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Volatility Connectedness of Major Cryptocurrencies: The Role of Investor Happiness

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Abstract

In this paper, we first obtain a time-varying measure of volatility connectedness involving fifteen major cryptocurrencies based on a dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model, and then analyze the role of investor sentiment in explaining the movement of the connectedness metric within a quantile-on-quantile framework. Our findings show that lower quantiles of investor happiness, built on Twitter feed data as a proxy for investor sentiment, is positively associated with the entire conditional distribution of connectedness, but the opposite is observed at higher values of investor happiness. In addition, when we look at the effect of sentiment on the common market volatility, we are able to deduce that as investors become exceedingly unhappy, overall market volatility increases and this is associated with high market connectedness. The heightened volatility possibly due to higher trading, seems to suggest that cryptocurrencies are used for hedging when investor sentiment is weak, with evidence in favor of this behavior being relatively stronger than the possible speculative motive associated with happy investors, as low total connectedness is coupled with high common volatility. Our results tend to suggest that, relatively more diversification opportunities are available when investors are happy rather than when sentiment is weak.

Keywords: Cryptocurrency Market, DCC-GARCH, Volatility Connectedness, Investor Happiness, Quantile-on-Quantile Regression

JEL codes: C22, C32, G10.

1 Introduction

Volatility is the single most and fundamentally important concept in the discipline of finance and is synonymous with the measure of risk. Hence, uncovering volatility linkages among markets or assets helps market participants and academic researchers in making important inferences on the overall dynamics of the risk in the financial system. For example, the transmission of second moments of the return distribution among assets and markets can be used to understand how volatility shocks in one asset or market can predict the volatility in another asset or market. Furthermore, the identity and role of exogenous factors that can affect the dynamics of volatility linkages are of paramount importance. The above issues have been broadly applied to conventional financial markets (e.g., stocks, bonds, commodities) and their implications cover asset allocation, risk management, derivative pricing, and regulatory formulation (see for example, Chang et al. (2018), Tiwari et al. (2018), Baur and Hoang (2019) for detailed reviews of this literature). However, they remain largely understudied in the cryptocurrency markets that continue to attract debate and attention from the media and the financial community. The cryptocurrency markets constitute an investment vehicle for many investors, and they notably exhibit high price volatility. The associated market participants are in general not well informed about volatility transmission among leading cryptocurrencies and the exogenous variables that can affect the dynamics of volatility spillovers.

Against this backdrop, the objective of this paper is to analyze, daily volatility spillover across fifteen major cryptocurrencies using a full-fledge time-varying framework, as recently developed by Gabauer (2020), based on the underlying dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model originally proposed by Engle (2002). In addition, given conflicting role of cryptocurrencies as hedge (Bouri et al., 2017a,b; Shahzad et al., 2019) and purely used for speculation (Baur et al., 2018; Klein et al., 2018), and hence the importance of investor sentiment, we also aim to provide a possible explanation of the total volatility connectedness and common market volatility across the major cryptocurrencies using a social media-based investor happiness index built on Twitter feed data. An advantage of the happiness index used in our study is that it is global in nature, given the dominance of Twitter users in the ten countries serving as major players in the world financial system, thus allowing us to capture investor sentiment at a broader level. The idea is to understand whether the connectedness in the market is actually driven by speculation (likely to be associated with strong investor sentiment), or due to the possible hedging role of cryptocurrencies (during periods of weak investor sentiment), with both these features discussed in great detail in the abovementioned literature. The empirical analysis to examine the link between investor happiness and volatility spillovers across the major cryptocurrencies via the total connectedness index (TCI) and common market volatility is based on the quantile-on-quantile (QQ) approach recently developed by Sim and Zhou (2015). The QQ model, as a generalization of the standard quantile regression allowing us to examine how the conditional quantiles (states) of the TCI relate to the quantiles (levels) of the happiness index.

Intuitively, if investor sentiment is high, and there is more trading in cryptocurrencies, the volatility connectedness associated with the resulting higher volatility can be positively related with investor sentiment, and hence suggest that cryptcurrencies are driven by possible speculation, especially if the underlying market volatility is not found to increase during periods of weak sentiment. But if investor sentiment is low, and there is still more trading in cryptocurrencies causing the volatility to increase, and the connectedness in this phase is found to be positively related to sentiment, then cryptocurrencies can indeed be considered as a hedge against risks (that might have created low sentiments in the first place), even if volatility increases, remains unaffected or decreases during episodes of high investor sentiment. In other words, volatility connectedness can be associated with both increases or decreases of overall market volatility. Naturally, to get a clear understanding of how the TCI is related to the common cryptocurrency market volatility, and hence, determine whether cryptocurrencies actually acts as a hedge or are purely driven by market speculation, we need an underlying measure of overall market volatility. We achieve this by using the framework of Barigozzi and Hallin (2016), which allows us to to decompose cryptocurrency returns volatility into both common and idiosyncratic components using an entirely non-parametric and model-free two-step general dynamic factor approach. Then we use the QQ approach again to relate investor happiness with the common market volatility associated with the fifteen cryptocurrencies.

To the best of our knowledge, this is the first paper to derive time-varying connectedness of volatility spillover, and then relate this connectedness and underlying market volatility with investor sentiment to provide an understanding of whether variances in returns (i.e., volatility) of cryptocurrencies can be associated with hedging or speculation. The remainder of this paper is organised as follows. We present a review of the literature associated with spillovers in the cryptocurrency market in Section 2, then in Section 3, we describe the data. After that in Section 4, we and set out the empirical methods employed in the study, followed by the discussion of the findings of the study in In Section 5. Finally, Section 6 summarizes the key results and the associated investment implications.

2 Literature Review

The network of connectedness and shock spillovers in the cryptocurrency market continue to induce considerable debate in the academic literature. This is mainly driven by the complexity of the system of connectedness in this controversial and highly volatile market. Existing studies consider multiple methodologies, including GARCH models and Granger causality tests. Katsiampa et al. (2019) use bivariate GARCH models to examine the conditional volatility dynamics and conditional correlations across Bitcoin, Ethereum and Litecoin. They show that the future volatility of returns is shaped by their own current shocks and current volatility. They indicate the presence of two-way return flows between Bitcoin and both Ether and Litecoin, and a one-way flow from Ether to Litecoin. Katsiampa et al. (2019) report evidence of two-way volatility flows between all the pairs of cryptocurrencies under study, and that the pairwise conditional correlations are positive and vary with time. Bouri et al. (2019a) apply a

Granger causality approach in the frequency domain and find that Bitcoin is not the only transmitter of volatility, highlighting the importance of other large cryptocurrencies to the network of volatility spillovers. In another study, Bouri et al. (2019b) apply a jump-analysis to the price process of 12 leading cryptocurrencies based on GARCH models. They show evidence of jumps and co-jumps, with Bitcoin and other large cryptocurrencies playing central roles.

