows, instead, that this is not the case for bitcoin and the global assets. For bitcoin and the remaining cryptocurrencies, confidence intervals indicate that these differences are borderline significant at the 0.10 level, with the upper bound of the confidence interval on the difference lying around zero for most of the values of q. On the contrary, for bitcoin and the global assets the difference is always close to zero and never statistically significant.

3. Measuring contagion in cryptocurrencies

In this section we first present the model we use to estimate the conditional tail-risk exposure and then the resulting estimates.

3.1. Model

In this paper we follow Adrian and Brunnermeier (2016) and estimate $CoVaR$ with quantile regressions (Koenker and Bassett Jr, 1978; Koenker, 2005). This is not the only possible estimation technique. For example, $CoVaR$ can also be estimated with generalized autoregressive heteroskedasticity (GARCH) models. We leave the interested reader to the detailed discussion in Adrian and Brunnermeier (2016) for further details and proofs. We denote with r^i the log returns on asset $i = 1, \ldots, I$, and with r^j the log returns on asset $j = 1, \ldots, J$. For example, asset i can be bitcoin, and asset j a different cryptocurrency, like ether, ripple, or litecoin, or, rather, another global asset, like gold. Define with VaR_q^j the maximum return for asset j at a confidence level of $1-q$, i.e., the q quantile

$$Pr(r^j \leq VaR_q^j) = q. \tag{1}$$

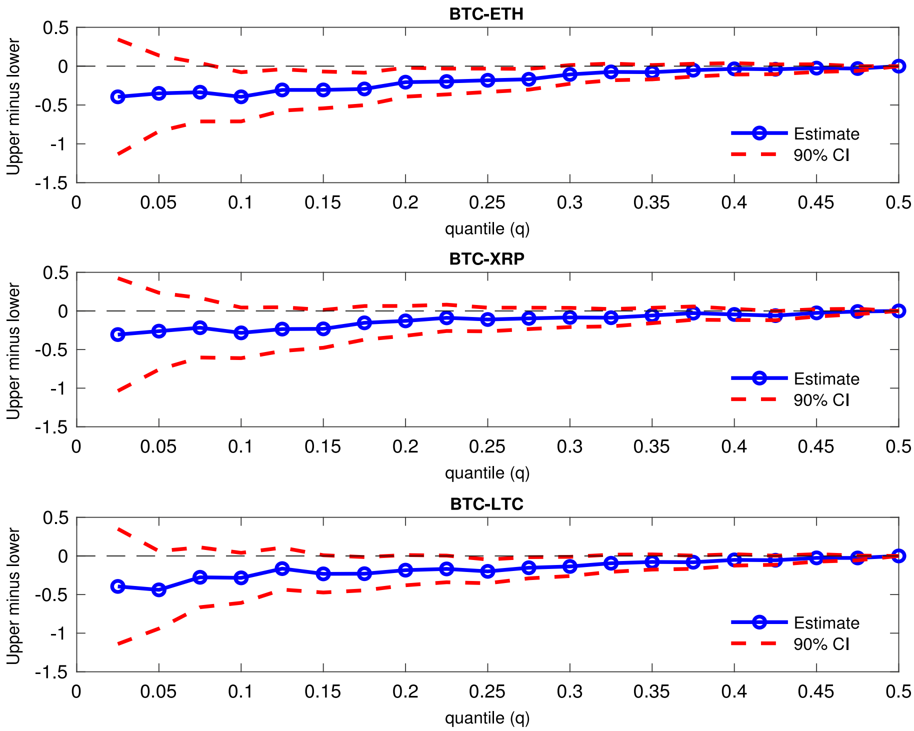

Fig. 2. Quantile dependence: Bitcoin and cryptocurrencies. *Notes:* The figure plots the difference in upper and lower quantile dependence between the standardized residuals for bitcoin (BTC) and, respectively, ether (ETH), ripple (XRP), and litecoin (LTC), along with 90% bootstrap confidence intervals. The sample starts on 2/9/2015 for bitcoin; 9/3/2016 for ether; 17/1/2017 for ripple; and 2/8/2015 for litecoin, and ends on 4/15/2018. For details on "quantile dependence" plots refer to Patton (2009, 2012).

Intuitively, VaR_q^j (i.e., the value-at-risk) corresponds to the maximum return in a bad state of the world, i.e., in a situation of aggregate distress for asset j. We define $CoVaR_q^{i|j}$ as the VaR of asset i conditional upon asset j being in a state of distress (i.e., being at its VaR_q^j), i.e., the q-quantile of the conditional probability distribution

$$Pr(r^i \leq CoVaR_q^{i|j} \mid r^j = VaR_q^j) = q \tag{2}$$

In order to estimate the conditional risk we use the following quantile regression

$$r_{t+1}^i = \beta_{0,q}^{i|j} + \beta_{1,q}^{i|j} r_{t+1}^j + \epsilon_{t+1}^{i|j}, \tag{3}$$

$CoVaR$ is then obtained as fitted value of the quantile regression (3) when r^j is at its VaR_q^j. The coefficient $\beta_{1,q}^{i|j}$ measures how vulnerable asset i is with respect to a state of distress of asset j, with $i \neq j$.

$$CoVaR_q^{i|r^j=VaR_q^j} = \hat{\beta}_{0,q}^{i|j} + \hat{\beta}_{1,q}^{i|j} VaR_q^j, \tag{4}$$

We measure the vulnerability of asset i to tail-risk in asset j with $\Delta CoVaR_q^{i|j}$

$$\begin{aligned}\Delta CoVaR_q^{i|j} &= CoVaR_q^{i|r^j=VaR_q^j} - CoVaR_q^{i|r^j=VaR_{0.5}^j} \\ &= \hat{\beta}_{1,q}^{i|j}\left(VaR_q^j - VaR_{0.5}^j\right)\end{aligned} \tag{5}$$

$\Delta CoVaR$ measures the difference between the $CoVaR$ of asset i conditional on a state of distress in asset j and the *median* state (i.e., $q = 0.5$). Therefore, the larger (in absolute value) the $\Delta CoVaR$, the higher the vulnerability of asset i to contagion from tail-risk events of j. In this paper, we use $\Delta CoVaR$ as a measure of vulnerability of individual assets to tail-risk in alternative assets. On the contrary, Adrian and Brunnermeier (2016) use $\Delta CoVaR$ to measure the systemic risk of individual financial institutions, i.e., the vulnerability of the entire financial market with respect to a state of distress of a single financial institution.

3.2. Estimation results

We estimate $CoVaR$ and $\Delta CoVaR$ for a set of assets that includes the four cryptocurrencies (i.e., bitcoin, ether, ripple, and litecoin), as well as gold, the VIX volatility index, a commodity index, and a U.S. equity market index. In what follows, all estimates

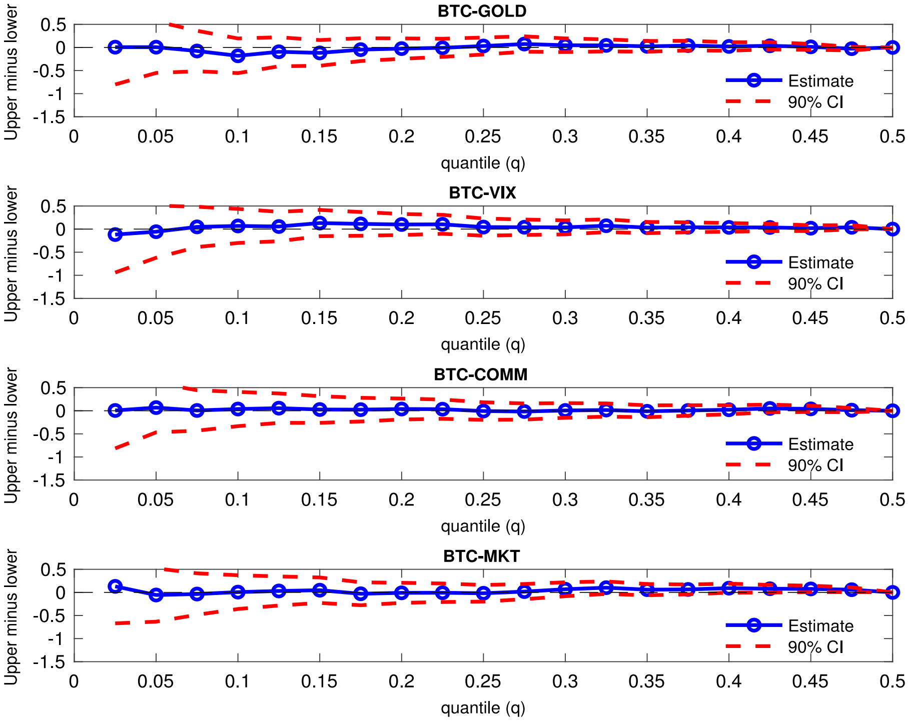

Fig. 3. Quantile dependence: Bitcoin and global assets. *Notes:* The figure plots the difference in upper and lower quantile dependence between the standardized residuals for bitcoin (BTC) and, respectively, gold, the CBOE volatility index (VIX), a commodity index (COMM), and the S&P 500 (MKT), along with 90% bootstrap confidence intervals. The sample starts on 2/9/2015 for bitcoin; 9/3/2016 for ether; 17/1/2017 for ripple; and 2/8/2015 for litecoin, and ends on 4/15/2018. For details on "quantile dependence" plots refer to Patton (2009, 2012).