Other studies apply the connectedness measures of Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014). Considering 18 large cryptocurrencies, Koutmos (2018) finds that the spillovers are time-varying and points to the growing interdependence among cryptocurrencies, which reflects a higher degree of contagion risk. The author also reveals the central role played by Bitcoin in the network of return and volatility spillovers. Corbet et al. (2018) focus on the return and volatility spillovers among three large cryptocurrencies (Bitcoin, Ripple, and Litecoin). Using time domain connectedness measures, they find that Bitcoin returns have a significant impact on the returns of Ripple and Litecoin, whereas the feedback impact is marginal. This result indicates the dominance of Bitcoin in the network of return connectedness. However, the authors show results for volatility spillovers that are different from those of Koutmos (2018). They find that Litecoin and Ripple influence Bitcoin, while the latter has a marginal impact on Litecoin and Ripple. Furthermore, Ripple and Litecoin are strongly interconnected through both return and volatility channels. Corbet et al. (2018) also show that the three digital assets are segmented from conventional assets, pointing to their potential ability to act as diversifiers. Yi et al. (2018) study the volatility of leading cryptocurrencies to make inferences about whether Bitcoin is the dominant volatility transmitter among cryptocurrencies. Their results show that volatility spillovers are tight and vary with time, and that Bitcoin is the only influential cryptocurrency. Ji et al. (2019) focus on the return and volatility series of six large cryptocurrencies. They indicate that Litecoin and Bitcoin are clear leaders in the network of returns. In contrast to the results of Corbet et al. (2018) and in line with Koutmos (2018), they show that Bitcoin is central in the network of volatility spillovers. Further results show that Dash has a very marginal role, which points to its ability to act as a diversifier.

While the above literature reveals important aspects of the network of volatility spillovers across leading cryptocurrencies, it is silent about the role of sentiment in driving the total connectedness, and the underlying behavior of overall market volatility in relation to sentiment – analyses of which can provide conclusive evidence on the hedging and/or speculative roles of cryptocurrencies. This void is what our paper aims to fill. A paper that can be somewhat related to our work, in terms of associating what drives market connectedness, is that by Antonakakis et al. (2019). While it concentrates on the spillover effects of returns, rather than volatility like us, among leading cryptocurrencies via the application of a time-varying parameter factor augmented vector autoregressive (TVP-FAVAR) model, they show that total connectedness of returns is positively related to higher periods of volatility in the cryptocurrencies. Our paper differs from Antonakakis et al. (2019) not only in the methodology used and its focus on volatility connectedness but also how volatility connectedness is related to sentiment as reflected in the happiness index.

3 Data

The daily data used in this study are extracted from: https://coinmarketcap.com/, and cover the period of 7th August, 2015 to 11th March, 2020 (i.e., 1679 observations), which include booms and busts in the cryptocurrency markets. Fifteen leading and liquid cryptocurrencies are involved in this study, namely Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Monero, Dash, NEM, Dogecoin, MonaCoin, Bytecoin, Siacoin, DigiByte, BitShares, and Verge. These represent more than 80% of the total market capitalization of all cryptocurrencies. As the raw series are non-stationary according to the ERS (Elliott et al., 1996) unit-root test we decide to take the first differences of the natural logarithmic values of these series, which can then be interpreted as the daily percentage changes, or log-returns to be precise. The resulting series, along with the happiness index which we describe below, are illustrated in Figure 1.

[Insert Figure 1 around here]

The findings indicate that the series are significantly non-normally distributed (D'Agostino, 1970; Anscombe and Glynn, 1983; Jarque and Bera, 1980) and stationary at 1% significance level. Notably, we find pronounced autocorrelation in the squared series (Fisher and Gallagher, 2012) implying that modelling time-varying variance-covariance structure is appropriate.

[Insert Table 1 around here]

Next, we turn to the description of our metric of investor sentiment, which we aim to relate to total volatility connectedness and common market volatility of the fifteen cryptocurrencies. Investor sentiment is not directly measurable or observable, and hence traditionally, two routes have been taken to measure investor sentiment namely, market- and survey-based metrics (see Bathia and Bredin (2013), and Bathia et al. (2016) for more details). Given the shortcomings associated with the market- and survey-based approaches to measure investment sentiment as discussed in detail by Da et al. (2015),[1] we utilize the daily happiness index, obtained from Hedonometer.org, as our proxy for investor sentiment.[2] The raw daily happiness scores are derived from a natural language processing technique based on a random sampling of about 10% (50 million) of all messages posted in Twitter's Gardenhose feed. To quantify the happiness of the atoms of language, Hedonometer.org merge the 5,000 most frequent words from a collection of four corpora: Google Books, New York Times articles, Music Lyrics and Twitter messages, resulting in a composite set of roughly 10,000 unique words. Then, using Amazon's Mechanical Turk service, Hedonometer.org scores each of these words on a nine point scale of happiness, with 1 corresponding to "sad" and 9 to "happy". Words in messages written in English (containing roughly 100 million words per day) are assigned a happiness score based on the average happiness score of the words contained in the messages.

[1] Da et al. (2015) internet-based measures of investor sentiment are generally more transparent relative to the other alternatives that adopt market and survey-based approaches. This is because the market-based method captures the equilibrium outcome of many economic forces other than investor sentiment, while the survey-based method is more likely to be prone to measurement errors as it inquires about attitudes. Another disadvantage of these traditional approaches to capture investor sentiment is that they tend to produce metrics at lower (monthly or quarterly) frequencies.

[2] The data is available for download from: https://hedonometer.org/api.html.

4 Methodologies

In this section, we outline each of our three methods that we use in our study to derive our empirical results, starting with the DCC-GARCH-based total connectedness index, the common and idiosyncratic components of volatility, and the QQ regression model.

4.1 DCC-GARCH Based Connectedness Approach

We start this section by introducing the DCC-GARCH based volatility connectedness approach of Gabauer (2020) which can be seen as an alternative to the VAR based connectedness approach of Diebold and Yilmaz (2012, 2014). One advantage of this approach is that no arbitrarily chosen window size has to be selected to retrieve dynamic connectedness measures. Another one is that contrary to Antonakakis (2012); Beirne et al. (2013) and Hoesli and Reka (2013) only one instead of two models are needed to estimate the conditional volatility transmission mechanism.