are based on the $q = 5\%$ quantile and daily frequency, while we report results for different quantile values and weekly frequency in the appendix. Henceforth, we multiply the log returns on the VIX index by -1, so that negative returns correspond to an increase in the value of the index and, thus, to *bad times* in financial markets. In Table 3 we report our main results. We organize the table so that, for all estimates, the left-hand variables of Eq. (3) are on the table rows (i.e., variables i), and the right-hand conditioning variables on the table columns (i.e., variables j). Standard errors by bootstrap are reported in brackets. The first panel reports the estimates for the conditional value-at-risk. Results can be summarized as follows. First, on average, the estimates for $CoVaR$ are larger, in absolute value, for cryptocurrencies than for the global assets by a factor of 10, with the exception of the volatility index VIX. Second, $CoVaR$ estimates for all asset pairs are significantly different from zero at standard confidence levels. The middle panel reports the q-quantile slope coefficients on the conditioning asset (i.e., $\beta^{i|j}_{1,q}$ from Eq. (3)). Interestingly, standard errors indicate that, for all the cryptocurrencies, the coefficients on other cryptocurrencies are positive and significant, while they are mostly small and not significant for the global assets. We more formally test this observation running a simple test for the bitcoin quantile regression. Specifically, we estimate the following augmented version of Eq. (3)

$$r^{BTC}_{t+1} = \beta^{i|j}_{0,q} + \beta^{i|j}_{1,q} r^{ETH}_{t+1} + \sum_{k=1}^{K} \phi^{i|j}_{k,q} r^{k}_{t+1} + \epsilon^{i|j}_{t+1}, \tag{6}$$

where r^k are the returns on the non-crypto assets. Following Koenker and Xiao (2002), we estimate a chi-square test on the joint significance of the $\phi^{i|j}_{k,q}$ and cannot reject the null of all coefficients equal to zero (the p-value is equal to 38%). This result is exemplified by Fig. 4, which plots the fit of the quantile regression (6), together with the 95% confidence interval, for the unrestricted (blue line) and restricted (red dots) model with $\phi^{i|j}_{k,q}$ all set to 0. The figure shows that the fit, and confidence bands, of the two models are very similar, confirming the conclusion from the chi-square test. Taken together these results confirm the preliminary observations from the "quantile dependence" plots. Therefore, we conclude that cryptocurrencies are not only highly correlated unconditionally, but also in the left tail of the distribution. In other words, when the price of one of the cryptocurrency drops significantly, also the price of the other cryptocurrencies tends to drop significantly. On the contrary, tail events in all the other assets do not seem to have a significant effect on the values of cryptocurrencies. Similarly, we find that tail-events for cryptocurrencies do not have a significant negative effect on the other assets, with the exception of the VIX index which has positive and significant q-quantile slope coefficients on bitcoin and ripple. These results indicate that when bitcoin and ripple prices experience large drops in value, the value of the VIX volatility index, often referred to as a *fear index*, tends to shoot up. The bottom panel reports results for the $\Delta CoVaR$, our measure of vulnerability of asset i to tail-risk in asset j. $\Delta CoVaR$ measures the difference in the conditional value-at-risk with respect to its value in the median state (i.e., the quantile $q = 0.5$). For the cryptocurrencies, we find that ether, ripple and litecoin

Table 3
Conditional tail-risk.

i/j	BTC	ETH	XRP	LTC	GOLD	VIX	COMM	MKT
	$CoVaR_q^{i\|VaR^j}$							
BTC	–	−10.19	−9.71	−10.38	−9.93	−8.17	−9.70	−8.22
	[–]	[0.99]	[0.79]	[0.91]	[1.39]	[1.28]	[1.25]	[1.45]
ETH	−13.71	–	−11.19	−12.21	−11.87	−10.00	−12.62	−10.31
	[0.91]	[–]	[1.29]	[1.15]	[1.91]	[1.77]	[1.75]	[1.93]
XRP	−14.75	−14.52	–	−14.35	−12.22	−11.25	−14.04	−11.01
	[2.33]	[2.27]	[–]	[1.50]	[2.34]	[2.07]	[2.48]	[2.00]
LTC	−13.74	−12.56	−11.17	–	−12.55	−12.36	−9.10	−9.96
	[0.97]	[1.32]	[1.45]	[–]	[2.00]	[1.67]	[1.65]	[2.05]
GOLD	−1.18	−1.15	−0.96	−1.09	–	−1.04	−1.09	−1.07
	[0.13]	[0.14]	[0.12]	[0.11]	[–]	[0.09]	[0.13]	[0.16]
VIX	−18.48	−15.05	−15.33	−13.59	−12.21	–	−17.21	−22.55
	[2.54]	[3.52]	[2.23]	[2.75]	[4.16]	[–]	[2.52]	[2.08]
COMM	−1.73	−2.42	−2.04	−2.24	−2.37	−2.75	–	−2.61
	[0.38]	[0.29]	[0.29]	[0.32]	[0.37]	[0.21]	[–]	[0.21]
MKT	−1.63	−1.66	−1.41	−1.24	−0.57	−1.51	−1.52	–
	[0.34]	[0.23]	[0.23]	[0.33]	[0.30]	[0.12]	[0.18]	[–]
	β_q							
BTC	–	0.32	0.14	0.33	1.81	−0.04	0.64	−0.29
	[–]	[0.08]	[0.05]	[0.06]	[1.12]	[0.08]	[0.57]	[1.03]
ETH	0.74	–	0.13	0.43	1.70	0.02	1.27	0.37
	[0.09]	[–]	[0.07]	[0.08]	[1.53]	[0.13]	[0.72]	[1.46]
XRP	0.46	0.34	–	0.41	−0.11	−0.07	0.66	−1.71
	[0.22]	[0.17]	[–]	[0.12]	[1.85]	[0.13]	[1.02]	[1.61]
LTC	0.78	0.42	0.12	–	1.43	0.12	−0.58	−0.59
	[0.09]	[0.11]	[0.08]	[–]	[1.58]	[0.11]	[0.75]	[1.49]
GOLD	0.02	0.01	−0.01	0.00	–	0.00	0.03	0.05
	[0.01]	[0.01]	[0.01]	[0.01]	[–]	[0.00]	[0.05]	[0.12]
VIX	0.64	0.24	0.22	0.10	−0.27	–	3.12	11.71
	[0.22]	[0.25]	[0.13]	[0.19]	[3.26]	[–]	[1.00]	[1.43]
COMM	−0.03	0.04	0.00	0.02	0.25	0.10	–	1.05
	[0.04]	[0.02]	[0.01]	[0.02]	[0.28]	[0.01]	[–]	[0.15]
MKT	0.05	0.04	0.02	0.01	−0.45	0.07	0.38	–
	[0.03]	[0.02]	[0.01]	[0.02]	[0.22]	[0.01]	[0.08]	[–]
	$\Delta CoVaR_q^{i\|VaR^j}$							
BTC	–	−3.15	−1.63	−3.25	−1.95	0.46	−1.27	0.34
	[–]	[0.76]	[0.58]	[0.61]	[1.21]	[1.07]	[1.15]	[1.19]
ETH	−6.76	–	−1.60	−4.28	−1.84	−0.28	−2.54	−0.42
	[0.79]	[–]	[0.87]	[0.76]	[1.65]	[1.60]	[1.44]	[1.68]
XRP	−4.16	−3.36	–	−4.11	0.11	0.84	−1.32	1.96
	[1.98]	[1.65]	[–]	[1.21]	[2.00]	[1.67]	[2.05]	[1.85]
LTC	−7.06	−4.12	−1.45	–	−1.54	−1.52	1.16	0.68
	[0.85]	[1.08]	[0.90]	[–]	[1.71]	[1.38]	[1.50]	[1.71]
GOLD	−0.17	−0.12	0.07	−0.05	–	−0.02	−0.05	−0.06
	[0.11]	[0.11]	[0.09]	[0.08]	[–]	[0.04]	[0.10]	[0.13]
VIX	−5.84	−2.31	−2.58	−0.96	0.29	–	−6.24	−13.49
	[2.03]	[2.49]	[1.59]	[1.88]	[3.52]	[–]	[2.00]	[1.64]
COMM	0.24	−0.38	−0.02	−0.20	−0.27	−1.22	–	−1.21
	[0.33]	[0.23]	[0.12]	[0.23]	[0.31]	[0.17]	[–]	[0.17]
MKT	−0.45	−0.43	−0.28	−0.15	0.48	−0.90	−0.77	–
	[0.28]	[0.19]	[0.15]	[0.20]	[0.24]	[0.10]	[0.15]	[–]

Notes: The table reports estimates for the conditional value-at-risk with confidence q% (top panel), q-quantile OLS slope coefficients (middle panel), and $\Delta CoVaR_q^{VaR^j}$ (bottom panel). In all estimates, the left-hand variables on the regressions are on the rows of the table (i.e., variables i), and the right-hand conditioning variable on the columns of the table (i.e., variables j). In brackets we report standard errors computed by bootstrap. The returns for the VIX index are multiplied by −1, so that negative returns correspond to an increase in the actual index. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and https://cryptocompare.com/. The confidence level is $q = 5$%. For details on the construction of the conditional value-at-risk refers to Section 3.

have the largest (in absolute value) $\Delta CoVaR$ and are the most vulnerable to tail-risk in the market for bitcoin, while bitcoin appears to be the more resilient of the three cryptocurrencies to shocks to the other two cryptocurrencies. Interestingly, we find that while the cryptocurrencies' $\Delta CoVaR$ with respect to the VIX index are not statistically significant from zero, the opposite is not true. For example, the fact that bitcoin is at its VaR_q, with $q = 0.05$, is associated to an additional −584bp drop in the VIX returns with respect to the case in which bitcoin is at its $VaR_{0.5}$, i.e., its median state.

In Table 4 we report additional characteristics of bitcoin, ether, ripple, and litecoin during tail events in all the other assets, i.e., when these assets are in a state of distress. Specifically, we consider only observations corresponding to returns equal or smaller than the corresponding conditional value-at-risk, and compute the ratios between the average volume in those observation with

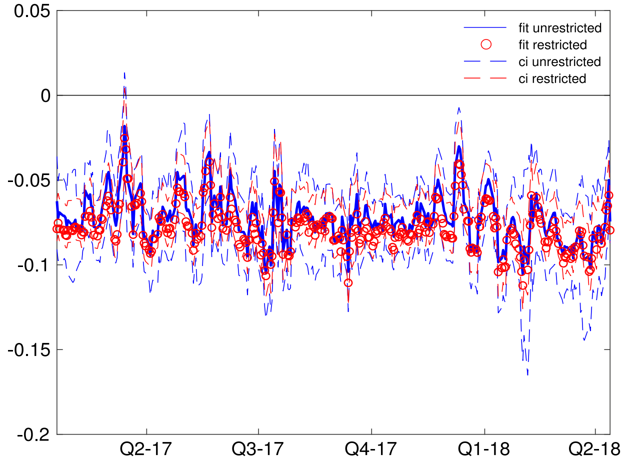

Fig. 4. Fit Bitcoin quantile regression. *Notes:* The figure plots the fit of the quantile regression (6) for the unrestricted (blue line) and restricted (red dots) model with $\phi^{i|j}_{k,q}$ all set to 0. We denote with dashed lines the 95% confidence intervals constructed by bootstrap. The confidence level for the quantile regression is $q = 5\%$. Data are daily for the period 1/18/2017 to 4/15/2018 from cryptocompare.com.