The DCC-GARCH model in the spirit of Engle (2002) estimates the time-varying conditional variances and covariances in a system of multiple time series which can be written as follows:

$$\boldsymbol{x}_t = \boldsymbol{\mu}_t + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{H}_t) \tag{1}$$

$$\boldsymbol{\epsilon} = \boldsymbol{H}_t^{1/2} \boldsymbol{\epsilon}_t \qquad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{I}) \tag{2}$$

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{3}$$

where $\boldsymbol{\mu}_t$, and $\boldsymbol{u}_t$ are $m \times 1$ dimensional vectors representing the conditional mean and standardized error term, respectively. Furthermore, $\boldsymbol{R}_t$ and $\boldsymbol{D}_t = diag(h_{11t}^{1/2}, ..., h_{mmt}^{1/2})$ are $m \times m$ dimensional matrices, illustrating the dynamic conditional correlations and the time-varying conditional variances. The elements in $\boldsymbol{D}_t$ are estimated by Bollerslev (1986) GARCH models for each series. Based on the study of Hansen and Lunde (2005) one shock and one persistency parameter is assumed:

$$h_{ii,t} = \omega + \alpha \epsilon_{i,t-1}^2 + \beta h_{ii,t-1}. \tag{4}$$

In the second stage, the dynamic conditional correlations are computed as follows:

$$\boldsymbol{R}_t = diag(q_{iit}^{-1/2}, ..., q_{mmt}^{-1/2}) \boldsymbol{Q}_t diag(q_{iit}^{-1/2}, ..., q_{mmt}^{-1/2}), \tag{5}$$

$$\boldsymbol{Q}_t = (1 - a - b)\bar{\boldsymbol{Q}} + a \boldsymbol{u}_{t-1} \boldsymbol{u}_{t-1}' + b \boldsymbol{Q}_{t-1}, \tag{6}$$

where $\boldsymbol{Q}_t$, and $\bar{\boldsymbol{Q}}$ are $m \times m$ dimensional positive-definite matrices which represent the conditional and unconditional standardized residuals' variance-covariance matrices, respectively. a (α) and b (β) are non-negative shock and persistency parameters satisfying, $a + b < 1$ ($\alpha + \beta \leq 1$). As long as $a + b < 1$ is fulfilled $\boldsymbol{Q}_t$ and hence $\boldsymbol{R}_t$ are varying over time otherwise this model would converge to the CCC-GARCH model (Bollerslev, 1990) where $\boldsymbol{R}_t$ is constant over time.

In the same spirit as the GIRF, the VIRF represents the impact of a shock in variable i on variable j's conditional volatilities, which can be written by,

$$\boldsymbol{\Psi}^g_{j,t}(J) = VIRF(J, \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) = E(\boldsymbol{H}_{t+J}|\boldsymbol{\epsilon}_{j,t} = \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) - E(\boldsymbol{H}_{t+J}|\boldsymbol{F}_{t-1}). \tag{7}$$

Forecasting the conditional variance-covariances using the DCC-GARCH model (Engle and Sheppard, 2001) lies at the heart of the VIRF and can be accomplished iteratively in three steps. First, the univariate GARCH(1,1) will forecast the conditional volatilities ($\boldsymbol{D}_{t+h}|\boldsymbol{F}_t$) by,

$$E(h_{ii,t+1}|\boldsymbol{F}_t) = \omega + \alpha\delta^2_{1,t} + \beta h_{ii,t} \qquad h = 1 \tag{8}$$

$$E(h_{ii,t+h}|\boldsymbol{F}_t) = \sum_{i=0}^{h-1} \omega(\alpha+\beta)^i + (\alpha+\beta)^{h-1}E(h_{ii,t+h-1}|\boldsymbol{F}_t) \qquad h > 1 \tag{9}$$

whereas in a second step, $E(\boldsymbol{Q}_{t+h}|\boldsymbol{F}_t)$ is predicted according to,

$$E(\boldsymbol{Q}_{t+1}|\boldsymbol{F}_t) = (1-a-b)\bar{\boldsymbol{Q}} + a\boldsymbol{u}_t\boldsymbol{u}'_t + b\boldsymbol{Q}_t \qquad h = 1 \tag{10}$$

$$E(\boldsymbol{Q}_{t+h}|\boldsymbol{F}_t) = (1-a-b)\bar{\boldsymbol{Q}} + aE(\boldsymbol{u}_{t+h-1}\boldsymbol{u}'_{t+h-1}|\boldsymbol{F}_t) + bE(\boldsymbol{Q}_{t+h-1}|\boldsymbol{F}_t) \qquad h > 1 \tag{11}$$

where $E(\boldsymbol{u}_{t+h-1}\boldsymbol{u}'_{t+h-1}|\boldsymbol{F}_t) \approx E(\boldsymbol{Q}_{t+h-1}|\boldsymbol{F}_t)$ (see, Engle and Sheppard, 2001) which helps to forecast the dynamic conditional correlations and finally the conditional variance-covariances:

$$E(\boldsymbol{R}_{t+h}|\boldsymbol{F}_t) \approx diag(E(q^{-1/2}_{iit+h}|\boldsymbol{F}_t), ..., E(q^{-1/2}_{mmt+h}|\boldsymbol{F}_t))E(\boldsymbol{Q}_{t+h})diag(E(q^{-1/2}_{iit+h}|\boldsymbol{F}_t), ..., E(q^{-1/2}_{mt+h}|\boldsymbol{F}_t)) \tag{12}$$

$$E(\boldsymbol{H}_{t+h}|\boldsymbol{F}_t) \approx E(\boldsymbol{D}_{t+h}|\boldsymbol{F}_t)E(\boldsymbol{R}_{t+h}|\boldsymbol{F}_t)E(\boldsymbol{D}_{t+h}|\boldsymbol{F}_t). \tag{13}$$

After the construction of GIRFs and VIRFs, we focus on the computation of the dynamic connectedness measures.

To compute all dynamic connectedness measures five steps are required.

Step I: The generalized forecast error variance decomposition (GFEVD, $\tilde{\psi}^g_{ij,t}(K)$), that represents the *pairwise directional connectedness from j to i*, can be based either on the GIRFs or on the VIRFs. In more details, the GFEVD explains the impact a shock in variable j has on variable i in term of its forecast error variance share. This is calculated by:

$$\tilde{\psi}^g_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N}\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}} \tag{14}$$

where $\sum_{j=1}^{N} \tilde{\psi}^g_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\psi}^g_{ij,t}(J) = m$. The numerator represents the cumulative effect of the ith shock while the denominator represents the aggregate cumulative effect of all the shocks.