Table 4
Cryptocurrencies during conditional tail events.

i/j	BTC	ETH	XRP	LTC	GOLD	VIX	COMM	MKT
	Vol^{dollar}							
BTC	–	2.95	2.88	2.95	2.92	2.48	2.88	2.46
ETH	3.05	–	2.69	2.55	2.47	2.40	2.64	2.46
XRP	2.46	2.31	–	2.37	2.35	2.28	2.25	2.28
LTC	2.57	2.18	2.31	–	2.18	2.18	1.92	2.15
	Vol^{crypto}							
BTC	–	2.32	2.21	2.32	2.26	2.01	2.21	2.03
ETH	2.71	–	2.29	2.37	2.27	2.12	2.43	2.17
XRP	2.34	2.23	–	2.18	2.03	2.01	2.12	2.01
LTC	2.17	2.18	2.10	–	2.18	2.18	1.86	2.05
	$p^h - p^l$							
BTC	–	2.66	2.54	2.66	2.60	2.26	2.54	2.24
ETH	2.87	–	2.59	2.63	2.57	2.48	2.69	2.47
XRP	3.22	3.10	–	2.99	2.55	2.51	2.89	2.51
LTC	2.93	2.65	2.58	–	2.65	2.65	2.21	2.37

Notes: The table reports the ratios between the daily volume in U.S. dollars (top panel, Vol^{dollar}) and cryptocurrency (middle panel, Vol^{crypto}) when cryptocurrency returns are below or equal the conditional value-at-risk estimates from Table 3 with respect to the unconditional averages. Similarly, the bottom panel reports the ratios between the difference between high and low prices of the day over closing prices ($p^h - p^l$) when cryptocurrency returns are at or below the conditional value-at-risk estimates. For all estimates, the left-hand variables on the regressions are on the rows of the table (i.e., variables i), and the right-hand conditioning variable on the columns of the table (i.e., variables j). Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

respect to the unconditional average, and between the difference between high and low daily prices with respect to the closing price. Interestingly, we find that when returns are equal or below the conditional value-at-risk, volume is on average twice as large as the unconditional mean. Similarly, the difference between the high and low price of the day, as a fraction of the closing price, is more than twice as large as the unconditional mean. Therefore, we can rule out the possibility that tail-events in the cryptocurrency markets are driven by lack of liquidity. On the contrary, it appears that during tail events the demand and supply by investors is above average as well as the intra-day price volatility.

3.3. Cryptocurrency portfolios

The results from our empirical estimation show that cryptocurrencies are highly correlated one with the other, both unconditionally and conditionally to one of them being in a situation of distress, and instead poorly correlated with all the other global assets we consider, included gold to which cryptocurrencies are often compared to. The extremely high daily volatility in cryptocurrency returns also points to the importance of idiosyncratic shocks to these assets. It is therefore interesting to see how far a simple portfolio containing these four cryptocurrencies can go in reducing overall risk, both unconditionally and conditionally. This is of

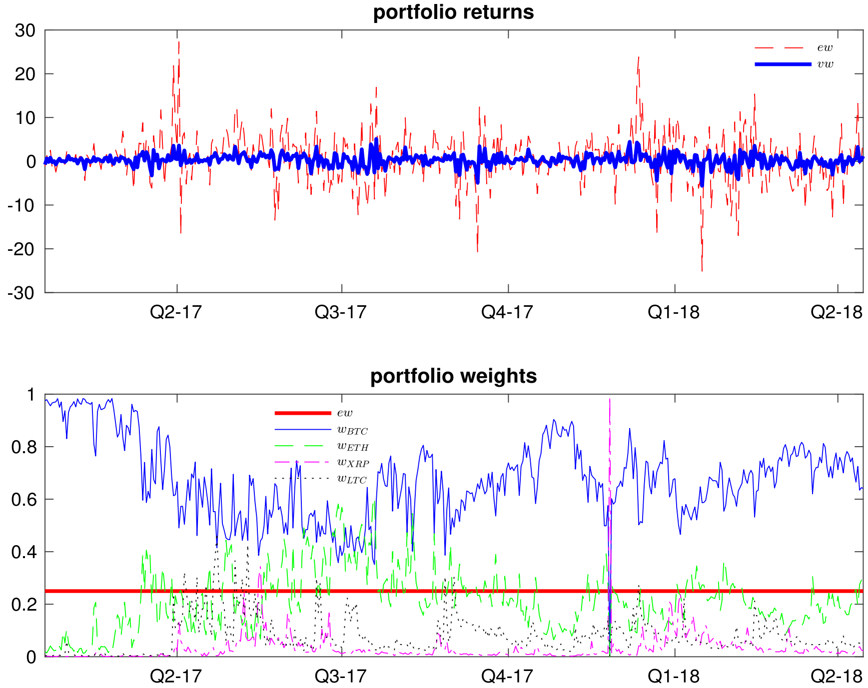

Fig. 5. Cryptocurrency portfolios. *Notes:* The figure plots the daily returns on a equally weighted (EW) and volume weighted (VW) portfolios of cryptocurrencies (top panel), and corresponding portfolios weights in the bottom panel. The cryptocurrencies we consider are bitcoin (BTC), ether (ETH), ripple (XRP) and litecoin (LTC). Portfolios are rebalanced daily. Data are daily for the period 1/18/2017 to 4/15/2018 from cryptocompare.com.

interest as financial companies are starting to offer index funds that track baskets of cryptocurrencies.[6] We build two portfolios: the first is simply an equally-weighted basket of bitcoin, ether, ripple, and litecoin; the second is a volume-weighted portfolio of the four cryptocurrencies. Note that the volume-weighted portfolio is based on daily volume, measured in U.S. dollars, on just two exchanges: Bitfinex for bitcoin, ether and litecoin, and Bitstamp for ripple. Therefore, we use data on volume to proxy for the relative importance of these cryptocurrencies. A natural alternative would be to use data on relative market capitalization which are not available at daily frequency on cryptocompare.com.[7] Both portfolios are rebalanced daily. Fig. 5 plots the returns of the two portfolios (top panel), and the time-varying weights (bottom panel), while Table 5 reports some descriptive statistics as well as estimates for the portfolios' $CoVaR$ (second panel), slope coefficients on conditioning variable in the quantile regressions (third panel), and simple OLS slope coefficients (fourth panel). The volume-weighted portfolio has a lower daily return (26bp vs. 79bp), but also lower volatility (140bp vs. 581bp). Adjusting for risk, the Sharpe-ratio for the volume-weighted portfolio is 19%, while it is 14% for the equally-weighted portfolio, which is also characterized by larger values of kurtosis and smaller unconditional value-at-risk (respectively, −207bp vs. −862bp daily). Note that the skewness of the volume-weighted portfolio, at −0.26, is more negative than that of any single currency. This result indicates that the portfolio provides an amplification of the drawdowns. For this reason, we also report a certainty equivalent (CE) measure based on the mean–variance approximation of power utility in Cremers et al. (2003). The certainty equivalent shows that the equally-weighted portfolio provides a higher utility. The bottom panel of Fig. 5 shows that the volume-weighted portfolios is almost entirely invested in bitcoin at the beginning of the sample. Starting in Q2-2017 first ether, and then ripple and litecoin, enter the portfolio. The weight for ether fluctuates around 1/4, while the weights for ripple and litecoin are generally always smaller than 1/5. As for the individual cryptocurrencies, also for the portfolios of cryptocurrencies the estimates for the conditional value-at-risk are negative, large in absolute value, and significantly different from zero. Interestingly, by reducing the idiosyncratic component, cryptocurrency portfolios offer more precise estimates of the conditional correlation with other assets. In fact, the q-quantile slope coefficients of both the equally and volume-weighted portfolios with respect to returns on gold and the commodity index are positive and significant. This indicates that the large and negative estimates for the portfolios' $CoVaR$ are not simply the result of large and negative constants, but rather depend on the tail-exposure of the portfolios to these assets. On the contrary, the q-quantile slope coefficients with respect to the VIX index and the U.S. market are not statistically

[6] For example, in March 2018 Coinbase announced the Coinbase Index Fund, that will track the performance of the four tokens that currently trade on the San-Francisco-based company's GDAX exchange. Lee et al. (2017) look at the properties of portfolios of cryptocurrencies and argue that exactly their low correlation with standard asset classes make them attractive for investors. Trimborn and Härdle (2016) propose a new market-weighted benchmark for the crypto market, and name it CRIX. The number of constituents of CRIX changes with the introduction of new cryptocurrencies, and is set according to a rule that trades off market value and liquidity of the new assets.

[7] Results are robust to use weights based on market capitalization and a lower rebalancing frequency and are available upon request.

Table 5
Cryptocurrency portfolios.

	$Mean(\%)$	$Std(\%)$	SR	$Skew$	$Kurt$	$VaR_q(\%)$	CE	T
	crypto portfolio characteristics							
ew	0.79	5.81	0.14	−0.03	5.95	−8.62	2.74	453
vw	0.26	1.40	0.19	−0.26	4.55	−2.07	2.73	453
	$CoVaR_q^{i\|VaR^j}$							
i/j	GOLD	VIX	COMM	MKT				
ew	−11.90	−8.36	−12.06	−8.25				
	[1.87]	[1.74]	[1.83]	[1.70]				
vw	−2.74	−2.23	−2.58	−1.91				
	[0.38]	[0.37]	[0.33]	[0.41]				
	β_q							
i/j	GOLD	VIX	COMM	MKT				
ew	3.14	−0.02	1.49	−0.40				
	[1.52]	[0.11]	[0.73]	[1.35]				
vw	0.65	0.01	0.25	−0.15				
	[0.30]	[0.02]	[0.14]	[0.29]				
	β_{ols}							
i/j	GOLD	VIX	COMM	MKT				
ew	0.53	0.05	0.17	0.57				
	[0.44]	[0.03]	[0.22]	[0.47]				
vw	0.13	0.01	0.04	0.13				
	[0.11]	[0.01]	[0.05]	[0.11]				

Notes: The table reports descriptive statistics (top panel); conditional value-at-risk (second panel); q-quantile slope coefficients (third panel); OLS slope coefficients (fourth panel) for two cryptocurrency portfolios. The first portfolio is equally-weighted (ew) and the second is volume-weighted (vw). Means, standard deviations, and value-at-risk estimates are in percentages. CE denotes a certainty equivalent measure based on the mean–variance approximation of power utility in Cremers et al. (2003). For the regressions in the second to fourth panel, the left-hand variables on the regressions are on the table rows (i.e., variables i), and the right-hand conditioning variable on the table columns (i.e., variables j). In brackets we report standard errors computed by bootstrap for the conditional value-at-risk and quantile regressions, and with Newey and West (1986) correction for OLS. The confidence level is $q = 5\%$. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

significant. The two portfolios of cryptocurrencies show the intuitive result that combining assets with relatively low correlations achieve diversification benefits. We now consider a mean–variance optimal portfolio when the set of assets includes cryptocurrencies, portfolios of cryptocurrencies, and other asset classes. Specifically, the other asset classes are the U.S. equity market, gold, a index of commodity, a U.S. corporate bond index, and a U.S. 3-month Treasury index. We compute the efficient frontier and mean–variance optimal portfolio. In order to account for the relatively low liquidity of cryptocurrencies, we take transaction costs for cryptocurrencies from Borri and Shakhnov (2018b), while we assume that transaction costs are zero for the other assets and consider a scenario in which the initial asset is a *naive* portfolio with weights 60% on the U.S. equity market and 40% on the U.S. For this scenario, we compute the "net" efficient frontier and mean–variance optimal portfolio. Specifically, transaction costs are equal to 0.2% for "taker" of liquidity and 0.10% for "maker" of liquidity for bitcoin, ether and litecoin traded on Bitfinex; and are equal to 0.25% for both "taker" and "maker" of liquidity for ripple on Bitstamp. Fig. 6 plots the efficient frontier with (dotted line) and without transaction costs. A green dot denotes the initial portfolio (i.e., the 60–40 *naive* portfolio), and red dots all the available assets. Note how both the equally and volume-weighted crypto portfolios, and ether and ripple, are close to the "gross" efficient frontier (i.e., the frontier computed without transaction costs). The "net" frontier, which accounts for transaction costs, is shifted inward with respect to the "gross" frontier and the vertical distance between the two frontiers is larger the bigger the distance from the initial portfolio. In the case of no transaction costs, the optimal portfolio, i.e., the portfolio with the maximum Sharpe ratio, has weights equal to approximately 17% on the U.S. corporate bond index, 27% on gold, 24% on the commodity index and 31% on the volume-weighted crypto portfolio. On the contrary, when we account for transaction costs, the optimal portfolio has weights equal to 22% on the U.S. corporate bond index, 37% on gold, 35% on the commodity index and only 2% on both the equally-weighted crypto portfolio and ether. Therefore, when we account for transaction costs, the share of the optimal portfolio invested in crypto assets is very small. Even though the assumption of no transaction costs for non-crypto assets introduces a clear bias against crypto assets, this assumption is justified by the fact that transaction costs for traditional assets are typically very small. In addition, accounting for transaction costs for traditional assets would introduce a bias in favor of the initial portfolio, which we assume has zero weights on crypto assets.

4. Time-varying CoVaR

In the previous section we presented the estimates for the conditional tail-risk of bitcoin, ether, ripple, and litecoin, using either cryptocurrencies or different global assets as conditioning variables, that are constant over time. In practice, it is likely that conditional tail-risk is time-varying and, for example, higher during global economic downturns or periods of distress in global markets. For this reason, in this section we follow Adrian and Brunnermeier (2016) and consider an extension of the model illustrated in Section 3 that allows for time-varying conditional risk. In addition, we present results from panel forecasting regressions of $CoVaR$ and $\Delta CoVaR$ at different horizons in order to calculate a forward-looking tail-risk that can be a useful risk-management tool.

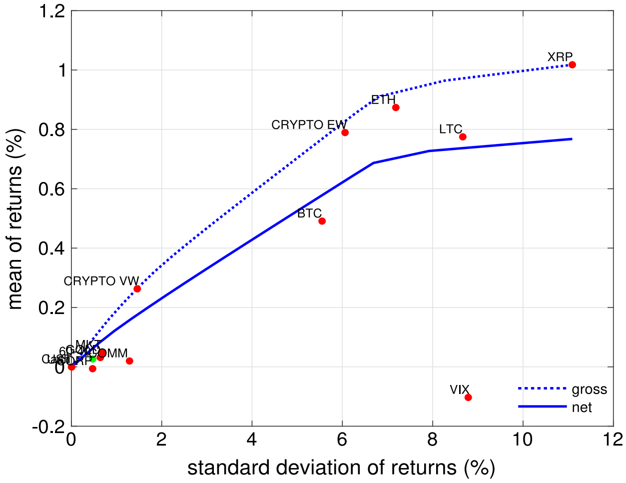

Fig. 6. Efficient frontier with and without transaction costs. *Notes:* The figure plots the efficient frontier with and without transaction costs. The set of asset includes the four cryptocurrencies (i.e., BTC, ETH, XPR and LTC), a equally-weighted (EW) and volume-weighted (VW) portfolios of cryptocurrencies, GOLD, the VIX, COMM, MKT, a U.S. 3-month T-bill, and a U.S. Corporate Bond Index. Transaction costs for the cryptocurrencies are from Borri and Shakhnov (2018b). In the construction of the frontiers we assume an initial portfolio invested 60% in the U.S. equity market and 40% in the U.S. Corporate Bond Index. Data are daily for the period 1/18/2017 to 4/15/2018 from cryptocompare.com and Datastream. The corporate index is the ICE Bank of America Merrill Lynch U.S. Corporate Index. The T-bill index is the Barclays U.S. Treasury Bills 1–3 months.

Table 6
Time-varying conditional tail risk.

	$Mean$	Std	Min	$Skewness$	$Kurtosis$	$AC(1)$	T
	$CoVaR_q$						
$BTC\|ETH$	−10.18	1.93	−15.50	−0.28	3.25	0.75	322
$BTC\|XRP$	−11.18	2.34	−17.16	−0.52	3.03	0.93	322
$BTC\|LTC$	−10.79	2.78	−17.75	−0.59	3.05	0.95	322
$ETH\|BTC$	−13.29	2.84	−21.52	−0.36	2.80	0.62	322
$ETH\|XRP$	−11.72	1.92	−18.75	−0.06	3.78	0.65	322
$ETH\|LTC$	−12.87	2.48	−19.17	−0.57	2.88	0.94	322
$XRP\|BTC$	−15.45	5.71	−31.23	−0.53	2.88	0.81	322
$XRP\|ETH$	−16.15	5.49	−29.70	−0.22	2.72	0.70	322
$XRP\|LTC$	−14.54	5.19	−27.70	−0.25	2.92	0.84	322
$LTC\|BTC$	−13.57	3.74	−23.22	−0.64	3.12	0.93	322
$LTC\|ETH$	−13.69	3.44	−22.82	−0.24	3.21	0.75	322
$LTC\|XRP$	−12.95	2.50	−19.13	−0.49	2.88	0.94	322
	$\Delta CoVaR_q$						
$BTC\|ETH$	−2.96	0.58	−5.17	−0.13	3.65	0.69	322
$BTC\|XRP$	−2.22	0.33	−3.56	0.31	5.24	−0.05	322
$BTC\|LTC$	−2.96	0.79	−5.51	−0.46	3.16	0.75	322
$ETH\|BTC$	−5.67	1.50	−9.75	0.02	2.94	0.42	322
$ETH\|XRP$	−2.13	0.31	−3.42	0.31	5.24	−0.05	322
$ETH\|LTC$	−4.76	1.27	−8.87	−0.46	3.16	0.75	322
$XRP\|BTC$	−3.93	1.04	−6.76	0.02	2.94	0.42	322
$XRP\|ETH$	−3.76	0.74	−6.56	−0.13	3.65	0.69	322
$XRP\|LTC$	−4.77	1.27	−8.88	−0.46	3.16	0.75	322
$LTC\|BTC$	−4.86	1.28	−8.36	0.02	2.94	0.42	322
$LTC\|ETH$	−4.10	0.81	−7.16	−0.13	3.65	0.69	322
$LTC\|XRP$	−1.43	0.21	−2.29	0.31	5.24	−0.05	322

Notes: The table reports descriptive statistics for the estimates of the time-varying conditional value-at-risk for each cryptocurrency (i.e., BTC, ETH, XRP, LTC) given one of the other cryptocurrency being at its value-at-risk. Time-varying conditional estimates are obtained adding lagged state variables in the regressions. The state variables are the lagged returns on gold, the VIX index, the commodity index and the U.S. stock market index. For the details on the construction of the time-varying conditional estimates refer to Section 4. All estimates are in percentages. The confidence level is $q = 5\%$. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