Step II: The *total directional connectedness TO others* measures how much of a shock in variable i is transmitted to all other variables j:

$$C^g_{i\to j,t}(K) = \frac{\sum_{j=1,i\neq j}^m \tilde{\psi}^g_{ji,t}(K)}{\sum_{j=1}^m \tilde{\psi}^g_{ji,t}(K)} \tag{15}$$

Step III: The *total directional connectedness FROM others* measures how much variable i is receiving from shocks in all other variables j:

$$C^g_{i\leftarrow j,t}(K) = \frac{\sum_{j=1,i\neq j}^m \tilde{\psi}^g_{ij,t}(K)}{\sum_{i=1}^m \tilde{\psi}^g_{ij,t}(K)} \tag{16}$$

Step IV: The *net total directional connectedness* represents the difference between the total directional connectedness TO others and the total directional connectedness FROM others, which can be interpreted as the influence variable i has on the analyzed network.

$$C^g_{i,t} = C^g_{i\to j,t}(K) - C^g_{i\leftarrow j,t}(K) \tag{17}$$

If the $C^g_{i,t} > 0$ ($C^g_{i,t} < 0$) variable i is considered as a net transmitter (*receiver*) since it is influencing all others more (*less*) than being influenced by them.

Step V: Traditionally, the *total connectedness index* (TCI) expresses the average amount of one variable's forecast error variance share explained by all other variables or in other words how much a shock in one variable influences all others on average. This can be expressed by:

$$C^g_t(K) = \frac{\sum_{i,j=1,i\neq j}^m \tilde{\psi}^g_{ij,t}(K)}{m}. \tag{18}$$

A high (*low*) TCI suggests a high (*low*) degree of volatility shock spillovers.

4.2 Decomposing Common and Idiosyncratic Components of Volatility

Consider a high-dimensional vector of stationary time series $\{Y_{it}, i \in N, t \in Z\}$, which can be decomposed into a common part X_{it} and an idiosyncratic part Z_{it} such as:

$$Y_{it} = X_{it} + Z_{it} =: \sum_{k=1}^{Q} b_{ik}(L)u_{kt} + Z_{it}, i \in N, t \in Z, \tag{19}$$

where $u = (u_1, u_2, ..., u_Q)'$ is Q-dimensional orthogonal white noise; L is the lag operator; and $b_{ik}(L)$ are one-sided square-summable filters. The common component $\{X_{it}; i = 1, ..., N; t = 1, ..., T\}$ is driven by pervasive factors; the Q-th eigenvalue of its spectral density matrix diverges, as $N \to \infty$ for almost all frequencies in the range $[-\pi, \pi]$. However, the idiosyncratic component $\{Z_{it}; i = 1, ..., N; t = 1, ..., T\}$ is stationary and possibly autocorrelated, though only mildly cross-correlated; that is, the eigenvalues of its spectral density matrix are uniformly bounded as $N \to \infty$.

For any n, since Y_n decomposes into two components X_n and Z_n, where X_n is driven by "common", that is, "market" shocks, and Z_n is orthogonal to the same, two distinct sources of volatility can be to be expected. And they are the volatility originating in the shocks driving the level-common components X_n (volatility of level-common components), and the volatility originating in the shocks driving the level-idiosyncratic components Z_n (volatility of level-idiosyncratic components). One can call "market volatility" the volatility of the level-common components, and "idiosyncratic" the volatility of the level-idiosyncratic ones.

4.3 Quantile-on-Quantile (QQ) Model

After obtaining the TCI and common market volatility series, we next use the QQ approach to examine the effect of investor sentiment proxied by the investor happiness index on the TCI and common volatility. The QQ model is built on the following nonparametric quantile regression framework, specific to our case

$$V_t = \beta^{\theta}(Sentiment_t) + u_t^{\theta} \tag{20}$$

where V_t, and $Sentiment_t$ are the total connectedness index or common market volatility of cryptocurrency returns and the investor sentiment index in period t respectively, θ is the θ-th quantile of the conditional distribution of the V_t and u_t^{θ} is a quantile error term whose conditional θ-th quantile is equal to zero. In this framework, the term $\beta^{\theta}(\cdot)$ is assumed to be an unknown functional form, which is to be determined from the data.

The standard quantile regression model in equation (20) allows the effect of investor sentiment index to vary across the different quantiles of the V_t; however, this model is unable to capture the dependence in its entirety as the term $\beta^{\theta}(\cdot)$ is indexed on the V_t quantile θ only and not the investor sentiment quantile. Therefore, in order to get a comprehensive insight on the effect of sentiment on V_t, we focus on the relationship between the θ-th quantile of V_t and the τ-th quantile of the sentiment, denoted by P^{τ}. This is done by examining equation (20) in the neighborhood of P^{τ} via a local linear regression. As $\beta^{\theta}(\cdot)$ is unknown, this function is approximated through a first-order Taylor expansion around a quantile P^{τ}, such that

$$\beta^{\theta}(P_t) \approx \beta^{\theta}(P^{\tau}) + \beta^{\theta'}(P^{\tau})(P_t - P^{\tau}) \tag{21}$$

where $\beta^{\theta'}$ is the partial derivative of $\beta^{\theta}(P_t)$ with respect to P (also called the marginal effect or response) and is similar in interpretation to the coefficient (slope) in a linear regression model. Next, renaming $\beta^{\theta}(P^{\tau})$ and $\beta^{\theta'}(P^{\tau})$ as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$ respectively, we rewrite equation (21) as

$$\beta^{\theta}(P_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(P_t - P^{\tau}). \tag{22}$$

Next, substituting equation (22) in equation (20), we obtain

$$S_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(P_t - P^\tau)}_{(*)} + u_t^\theta \tag{23}$$

where the term $(*)$ is the θ-th conditional quantile of V_t. Unlike the standard conditional quantile function, equation (23) captures the overall dependence structure between the θ-th quantile of V_t and the τ-th quantile of sentiment as the parameters β_0 and β_1 are doubly indexed in θ and τ. In the estimation of equation (23), $\hat{P}_t$ and $\hat{P}^\tau$, respectively and the local linear regression estimates of the parameters $\hat{\beta}_0$ and $\hat{\beta}_1$ are obtained by solving:

$$\min_{b_0,b_1} = \sum_{i=1}^{n} \rho_\theta \left[S_t - \hat{\beta} - \hat{\beta}_1(\hat{P}_t - \hat{P}^\tau) \right] K\left(\frac{F_n(\hat{P}_t - \tau)}{h} \right) \tag{24}$$

where $\rho(u)$ is the quantile loss function, defined as $\rho(u) = u(\theta - I(u < 0))$ and I is the indicator function. $K(\cdot)$ denotes the kernel function and h is the bandwidth parameter of the kernel. Because of its computational simplicity and efficiency, the Gaussian kernel is used to weight the observations in the neighborhood of P^τ. Specifically, in our analysis, these weights are inversely related to the distance between the empirical distribution function of $\hat{P}_t$, denoted by $F_n(\hat{P}_t) = \frac{1}{n}\sum_{k=1}^{n} I(\hat{P}_k < \hat{P}_t)$, and the value of the distribution function that corresponds with the quantile P^τ, denoted by τ. The bandwidth parameter h is selected using the cross-validation regression approach with a local linear regression.

5 Empirical Results and Discussion

5.1 Average and Dynamic Total Connectedness Measures

Table 2 demonstrates the averaged dynamic connectedness measures and provides an overview of the cryptocurrency transmission mechanism. The results indicate that on average 55.3% of a shock in one cryptocurrency spills over to all others. This means in turn that on average 44.7% of the shock affects itself in the upcoming periods and represent a highly interconnected market.

Moreover, the findings reveal that the main transmitters of shocks are Dash and Bitcoin by transmitting on average 85.6% and 84.8% of its shock, respectively whereas the least transmitting cryptocurrency is Bytecoin by transmitting on average 21.8% of its shock. This demonstrates which cryptocurrencies are increasingly contributing to the market interconnectedness and which are contributing less. Thus, Dash and Bitcoin are driving the market risk, which is not surprising given the importance of Bitcoin and Dash as leading cryptocurrencies.

The net total directional connectedness measures illustrate the power of one cryptocurrency as it is the difference between how much of a shock in one specific cryptocurrency is spilled over to all others and how much of a shock in all others is spilled over to one cryptocurrency. The results imply that Dash

(32.9%) and Bitcoin (19.9%) are the main net transmitter of shocks and hence influence others more than being influenced by them whereby Ripple (-29.2%) and Litecoin (-23.5%) has been the main receiver of shocks. Thus, Dash and Bitcoin are driving the market whereas Ripple and Litecoin are driven by the market.

In addition, this metric is of major importance for portfolio and risk management as it reveals the relative shock spillovers across cryptocurrencies. For instance, portfolio managers are more interested in cryptocurrencies that are driving the market than being driven by it, since an cryptocurrency that is influenced by a lot of others would be exposed to many more risk sources compared to cryptocurrencies that are mainly affected by their own past shocks and thus are exposed to a lower number of risk sources.

[Insert Table 2 around here]

Figure 2 shows the evolution of the dynamic total connectedness and hence the comovement of the cryptocurrency market risk. We find that the market interconnectedness decreased from the beginning of the sample period until mid 2016. This low lasts almost one year until it steadily increased until the end of 2017 when the price of Bitcoin dropped substantially which also affected the interrelatedness of the cryptocurrency market that dropped to less than 40%. After this drop, the cryptocurrency market became more interrelated and continuously increased until it reached the all-time high of around 75% in the beginning of 2019. Since then, the market risk decreased persistently but at a slow rate until the end of the sample period where it reaches around 65%. It should be noted that the cryptocurrency market integration increased considerably since the beginning of the sample period. As the cryptocurrency market is still young, the low interconnectedness values prior the Bitcoin downfall of 2017, can be explained by the fact that back then cryptocurrency price movements have been rather random, highly volatile, and unaffected by price changes of other cryptocurrencies. This pattern changed afterwards as shown by the substantial increase in the market integration which further reflects the importance of the obtained results for investors.[3]

[Insert Figure 2 around here]

5.2 Net Total Directional Connectedness

We continue with the dynamics of the net total directional connectedness measures as those give us an overview of how persistently cryptocurrencies are net transmitters or net receivers of shocks. From a portfolio perspective, a cryptocurrency that is throughout the sample period a net transmitter of shocks has a lower number of potential risk sources and hence is more interesting for investors.

Figure 3 shows that Dash is nearly a permanent net transmitter of shocks and moreover increases its net transmission ability over time as well which makes Dash an attractive asset for portfolio managers.

[3] We also estimated the TCI of returns from a full-fledged time-varying version of the approaches of Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014), as proposed based on a TVP-VAR by Antonakakis et al. (2020). We found that the pattern of movement of the volatility and returns-based TCIs were similar, and hence are in-line with the findings of Antonakakis et al. (2019), that return connectedness is positively correlated with cryptocurrency market uncertainty. Complete details of these results are available upon request from the authors.

On the contrary, Ripple is a permanent net receiver of shocks and hence driven by the market which makes it less attractive for investors. Bitcoin - which is seen since the beginning of cryptocurrencies seen as the 'cryptocurrency' - is the second highest net transmitter of shocks and besides a short period of time a persistent net transmitter of shocks throughout the period of analysis. It is also noteworthy that besides Dash and Bitcoin there are other cryptocurrencies with a prolonged period of a net transmission history, such as NEM, Monero, Verge, and Dogecoin. Dogecoin has become a net receiver of shocks after mid 2018 whereas Ethereum has been an important net transmitter of shocks during the time when Bitcoin has been at its lowest transmission level. Our results are in-line with previous findings that generally indicate the centrality of large and leading cryptocurrencies in the system of volatility spillovers (e.g., Koutmos, 2018; Corbet et al., 2018; Bouri et al., 2019a; Ji et al., 2019).

[Insert Table 3 around here]

5.3 Total Volatility Connectedness, Common Market Volatility and Investor Happiness

We now turn our attention to how investor sentiment, as proxied by the index of happiness relates to the TCI of cryptocurrency volatilities, and then in turn, also analyze how investor sentiment, affects common market volatility - with both being analyzed using the QQ model.

As a preliminary check, we first estimated a standard ordinary least squares (OLS) regression to examine the response of the TCI to the investor happiness index. The standard linear regressions yielded the conditional mean-based estimate of -0.5079, with the coefficient being significant at the 0.1% significance level. Therefore, the preliminary checks provide the initial evidence of a significant negative investor sentiment effect on connectedness patterns in the cryptocurrency market volatility. In other words, as market sentiment improves, the comovement of volatility amongst the fifteen cryptcourrencies decline. While the OLS result is informative, it fails to provide the complete picture of the relationship conditional on the normal and extreme states of TCI and the investor sentiment index, and the QQ approach discussed earlier allows us to assess this at the quantile level. Figure 4 present the QQ model result that relate the TCI of volatility with the happiness index. Specifically, we plot the estimates of the impact of the various quantiles of the happiness index on the quantiles of the TCI, i.e., $\beta_1(\theta, tau)$, described in equation (22). As explained earlier, these estimates are similar to the slope term in a linear regression model, reflecting the sensitivity of the TCI to investor sentiment. However, given that $\beta_1(\theta, tau)$ is doubly indexed in θ and τ, the estimates reported in the figure measure the relationship between the θ-th quantile of the TCI and the τ-th quantile of the happiness index. The plots are color-coded in such a way that the color represents the degree of sensitivity, with the TCI quantiles placed on the y-axis and the sentiment quantiles on the x-axis.