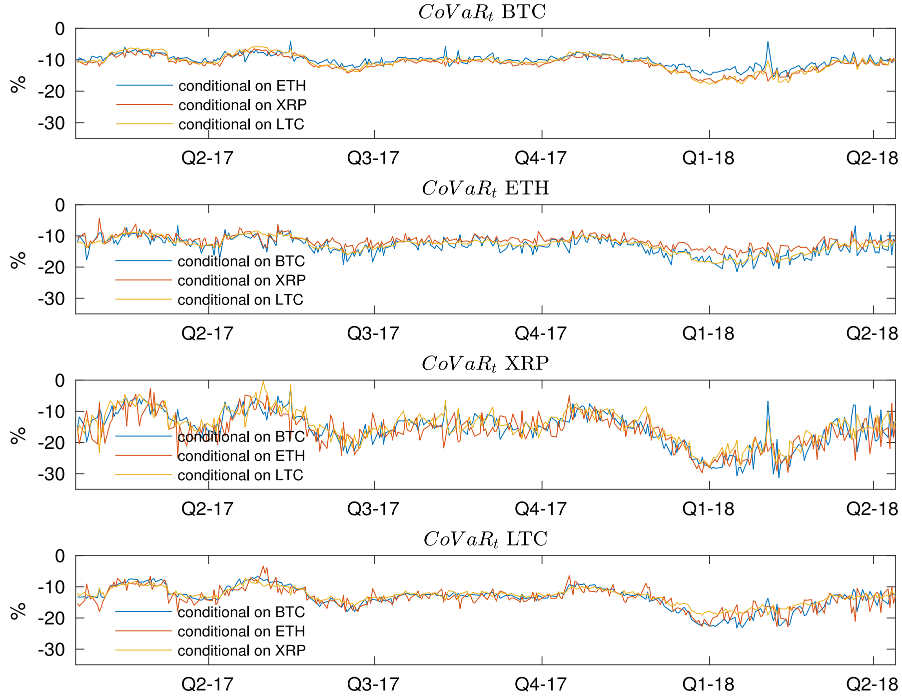

Fig. 7. Time-varying $CoVaR$. *Notes:* The figure plots estimates for the time-varying conditional value-at-risk for each cryptocurrency (i.e., BTC, ETH, XRP, LTC) given one of the other cryptocurrency being at its value-at-risk. Time-varying conditional estimates are obtained adding lagged state variables in the regressions. The state variables are the lagged returns on gold, the VIX index, the commodity index, the U.S. stock market index, and the historical 1-month bitcoin volatility. For details on the construction of the time-varying conditional estimates refer to Section 4. All estimates are in percentages. The confidence level is $q = 5\%$. Data are daily for the period 1/18/2017 to 4/15/2018 from cryptocompare.com.

4.1. *Time variation associated with systematic state variables*

In the previous section we presented estimates for $CoVaR$ and $\Delta CoVaR$ that are constant over time. To capture time-variation in the joint distribution of the cryptocurrency pairs, we estimate the following quantile regressions

$$r^i_{t+1} = \beta^{i|j}_{0,q} + \beta^{i|j}_{1,q} r^j_{t+1} + \sum_{k=1}^{K} \gamma^{i|j}_{k,q} r^k_t + \epsilon^{i|j}_{t+1}, \tag{7}$$

which correspond to Eq. (3) augmented by a set of state variables. Specifically, r^k are the lagged returns on a set of common factors that we use as conditioning variables. $CoVaR$ is then obtained as fitted value of the quantile regression (7)

$$CoVaR^{i|r^j=VaR^j_q}_{q,t} = \hat{\beta}^{i|j}_{0,q} + \hat{\beta}^{i|j}_{1,q} VaR^j_{q,t} + \sum_{k=1}^{K} \hat{\gamma}^{i|j}_{k,q} r^k_t, \tag{8}$$

Finally, we measure $\Delta CoVaR^{i|j}_{q,t}$ as

$$\Delta CoVaR^{i|j}_{q,t} = CoVaR^{i|r^j=VaR^j_{q,t}}_{q,t} - CoVaR^{i|r^j=VaR^j_{0.5,t}}_{q,t}. \tag{9}$$

We include in the estimation state variables that capture time variation in the conditional moments of asset returns. Including the state variables is important to disentangle the vulnerability of each asset with respect to tail-risk in asset j from the more general vulnerability with respect to global factors. The set of state variables includes: the returns on the US equity market, proxied by the S&P500; the log changes in the CBOE VIX volatility index; the returns on a broad commodity index, proxied by the S&P400 Commodity Chemicals; the returns on the gold price; and the 1-month bitcoin volatility at daily frequency. For the latter we use the Garman–Klass estimator with a 1-month rolling window. The Garman–Klass estimator is based on the high minus low spread and it is more efficient than the close-to-close estimator when intraday returns are not available (Glosten et al., 1993). Note that the state variables are not aggregate risk factors (in fact, they are lagged), but rather variables that condition the mean and the volatility of the $CoVaR^{i|j}_{q,t}$. We report in Table 6 and Fig. 7 the results of our time-varying estimates. We find that the averages of the $CoVaR$ and $\Delta CoVaR$ are robust and very similar to those obtained in the constant estimates. These results should not come as a surprise, as the empirical results presented in Section 3 show the small and not significant contemporaneous conditional correlations between cryptocurrencies and the global assets we take into consideration. Ripple is the cryptocurrency with the lowest $CoVaR$, while bitcoin

Table 7
State variable exposures.

	$GOLD$	VIX	$COMM$	MKT	$BTC\ VOL$
	Coefficients				
$BTC\|ETH$	0.09	−0.10	−0.11	0.04	−3.20
$BTC\|XRP$	0.05	0.09	0.03	−0.78	−6.11
$BTC\|LTC$	0.08	−0.01	0.04	−0.65	−5.34
$ETH\|BTC$	0.83	0.08	0.82	−1.78	−2.58
$ETH\|XRP$	0.56	−0.03	1.28	−0.49	−4.06
$ETH\|LTC$	0.98	0.03	0.16	−0.89	−3.39
$XRP\|BTC$	0.82	−0.06	1.05	−2.66	−11.61
$XRP\|ETH$	−4.34	−0.07	0.37	1.06	−10.33
$XRP\|LTC$	1.03	−0.27	−1.23	3.83	−9.83
$LTC\|BTC$	−1.69	0.02	0.34	−1.18	−6.60
$LTC\|ETH$	−2.07	−0.16	−1.24	3.28	−5.91
$LTC\|XRP$	−0.32	0.05	0.42	−0.30	−6.51
	t−statistics				
$BTC\|ETH$	0.23	−1.54	−0.35	0.31	−2.46
$BTC\|XRP$	0.35	0.91	0.27	−0.64	−4.61
$BTC\|LTC$	0.32	−0.27	0.28	−0.84	−3.76
$ETH\|BTC$	1.02	1.05	1.64	−1.65	−1.96
$ETH\|XRP$	0.56	−0.40	1.98	−0.43	−1.97
$ETH\|LTC$	0.96	0.56	0.52	−0.89	−1.78
$XRP\|BTC$	0.79	−0.64	1.43	−1.54	−8.25
$XRP\|ETH$	−3.21	−0.67	0.57	0.67	−6.52
$XRP\|LTC$	0.82	−1.52	−1.36	1.78	−6.46
$LTC\|BTC$	−1.56	0.57	0.81	−1.32	−4.15
$LTC\|ETH$	−1.76	−1.49	−1.83	2.08	−3.37
$LTC\|XRP$	−0.33	0.48	0.53	−0.44	−2.64

Notes: The table reports the coefficients (top panel) and t-statistics by bootstrap (bottom panel) for the state variables in the estimation of the time-varying $CoVaR$ for each cryptocurrency (i.e., BTC, ETH, XRP, LTC) given one of the other cryptocurrency being at its value-at-risk. The confidence level for the $CoVaR$ is $q = 5\%$. The state variables are the lagged returns on gold, the VIX index, the commodity index, the U.S. stock market index, and the 1-month time-varying volatility of bitcoin returns. For details on the construction of the time-varying conditional estimates and the t-statistics refer to Section 4 and Koenker and Hallock (2001). Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

the cryptocurrency with the largest $CoVaR$. In addition, Fig. 7 confirms that bitcoin is the more resilient of the cryptocurrencies to tail-risk in the other cryptomarkets, while ether, ripple, and litecoin are instead more exposed to bitcoin tail-risk. Table 7 reports the coefficients and t-statistics for the state variables and shows that the historical bitcoin volatility is the only variable that is always significantly different from zero and is associated to a negative sign. Intuitively, $CoVaR$s are larger in absolute value when the past bitcoin volatility is high. Results do not change if we replace the historical bitcoin volatility with the historical volatility of the other cryptocurrencies. In addition, we find that a limited number of common components explain most of the variation in the conditional $CoVaR$ and $\Delta CoVaR$. Table 8 reports results from a simple principle component analysis of the $CoVaR$ (top panel) and $\Delta CoVaR$ (bottom panel). In both cases, the first two components explain more than 90% of the total variation, and the first component is highly correlated, respectively, with the cross-sectional mean $CoVaR$ and $\Delta CoVaR$. This result indicates that most of the tail-risk exposure of the cryptocurrency we analyze depend on cryptocurrency-wide tail-risk. The table also reports, for each conditional risk measure, the loadings on the first five common components. Ripple is the cryptocurrency with the highest loadings on the first component, while bitcoin and ether with the lowest loadings.

4.2. Forward conditional tail-risk

In this section we link $CoVaR$ and $\Delta CoVaR$, for the four cryptocurrencies, to cryptocurrency-specific and macro variables. $CoVaR$ measures the value-at-risk of a given cryptocurrency, at some confidence level, conditional on a second cryptocurrency being at its value-at-risk. $\Delta CoVaR$ measures the difference between the $CoVaR$ of asset i conditional on a state of distress in asset j and the *median* state (i.e., $q = 0.5$). We calculate a forward-looking systemic risk measure that can serve as useful tool for risk-management and portfolio decisions and evaluate which variables can be used to predict it. First, we convert the frequency of each variable to weekly by taking weekly averages.[8] Second, for each cryptocurrency i, we regress $CoVaR^{i|j}_{q,t}$ on the lagged i-specific and macro variables common to all cryptocurrencies. More specifically, for a forecast horizon h equal to 1, 2, and 4−week, we estimate regressions

$$CoVaR^{i|j}_{q,t} = a + cM_{t-h} + bX^{i}_{t-h} + \eta^{i}_{t}$$

[8] We obtain similar results by converting variables to weekly frequency by constructing cumulated returns. These results are available upon request.

Table 8
Principal component analysis.