We observe that, while the results are generally consistent with the findings obtained from the OLS regressions, the relationship between sentiment and connectedness displays quantile specific patterns in terms of the strength of the sentiment effect to the extent that the sign of the effect can change direction at extreme low quantiles of investor happiness over the entire conditional distribution of the TCI, and also immediately around, i.e., above or below the median.[4] Very strong negative impact is observed from the quantile of 0.75 and above for sentiment over the entire quantile coverage of the TCI. In sum, starting from the median of the sentiment, if we increase or decrease investor happiness, then TCI tends to increase, irrespective of its initial level. While this relationship turns negative as we move further away from the median, with the effect being quite strong in particular as investor sentiment improves (but declines slightly at upper quantiles), it tends to turn positive as sentiment reaches very low levels.

An important question for us is then what do these results translate into in terms of the cryptocurrencies being possibly acting as hedge or used purely for speculative purposes. For this, we turn to the common market volatility (which is plotted in Figure 5),[5] and its relatingship with investor happiness using the QQ model in Figure 6. As can be seen from the figure, in general the relationship is primarily negative, with the strongest effects found over similar quantile ranges where TCI was found to be negatively related with sentiment, i.e., from around the quantiles of 0.75 to 0.90 of the sentiment index. In addition, in the neighbourhood of above or below the median of sentiment, common market volatility seems to move in the same direction as sentiment. Combining with the relationship observed with TCI and the sentiment index, we can say that, over the quantile ranges of 0.75 to 0.95, increases in sentiment was associated with declines in total connectedness, which in turn resulted from a decline in overall market volatility, possibly due to a decline in trading in cryptocurrencies in this region. At the same time, around the median, using the same logic, sentiment increases connectedness which is accompanied by higher market volatility, suggesting higher trading. This positive, but relatively weaker in strength, relationship also seems to hold at the extreme very high quantiles of the sentiment, indicative of higher trading, but associated with low connectedness. While this could be indicative of speculation, but the low corresponding connectedness of the market in general in this region might be suggesting that not necessarily all cryptocurrencies are used for such risk-taking activities when investors are extremely happy. Now, when we look at quantiles of sentiments below 0.25, a negative relationship with overall market volatility is observed. When we merge this information, with positive relationship between connectedness and sentiment in the similar region, we can safely say, that as investors become exceedingly unhappy, market connectedness increases and is associated with high overall volatility. The heightened volatility likely due to higher trading, seems to suggest that cryptocurrencies are used for hedging when investor sentiment is weak, and more importantly, evidence in favor of this behavior is relatively stronger than the speculative motive when investors are exceptionally happy. At the same time, our results also

[4]Following Tiwari et al. (2020), we also applied the two Gamma and two Exponential Random Variables Copulas model (GGEE), and the Pareto Mixture Copulas model (PPPP) on the AR(1)-exponential GARCH (EGARCH) marginal models of TCI and the investor sentiment to get an understanding of the tail dependence between these two variables. Consistent with the QQ results, these copula models provided strong evidence of positive lower tail dependence. Complete details of these results are available upon request from the authors.

[5]A simple correlation analysis revealed a positive and significant correlation between TCI and the common market volatility, while common market volatility was found to possess a statistically significant negative relationship with the happiness index. Complete details of these results are available upon request from the authors.

tend to suggest that, diversification opportunities across the cryptocurrencies are limited due to high connectedness when sentiment tends to decline from initially low levels, but it is indeed possible when it is generally high.

Overall, our findings establish a strong link regarding the impact of investor sentiment on volatility connectedness pattern, and also the overall common market volatility associated with fifteen major cryptocurrencies. The sentiment effect is found to be asymmetric on connectedness and common volatility[6], with implications for portfolio diversification and the hedging ability of the market contingent on the initial levels from which sentiment changes. These findings suggest that investors should factor into the role of sentiment shocks when making portfolio decisions associated with cryptocurrencies. They add to previous studies relating return spillovers with market uncertainty (e.g., Antonakakis et al., 2019; Ji et al., 2019) and economic uncertainty (e.g., Ji et al., 2019) or those dealing with volatility spillovers in the cryptocurrency without considering the exogenous factors driving volatility connectedness (e.g., Koutmos, 2018; Corbet et al., 2018).

6 Concluding Remarks

This paper contributes to the growing literature on volatility spillover across cryptocurrencies, by estimating for the first time a full-fledged time-varying model namely, the DCC-GARCH, to derive the connectedness across fifteen major cryptocurrencies. This way, we go beyond the existing literature which generally involves a rolling-window approach, for which results are known to be sensitive to the window-size, to derive the total connectedness among few major cryptocurrencies. More importantly, we depict the important role of investor happiness in explaining the volatility connectedness, within a quantile-on-quantile framework, with the decision to use a behavioral variable like sentiment, driven by the conflicting opinions about whether cryptocurrencies can serve as a hedge or are merely used for speculation. To obtain a solid answer to this debate, we also estimate the common market volatility using an entirely non-parametric and model-free two-step general dynamic factor approach, and relate it to sentiment also via the quantile-on-quantile method.

We show that volatility connectedness is indeed time-varying and the relationship between sentiment and connectedness displays quantile specific patterns with sentiment shocks at ends of the quantiles of the happiness index having distinctly different effects. In particular, the entire conditional distribution of connectedness is found to be positively related to sentiment at its lower quantiles of sentiment, but the opposite is observed at higher values of investor happiness. In addition, when we look at the effect of sentiment on the common market volatility, we are able to deduce that that as investors become exceedingly unhappy, overall market volatility increases and this is associated with high market connectedness. The heightened volatility possibly being a sign of higher trading, seems to suggest that cryptocurrencies

[6] An asymmetric effect is found in the volatility spillovers among cryptocurrencies by prevoous studies (Ji et al., 2019, e.g.,) although the asymmetric effect of sentiment (i.e., happiness index) on the volatility connectedness in the cryptocurrency markets is new.

are used for hedging when investor sentiment is weak. More importantly, evidence in favor of this behavior is relatively stronger than the speculative motive when investors are exceptionally happy, as total connectedness is found to be low, even when there is some evidence of increased common volatility. This latter observation, from the perspective of diversification within the cryptocurrencies, implies that more such opportunities are available when investors are happy rather than when sentiment is weak.