	1	2	3	4	5
	$CoVaR_q$				
$BTC\|ETH$	0.16	−0.11	−0.08	0.37	−0.20
$BTC\|XRP$	0.19	−0.05	0.01	−0.43	0.41
$BTC\|LTC$	0.24	−0.03	0.00	0.10	0.23
$ETH\|BTC$	0.19	−0.41	0.16	−0.37	−0.10
$ETH\|XRP$	0.13	−0.11	0.28	−0.23	−0.68
$ETH\|LTC$	0.21	−0.11	0.04	−0.17	0.13
$XRP\|BTC$	0.47	−0.49	0.10	0.42	−0.04
$XRP\|ETH$	0.41	0.63	0.47	0.13	−0.11
$XRP\|LTC$	0.42	0.06	−0.72	−0.15	−0.23
$LTC\|BTC$	0.32	−0.04	0.13	0.16	0.43
$LTC\|ETH$	0.26	0.38	−0.30	−0.03	−0.02
$LTC\|XRP$	0.21	0.05	0.16	−0.45	0.03
% Var.	83.24	10.17	4.57	1.07	0.95
	$\Delta CoVaR_q$				
$BTC\|ETH$	0.18	−0.07	−0.39	−0.17	−0.32
$BTC\|XRP$	0.03	0.15	0.24	−0.59	−0.01
$BTC\|LTC$	0.23	−0.29	0.15	0.00	0.36
$ETH\|BTC$	0.49	0.42	0.07	0.16	−0.25
$ETH\|XRP$	0.03	0.14	0.23	−0.56	−0.03
$ETH\|LTC$	0.37	−0.47	0.24	0.01	0.20
$XRP\|BTC$	0.34	0.29	0.05	0.11	−0.22
$XRP\|ETH$	0.22	−0.09	−0.50	−0.22	−0.19
$XRP\|LTC$	0.37	−0.47	0.25	0.01	−0.43
$LTC\|BTC$	0.42	0.36	0.06	0.14	0.48
$LTC\|ETH$	0.24	−0.10	−0.55	−0.24	0.40
$LTC\|XRP$	0.02	0.09	0.16	−0.38	0.07
% Var.	69.76	24.10	5.92	0.22	0.00

Notes: This table reports the principal component coefficients of the $CoVaR_{q,t}$ (top panel) and $\Delta CoVaR_{q,t}$ (bottom panel) presented in Table 6. The last row reports (in %) the share of the total variance explained by each common factor. The confidence level is $q = 5\%$. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

where $i, j = BTC, ETH, XRP, LTC$, $i \neq j$, X^i_{t-h} is the vector of cryptocurrency i-specific variables and M_{t-h} the vector of macro state variables lagged h days, and η^i_t is an error term. We estimate the same equation for $\Delta CoVaR^{i|j}_{q,t}$. The i-specific characteristics are the lagged value-at-risk (VaR), historical 1-month volatility, volume of transactions (measured in U.S. dollar billions), and currency returns. For the VaR we use a time-varying estimate constructed with the global state variables presented in Section 4. The macro variables are the lagged returns on the gold, VIX, commodity, and U.S. equity market indices. In Table 9 we ask whether the tail-risk measures can be forecast cross-sectionally by lagged individual and macro variables at different time horizons. We always include in the regressions a cryptocurrency fixed effect, and we report robust standard errors clustered at the cryptocurrency level. Recall that $CoVaR$, $\Delta CoVaR$, and the standard VaR are negative numbers and that we multiply returns on the VIX index by -1. First, we consider the i-specific variables. The table shows that high (in absolute value) currency specific value-at-risk, high volatility and volume, and low returns forecast large future negative $CoVaR$ and $\Delta CoVaR$ values. The predictability of all the i-specific variables declines with the horizon. In particular, the 1-month volatility is significant only at the 1-week horizon. Ardia et al. (2018) find evidence of regime changes in the bitcoin volatility and of a sort of "inverted leverage effect", i.e., the fact that the leverage effect defined as the higher reaction of current volatility levels to past negative returns does not seem to hold for bitcoin. We find instead that past returns forecast future $CoVaR$ and $\Delta CoVaR$ at all horizons. We leave for future work a complete analysis of whether this relationship is asymmetric. Second, we consider the macro variables common to all cryptocurrencies. The table shows that the VIX forecasts $CoVaR$ and $\Delta CoVaR$ at all horizons: past high values of the implied equity volatility are associated to higher tail-risk for cryptocurrencies. We also find that the commodity and U.S. equity market indices predict future tail-risk for cryptocurrencies at longer horizons (i.e., $h = 4$−week) and with different signs. Specifically, low commodity returns and high U.S. equity market returns forecast higher tail-risk. One interpretation of this result is that, for investors, commodities are a complementary asset to cryptocurrencies, while the U.S. equity market a substitute.

5. Conclusions

In this paper we study conditional tail-risk in the markets for bitcoin, ether, ripple and litecoin and find that cryptocurrencies are highly correlated, both unconditionally and conditionally, one with the other, but poorly correlated with other global assets, including gold, to which they are often compared to. We show that, despite this positive correlation, idiosyncratic risk can be significantly reduced and that portfolios of cryptocurrencies offer better risk-adjusted and conditional returns. These results suggest that portfolios

Table 9
$CoVaR$ and $\Delta CoVaR$ forecasts.

VARIABLES	h=1-week		h=2-week		h=4-week	
	$CoVaR^{i\|j}_{q,t}$	$\Delta CoVaR^{i\|j}_{q,t}$	$CoVaR^{i}_{q,t}$	$\Delta CoVaR^{i\|j}_{q,t}$	$CoVaR^{i\|j}_{q,t}$	$\Delta CoVaR^{i\|j}_{q,t}$
	i-specific variables					
VaR	0.634***	0.136**	0.518***	0.110**	0.157**	0.038
	(0.105)	(0.051)	(0.087)	(0.042)	(0.070)	(0.023)
VOLATILITY	−0.327***	−0.083***	−0.078	−0.032	0.131	0.030
	(0.049)	(0.019)	(0.092)	(0.026)	(0.098)	(0.035)
VOLUME	−0.037**	−0.007	−0.045**	−0.008	−0.059***	−0.011**
	(0.017)	(0.006)	(0.015)	(0.005)	(0.013)	(0.005)
RET	0.101***	0.017**	0.090***	0.018**	0.052**	0.018**
	(0.023)	(0.008)	(0.027)	(0.006)	(0.018)	(0.007)
	Macro variables					
GOLD	−0.191	−0.038	−0.320	−0.108	0.338**	0.079*
	(0.265)	(0.062)	(0.261)	(0.063)	(0.146)	(0.039)
VIX	0.116***	0.015**	0.190***	0.031***	0.277***	0.054***
	(0.033)	(0.006)	(0.043)	(0.009)	(0.038)	(0.011)
COMM	0.024	0.005	−0.110	−0.046	0.755***	0.185***
	(0.191)	(0.032)	(0.138)	(0.029)	(0.133)	(0.041)
MKT	0.110	0.149**	−0.996**	−0.052	−4.072***	−0.763***
	(0.254)	(0.066)	(0.390)	(0.061)	(0.606)	(0.172)
Observations	756	756	744	744	720	720
R-squared	0.355	0.282	0.297	0.225	0.209	0.158
Number of ID	12	12	12	12	12	12
FE	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES

Notes: The table reports the coefficients from panel forecasting regressions of $CoVaR^{i|j}_{q,t}$ and $\Delta CoVaR^{i|j}q,t$ on lagged individual and macro variables at horizons 1-week, 2-week and 4-week. Daily variables are collapsed at weekly frequency by taking weekly averages. Volume is in U.S. dollar billions. FE denotes fixed effect dummies. Robust standard errors clustered at the cryptocurrency levels are displayed in parenthesis. The confidence level is $q = 5\%$. Data are weekly for the period 1/18/2017 to 4/15/2018 from Datastream and cryptocompare.com.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table A.1
Top crypto exchanges.

#	Name	Markets	24h trades	24h volume	Marketshare
1	Bitfinex	16	>40,9993,948	$1118,631,919	29%
2	Coinone	6	>86,429,663	$403,864,129	10%
3	Coinbase GDAX	12	>28,392,720	$350,686,070	9%
4	Kraken	57	>39,168,826	$336,993,151	9%
5	Bitstamp	11	>21,557,885	$252,519,343	7%
6	HitBTC	288	>146,960,768	$219,813,294	6%
7	Bithumb	12	>19,327,401	$166,052,678	4%

Notes: This table reports the list of the top crypto exchanges by market share. Data are collected on April, 16 2018 from cryptocoincharts.info. Markets refers to the total number of currency pairs (fiat and crypto) traded on each exchange. The trading volume is in U.S. dollar.

Table A.2
Cryptocurrencies by market cap.

Name	Market Cap in bln $	Price in $	Volume in bln $ (24h)	Release Date	Supply Max in mln	Supply Circulating in mln
Bitcoin	140	8,106.82	5.6	9-Jan-09	21	16.9
Ethereum	50	513.45	1.7	30-Jul-15	No Cap	98.8
Ripple	26	0.65	0.7	26-Sep-13	100,000	39122.9
Litecoin	7	127.66	0.3	7-Oct-11	100,000	56.1
Total	326					

Notes: This table lists the main cryptocurrencies by market capitalization. Data are for April, 16 2018 from https://coinmarketcap.com/. "Total" refers to all the cryptocurrencies tracked by the data aggregator. Market capitalization is computed as market value of circulating supply, and is reported in U.S. dollar billions. Volume is annual, and in U.S. dollar billions. Supply is in millions of units.

Table A.3
Conditional tail risk (q = 1%).

i/j	BTC	ETH	XRP	LTC	GOLD	VIX	COMM	MKT
	$CoVaR_q^{i\|VaR^j}$							
BTC	–	−16.47	−17.06	−16.27	−25.40	−10.59	−19.59	−10.66
	[–]	[3.49]	[2.54]	[2.21]	[4.37]	[6.48]	[4.97]	[5.53]
ETH	−20.85	–	−18.01	−18.13	−30.22	−17.10	−26.88	−15.43
	[4.18]	[–]	[3.92]	[3.49]	[5.13]	[6.47]	[5.98]	[7.49]
XRP	−29.52	−30.73	–	−30.00	−16.59	−16.87	−17.97	−17.07
	[7.34]	[6.47]	[–]	[6.10]	[13.92]	[15.53]	[12.43]	[17.98]
LTC	−23.52	−21.57	−21.17	–	−21.14	−15.75	−28.18	−13.85
	[4.79]	[4.90]	[3.14]	[–]	[8.49]	[9.74]	[6.54]	[7.20]
GOLD	−1.79	−1.92	−1.74	−1.68	–	−1.91	−1.95	−1.81
	[0.31]	[0.27]	[0.23]	[0.18]	[–]	[0.37]	[0.24]	[0.37]
VIX	−50.37	−57.69	−24.31	−42.05	−18.25	–	−38.20	−50.59
	[16.74]	[11.23]	[14.50]	[14.03]	[14.81]	[–]	[11.08]	[4.57]
COMM	−2.11	−5.16	−2.25	−3.30	−3.41	−7.40	–	−4.39
	[0.99]	[1.04]	[0.79]	[0.63]	[1.22]	[0.95]	[–]	[1.23]
MKT	−4.03	−4.20	−3.06	−3.00	−2.11	−3.59	−3.03	–
	[1.03]	[0.77]	[0.91]	[0.93]	[1.40]	[0.63]	[0.80]	[–]
	β_q							
BTC	–	0.22	0.15	0.21	5.77	−0.11	0.72	−2.67
	[–]	[0.18]	[0.10]	[0.11]	[2.44]	[0.20]	[1.38]	[2.26]
ETH	0.60	–	0.11	0.22	7.78	0.01	2.32	−2.16
	[0.25]	[–]	[0.14]	[0.18]	[2.83]	[0.20]	[1.65]	[2.84]
XRP	0.64	0.51	–	0.50	−1.98	−0.09	−0.38	−1.34
	[0.38]	[0.34]	[–]	[0.34]	[8.10]	[0.37]	[2.70]	[5.48]
LTC	0.58	0.44	0.20	–	0.04	−0.16	2.23	−3.09
	[0.31]	[0.24]	[0.14]	[–]	[4.45]	[0.29]	[1.86]	[3.06]
GOLD	0.01	0.02	0.01	0.00	–	0.01	0.10	0.09
	[0.02]	[0.01]	[0.01]	[0.01]	[–]	[0.01]	[0.07]	[0.15]
VIX	1.12	1.33	−0.34	0.46	−7.03	–	3.82	14.20
	[0.97]	[0.52]	[0.39]	[0.56]	[7.54]	[–]	[3.00]	[1.87]
COMM	−0.07	0.11	−0.04	0.00	0.04	0.14	–	0.91
	[0.06]	[0.05]	[0.03]	[0.03]	[0.62]	[0.03]	[–]	[0.48]
MKT	0.10	0.10	0.03	0.04	−0.06	0.08	0.33	–
	[0.06]	[0.04]	[0.03]	[0.05]	[0.76]	[0.02]	[0.22]	[–]
	$\Delta CoVaR_q^{i\|VaR^j}$							
BTC	–	−3.73	−2.90	−3.62	−9.62	3.40	−2.39	6.36
	[–]	[3.13]	[1.94]	[1.90]	[4.06]	[6.12]	[4.56]	[5.39]
ETH	−9.14	–	−2.21	−3.76	−12.95	−0.25	−7.66	5.15
	[3.81]	[–]	[2.73]	[3.13]	[4.72]	[6.01]	[5.45]	[6.77]
XRP	−9.69	−8.77	–	−8.43	3.29	2.62	1.26	3.20
	[5.67]	[5.96]	[–]	[5.71]	[13.49]	[11.38]	[8.91]	[13.08]
LTC	−8.82	−7.56	−3.81	–	−0.07	5.01	−7.36	7.37
	[4.74]	[4.21]	[2.62]	[–]	[7.41]	[8.87]	[6.14]	[7.30]
GOLD	−0.19	−0.31	−0.11	−0.04	–	−0.31	−0.32	−0.22
	[0.29]	[0.25]	[0.19]	[0.11]	[–]	[0.37]	[0.23]	[0.36]
VIX	−16.91	−23.05	6.55	−7.83	11.71	–	−12.61	−33.89
	[14.69]	[9.07]	[7.50]	[9.54]	[12.55]	[–]	[9.91]	[4.47]
COMM	1.10	−1.83	0.82	−0.05	−0.07	−4.33	–	−2.17
	[0.83]	[0.83]	[0.58]	[0.50]	[1.04]	[0.92]	[–]	[1.14]
MKT	−1.57	−1.64	−0.58	−0.62	0.09	−2.37	−1.08	–
	[0.93]	[0.71]	[0.59]	[0.78]	[1.26]	[0.59]	[0.72]	[–]

Notes: The table reports estimates for the conditional value-at-risk with confidence q% (top panel), q-quantile OLS slope coefficients (middle panel), and $\Delta CoVaR_q^{VaR^j}$ (bottom panel). In all estimates, the left-hand variables on the regressions are on the rows of the table (i.e., variables i), and the right-hand conditioning variable on the columns of the table (i.e., variables j). In brackets we report standard errors computed by bootstrap. The returns for the VIX index are multiplied by −1, so that negative returns correspond to an increase in the actual index. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and https://cryptocompare.com/. The confidence level is q = 1%. For details on the construction of the conditional value-at-risk refers to Section 3.

of cryptocurrencies could offer attractive returns and hedging properties when included in investors' portfolios. However, when we account for liquidity, the share of crypto assets in investors' optimal portfolio is small. Finally, we find that cryptocurrency specific and macro variables can predict future conditional tail-risk. Specifically, high (in absolute value) currency specific value-at-risk, high volatility and volume, and low returns forecast large future negative $CoVaR$ and $\Delta CoVaR$ values. The predictability of all the i-specific variables declines with the horizon. VIX forecasts $CoVaR$ and $\Delta CoVaR$ at all horizons: past high values of the implied equity volatility are associated to higher tail-risk for cryptocurrencies. These results can serve as useful tool for risk-management and portfolio decisions.

Table A.4
Conditional tail risk (q = 10%).

i/j	BTC	ETH	XRP	LTC	GOLD	VIX	COMM	MKT
	$CoVaR_q^{i\|VaR^j}$							
BTC	–	−8.08	−7.49	−8.10	−8.32	−6.31	−7.06	−6.55
	[–]	[0.54]	[0.61]	[0.50]	[0.95]	[0.74]	[0.88]	[0.76]
ETH	−10.66	–	−7.63	−8.75	−9.04	−7.55	−8.94	−7.59
	[0.66]	[–]	[0.73]	[0.56]	[1.39]	[1.01]	[1.37]	[1.27]
XRP	−11.23	−9.83	–	−9.33	−8.06	−7.77	−9.43	−7.73
	[0.75]	[0.98]	[–]	[0.99]	[1.76]	[1.11]	[1.33]	[1.10]
LTC	−10.50	−9.16	−8.21	–	−8.07	−8.04	−7.85	−8.13
	[0.71]	[0.73]	[0.60]	[–]	[1.11]	[0.87]	[1.08]	[0.81]
GOLD	−0.89	−0.92	−0.79	−0.88	–	−0.86	−0.86	−0.85
	[0.11]	[0.08]	[0.09]	[0.08]	[–]	[0.09]	[0.10]	[0.08]
VIX	−8.34	−8.52	−7.18	−7.45	−7.15	–	−12.36	−10.82
	[1.58]	[1.25]	[1.13]	[1.37]	[1.68]	[–]	[1.07]	[0.51]
COMM	−1.48	−1.53	−1.44	−1.56	−1.36	−1.79	–	−1.73
	[0.18]	[0.18]	[0.12]	[0.15]	[0.17]	[0.09]	[–]	[0.09]
MKT	−0.70	−0.67	−0.64	−0.61	−0.41	−0.83	−1.15	–
	[0.12]	[0.11]	[0.07]	[0.12]	[0.15]	[0.07]	[0.09]	[–]
	β_q							
BTC	–	0.34	0.14	0.39	1.75	−0.04	0.19	−0.25
	[–]	[0.05]	[0.04]	[0.05]	[0.85]	[0.07]	[0.42]	[0.80]
ETH	0.75	–	0.12	0.39	2.08	0.06	1.08	0.18
	[0.07]	[–]	[0.05]	[0.05]	[1.30]	[0.09]	[0.67]	[1.31]
XRP	0.72	0.39	–	0.38	0.09	−0.04	1.03	−0.41
	[0.09]	[0.09]	[–]	[0.08]	[1.56]	[0.09]	[0.63]	[1.15]
LTC	0.72	0.42	0.16	–	−0.05	0.01	0.28	0.01
	[0.08]	[0.07]	[0.05]	[–]	[1.03]	[0.08]	[0.57]	[0.75]
GOLD	0.01	0.02	−0.00	0.01	–	0.00	0.01	0.06
	[0.01]	[0.01]	[0.01]	[0.01]	[–]	[0.01]	[0.05]	[0.09]
VIX	0.19	0.12	0.01	0.03	0.06	–	3.36	8.91
	[0.17]	[0.13]	[0.08]	[0.11]	[1.35]	[–]	[0.55]	[0.63]
COMM	0.00	0.02	−0.00	0.01	−0.09	0.08	–	1.06
	[0.02]	[0.02]	[0.00]	[0.01]	[0.17]	[0.01]	[–]	[0.11]
MKT	0.02	0.02	0.01	0.01	−0.13	0.06	0.38	–
	[0.01]	[0.01]	[0.01]	[0.01]	[0.13]	[0.01]	[0.05]	[–]
	$\Delta CoVaR_q^{i\|VaR^j}$							
BTC	–	−2.48	−1.01	−2.89	−1.52	0.32	−0.28	0.14
	[–]	[0.39]	[0.30]	[0.35]	[0.74]	[0.53]	[0.61]	[0.46]
ETH	−5.41	–	−0.91	−2.94	−1.80	−0.40	−1.57	−0.11
	[0.52]	[–]	[0.37]	[0.40]	[1.13]	[0.63]	[0.98]	[0.75]
XRP	−5.20	−2.83	–	−2.84	−0.08	0.26	−1.50	0.24
	[0.63]	[0.69]	[–]	[0.59]	[1.35]	[0.66]	[0.92]	[0.66]
LTC	−5.24	−3.06	−1.16	–	0.05	−0.07	−0.41	−0.00
	[0.58]	[0.50]	[0.36]	[–]	[0.89]	[0.58]	[0.83]	[0.43]
GOLD	−0.06	−0.16	0.02	−0.05	–	−0.03	−0.02	−0.04
	[0.09]	[0.06]	[0.04]	[0.05]	[–]	[0.05]	[0.08]	[0.05]
VIX	−1.40	−0.85	−0.05	−0.24	−0.05	–	−4.90	−5.12
	[1.23]	[0.91]	[0.55]	[0.81]	[1.17]	[–]	[0.80]	[0.36]
COMM	−0.04	−0.11	0.01	−0.10	0.07	−0.58	–	−0.61
	[0.16]	[0.13]	[0.03]	[0.10]	[0.14]	[0.06]	[–]	[0.06]
MKT	−0.16	−0.12	−0.07	−0.04	0.12	−0.46	−0.55	–
	[0.10]	[0.08]	[0.04]	[0.07]	[0.11]	[0.04]	[0.07]	[–]