As part of future research, it would be interesting to extend our analysis by considering alternative asset classes involving equities, bonds, currencies, commodities, along with the major cryptocurrencies.

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Table 1: Summary Statistics

	Sentiment	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Monero	Dash	NEM	Dogecoin	MonaCoin	Bytecoin	Siacoin	DigiByte	BitShares	Verge
Mean	5.996	0.002	0.003	0.002	0.001	0.002	0.003	0.002	0.003	0.002	0.001	0.001	0.002	0.002	0.001	0.003
Variance	0.002	0.001	0.005	0.005	0.003	0.006	0.004	0.003	0.007	0.004	0.006	0.013	0.009	0.009	0.005	0.02
Skewness	0.021	-0.178***	-3.451***	3.115***	1.152***	2.141***	0.993***	0.956***	2.025***	1.029***	3.027***	3.503***	1.076***	2.587***	0.747***	0.712***
	(0.771)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	1.581***	4.746***	72.875***	44.883***	11.712***	18.203***	8.250***	7.167***	19.410***	14.101***	24.972***	47.748***	7.122***	27.541***	8.991***	7.157***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	119***	1583***	374637***	143561***	9961***	24448***	5034***	3846***	27487***	14197***	46162***	162834***	3869***	54902***	5808***	3723***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-2.804***	-4.048***	-0.546	-10.616***	-4.465***	-16.472***	-4.572***	-6.480***	-7.253***	-7.362***	-6.278***	-6.697***	-18.239***	-8.136***	-12.819***	-12.012***
	(0.005)	(0.000)	(0.585)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	4632.607***	206.437***	29.581***	233.552***	112.717***	445.160***	190.946***	101.622***	65.866***	208.079***	233.690***	92.588***	300.052***	58.216***	151.854***	709.954***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: JB stands for the normality test introduced by Jarque and Bera (1980), ERS represents the unit-root test of Elliott et al. (1996) and $Q^2(20)$ is the weighted Ljung-Box statistics with a lag length of 20 provided by Fisher and Gallagher (2012). $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 2: Average Connectedness Table

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Monero	Dash	NEM	Dogecoin	MonaCoin	Bytecoin	Siacoin	DigiByte	BitShares	Verge	FROM
Bitcoin	35.6	6.2	2.5	7.6	4.2	8.9	8.9	7.2	9.1	2.3	2.2	5.2	0.1	0.1	0.1	64.4
Ethereum	7.8	36.6	3.4	5.6	4.8	7.8	10.8	6.7	6.0	2.5	1.8	6.1	0.1	0.1	0.0	63.4
Ripple	5.7	6.1	35.4	3.8	10.6	6.3	6.5	8.1	8.1	2.2	2.2	4.7	0.1	0.0	0.3	64.6
Litecoin	14.5	7.4	2.8	20.1	4.6	8.2	9.5	9.4	12.3	2.1	2.7	6.3	0.1	0.0	0.1	79.9
Stellar	6.1	5.5	6.5	4.1	39.0	6.8	6.6	8.5	7.3	2.0	1.9	5.3	0.2	0.3	0.1	61.0
Monero	9.9	6.6	3.1	5.6	5.2	38.2	10.8	5.8	5.6	2.2	1.9	4.9	0.1	0.2	0.1	61.8
Dash	7.2	6.7	2.4	4.8	3.7	8.0	47.3	6.2	4.4	2.0	1.6	5.3	0.1	0.1	0.1	52.7
NEM	7.2	5.3	3.6	5.7	5.9	5.2	7.7	44.6	4.9	2.8	1.6	5.0	0.0	0.4	0.1	55.4
Dogecoin	10.1	5.3	3.8	7.7	5.8	5.9	6.4	5.6	40.7	1.4	1.3	5.5	0.2	0.2	0.2	59.3
MonaCoin	5.1	4.6	2.3	3.0	3.2	4.5	5.5	6.5	2.8	56.5	1.8	3.9	0.1	0.1	0.1	43.5
Bytecoin	3.5	2.4	1.7	3.1	2.2	2.9	3.0	2.8	1.6	1.3	72.4	2.5	0.2	0.2	0.2	27.6
Siacoin	6.6	6.3	2.7	5.1	4.8	5.8	8.7	6.6	6.2	2.2	2.0	42.8	0.0	0.1	0.1	57.2
DigiByte	0.2	0.1	0.1	0.1	0.4	0.2	0.3	0.1	0.5	0.2	0.2	0.1	75.8	10.0	11.7	24.2
BitShares	0.2	0.3	0.1	0.1	0.6	0.6	0.6	1.3	0.7	0.2	0.4	0.3	12.0	65.7	16.9	34.3
Verge	0.2	0.1	0.3	0.1	0.1	0.3	0.4	0.2	0.4	0.2	0.3	0.2	9.9	12.1	75.1	24.9
Contribution TO others	84.4	62.8	35.4	56.4	55.9	71.3	85.6	75.0	69.8	23.6	21.8	55.3	23.1	23.9	30.1	TCI
NET directional connectedness	19.9	-0.7	-29.2	-23.5	-5.0	9.5	32.9	19.6	10.5	-19.8	-5.9	-2.0	-1.1	-10.4	5.3	55.3

Notes: Results are based on a DCCH-GARCH(1,1) model and a 100-step-ahead generalized forecast error variance decomposition.