Notes: The table reports estimates for the conditional value-at-risk with confidence q% (top panel), q-quantile OLS slope coefficients (middle panel), and $\Delta CoVaR_q^{VaR^j}$ (bottom panel). In all estimates, the left-hand variables on the regressions are on the rows of the table (i.e., variables i), and the right-hand conditioning variable on the columns of the table (i.e., variables j). In brackets we report standard errors computed by bootstrap. The returns for the VIX index are multiplied by −1, so that negative returns correspond to an increase in the actual index. Data are daily for the period 1/18/2017 to 4/15/2018 from Datastream and https://cryptocompare.com/. The confidence level is q = 10%. For details on the construction of the conditional value-at-risk refers to Section 3.

Appendix A

A.1. Cryptomarkets

Cryptocurrencies are traded 24/7, every day of the week, including holidays, on several exchanges across the globe. There are two types of exchanges:

Table A.5
Conditional tail-risk (weekly frequency).

i/j	BTC	ETH	XRP	LTC	GOLD	VIX	COMM	MKT
	$CoVaR_q^{i\|VaR^j}$							
BTC	–	−11.66	−14.92	−12.70	−7.29	−10.15	−7.96	−17.44
	[–]	[3.28]	[3.24]	[3.65]	[3.96]	[3.69]	[4.22]	[4.23]
ETH	−16.27	–	−16.62	−15.28	−12.17	−9.05	−11.85	−20.94
	[3.88]	[–]	[2.54]	[3.55]	[4.45]	[3.09]	[4.06]	[4.56]
XRP	−21.48	−20.78	–	−20.45	−20.74	−19.82	−20.63	−16.15
	[6.74]	[5.16]	[–]	[5.15]	[6.64]	[5.29]	[6.75]	[6.82]
LTC	−27.28	−25.65	−17.25	–	−22.27	−23.62	−5.00	−25.71
	[5.62]	[4.32]	[4.95]	[–]	[6.81]	[3.31]	[5.53]	[7.08]
GOLD	−3.08	−2.70	−2.57	−2.05	–	−1.75	−2.49	−2.26
	[0.53]	[0.31]	[0.20]	[0.37]	[–]	[0.38]	[0.56]	[0.56]
VIX	−18.76	−18.60	−26.80	−24.47	−13.84	–	−36.47	−41.10
	[12.97]	[8.84]	[11.80]	[11.12]	[17.92]	[–]	[12.55]	[6.35]
COMM	−2.80	−5.21	−5.37	−1.43	−9.19	−5.53	–	−6.72
	[2.04]	[1.76]	[1.68]	[1.73]	[1.36]	[2.10]	[–]	[2.27]
MKT	−0.96	−1.62	−2.70	−1.36	−2.15	−2.64	−3.35	–
	[1.60]	[1.17]	[1.10]	[1.31]	[1.70]	[0.46]	[1.23]	[–]
	β_q							
BTC	–	0.10	0.21	0.21	−2.10	−0.07	−0.47	1.68
	[–]	[0.08]	[0.08]	[0.11]	[1.47]	[0.15]	[0.68]	[1.49]
ETH	0.40	–	0.12	0.07	−1.19	−0.20	−0.55	2.52
	[0.09]	[–]	[0.08]	[0.11]	[1.53]	[0.13]	[0.64]	[1.69]
XRP	0.17	0.01	–	−0.00	0.07	−0.03	0.03	−1.61
	[0.22]	[0.17]	[–]	[0.15]	[2.36]	[0.20]	[1.04]	[2.36]
LTC	0.65	0.34	−0.08	–	1.15	0.31	−2.69	2.21
	[0.09]	[0.11]	[0.13]	[–]	[2.38]	[0.15]	[0.86]	[2.42]
GOLD	0.05	0.02	0.01	−0.01	–	−0.02	0.05	0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[–]	[0.02]	[0.09]	[0.18]
VIX	−0.01	−0.02	0.19	0.17	−3.40	–	2.62	8.17
	[0.22]	[0.25]	[0.27]	[0.33]	[5.06]	[–]	[1.65]	[2.16]
COMM	−0.12	0.02	0.03	−0.10	1.54	0.01	–	1.36
	[0.04]	[0.02]	[0.05]	[0.05]	[0.48]	[0.07]	[–]	[0.63]
MKT	−0.08	−0.03	0.02	−0.04	0.01	0.07	0.27	–
	[0.03]	[0.02]	[0.03]	[0.03]	[0.50]	[0.02]	[0.17]	[–]
	$\Delta CoVaR_q^{i\|VaR^j}$							
BTC	–	−1.65	−4.03	−4.00	4.92	1.27	2.57	−4.55
	[–]	[2.13]	[1.57]	[2.02]	[3.45]	[2.82]	[3.69]	[4.01]
ETH	−6.15	–	−2.29	−1.32	2.79	3.88	3.01	−6.80
	[2.82]	[–]	[1.54]	[1.98]	[3.59]	[2.61]	[3.48]	[4.56]
XRP	−2.65	−0.12	–	0.07	−0.16	0.53	−0.16	4.36
	[5.56]	[3.13]	[–]	[2.82]	[5.52]	[3.96]	[5.69]	[6.36]
LTC	−9.92	−5.67	1.46	–	−2.69	−5.93	14.71	−5.97
	[4.51]	[2.75]	[2.53]	[–]	[5.58]	[2.85]	[4.69]	[6.53]
GOLD	−0.82	−0.39	−0.27	0.15	–	0.46	−0.30	−0.02
	[0.41]	[0.22]	[0.14]	[0.27]	[–]	[0.32]	[0.51]	[0.50]
VIX	0.09	0.33	−3.60	−3.14	7.97	–	−14.32	−22.05
	[6.68]	[6.95]	[5.16]	[6.25]	[11.85]	[–]	[9.03]	[5.83]
COMM	1.91	−0.41	−0.60	1.87	−3.61	−0.17	–	−3.68
	[1.66]	[1.14]	[0.89]	[0.94]	[1.13]	[1.40]	[–]	[1.70]
MKT	1.18	0.55	−0.40	0.67	−0.02	−1.44	−1.50	–
	[1.11]	[0.70]	[0.58]	[0.62]	[1.17]	[0.31]	[0.92]	[–]

Notes: The table reports estimates for the conditional value-at-risk with confidence q% (top panel), q-quantile OLS slope coefficients (middle panel), and $\Delta CoVaR_q^{VaR^j}$ (bottom panel). In all estimates, the left-hand variables on the regressions are on the rows of the table (i.e., variables i), and the right-hand conditioning variable on the columns of the table (i.e., variables j). In brackets we report standard errors computed by bootstrap. The returns for the VIX index are multiplied by −1, so that negative returns correspond to an increase in the actual index. Data are weekly for the period 1/18/2017 to 4/15/2018 from Datastream and https://cryptocompare.com/. The confidence level is $q = 5\%$. For details on the construction of the conditional value-at-risk refers to Section 3.

1. exchanges on which investors can trade cryptocurrency pairs (i.e., bitcoin for ethereum), and where they can deposit and withdraw only cryptocurrencies;
2. exchanges on which investors can trade fiat for cryptocurrencies (i.e., bitcoin for U.S. dollar), and where investors can deposit and withdraw both fiat and cryptocurrencies.

Table A.1 reports a list of the top exchanges by market share as of April, 2018 obtained through cryptocoincharts.info. The "market" is intended as the whole cryptocurrencies' market. The third column reports the total number of currency pairs that can be traded, which is as large as 288 for HitBTC, an exchange on which only cryptocurrencies are traded. The table also reports the daily trading volume (in U.S. dollar); and daily number of trades. The exchange with the largest market share is Bitfinex, which has 29% of the market. Bitstamp, the exchange we use in order to obtain ripple prices, has instead a market capitalization of 7%.

The number of cryptocurrencies has increased substantially since the first launch of bitcoin sometime in 2009. Table A.2 lists four of the cryptocurrencies with the largest market capitalization, as of April 2018, together with their U.S. dollar price, daily volume, release date, maximum and currently circulating supply. The maximum supply denotes the largest number of units that can be mined according to the technology of each cryptocurrency. Not all the cryptocurrencies are the same. For example, Ripple uses a centralized clearing system, and allows almost instant transactions with very limited costs. Ethereum, instead, is not just a digital currency, but rather a blockchain platform that features smart contracts, the Ethereum Virtual Machine (EVM), and allows users to create digital tokens that can be used to represent virtual shares, assets, proofs of membership, etc. Litecoin is technologically almost identically to Bitcoin, and was created to overcome some of the inefficiencies of the latter.

A.2. Robusteness

In this section we first report estimates for $CoVaR$, from Section 3, for difference confidence levels, and then for weekly, rather than daily, frequency. Specifically, Table A.3 considers a confidence level $q = 1\%$ and Table A.4 a confidence level $q = 10\%$. Results are qualitatively similar to those presented and discussed in Section 3. Table A.5 presents the $CoVaR$ and $\Delta CoVaR$ estimates at weekly frequency. The table shows that our baseline results are also robust to switching to a lower frequency. In particular, $CoVaR$ and $\Delta CoVaR$ estimates are larger (in absolute value) and, mostly, significantly different from zero for cryptocurrencies while, on average, smaller and not significantly different from zero for other global assets. However, the precision of the estimates is lower. This is not surprising as they are based only on about 15 months of data.

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