Figure 1: Daily Percentage Changes

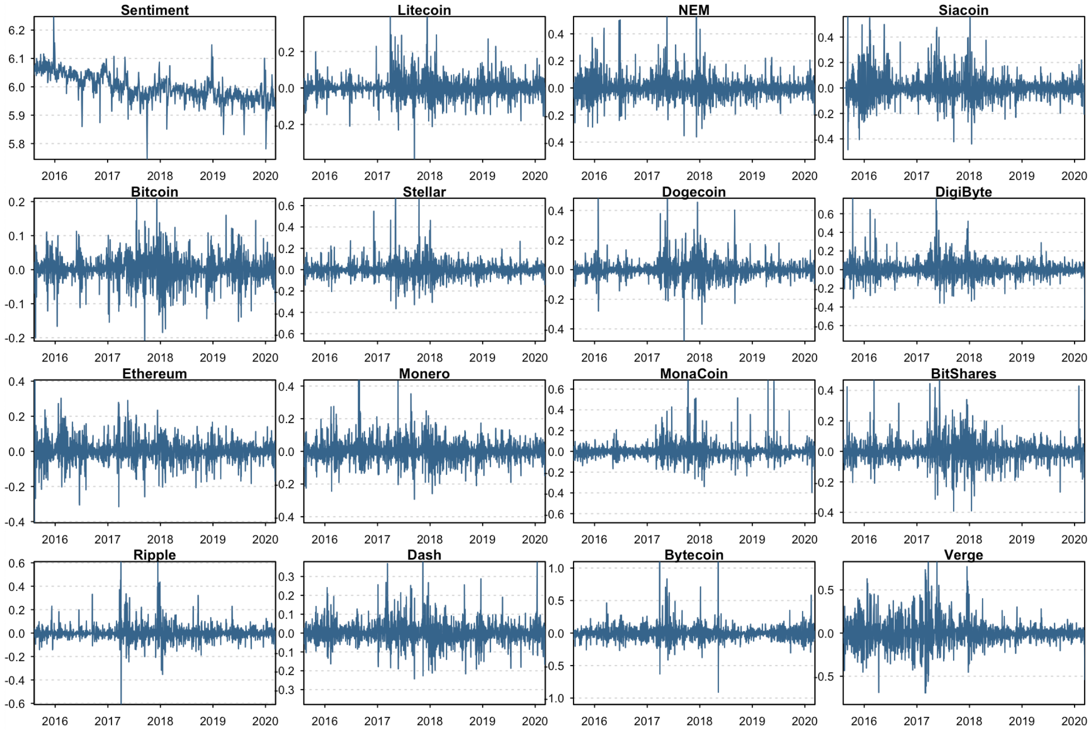
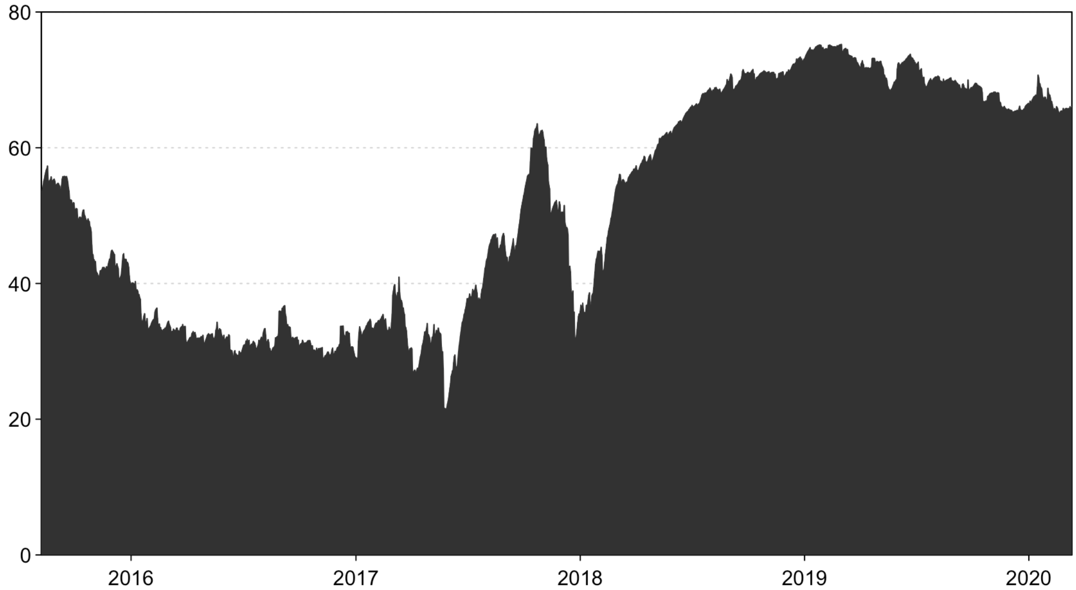
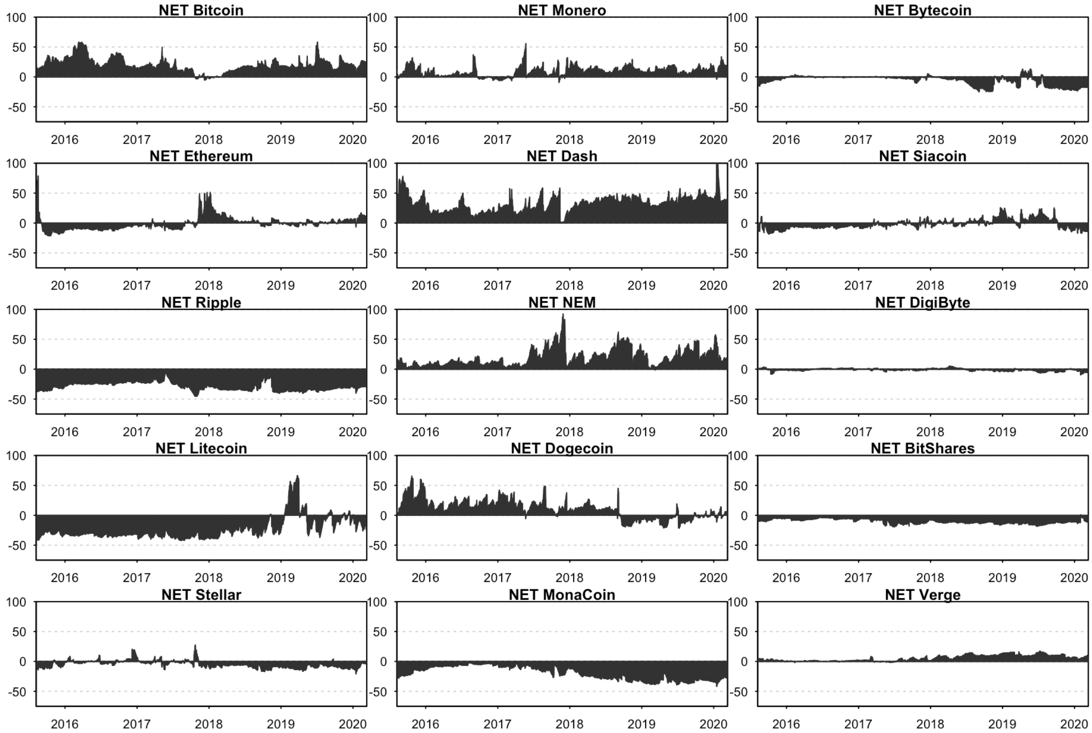


Figure 2: Dynamic Total Connectedness



Notes: Results are based on a DCCH-GARCH(1,1) model and a 100-step-ahead generalized forecast error variance decomposition.

Figure 3: Dynamic Net Total Directional Connectedness



Notes: Results are based on a DCCH-GARCH(1,1) model and a 100-step-ahead generalized forecast error variance decomposition.

Figure 4: Quantile Slope Estimates of the Impact of Investor Happiness on Volatility Connectedness

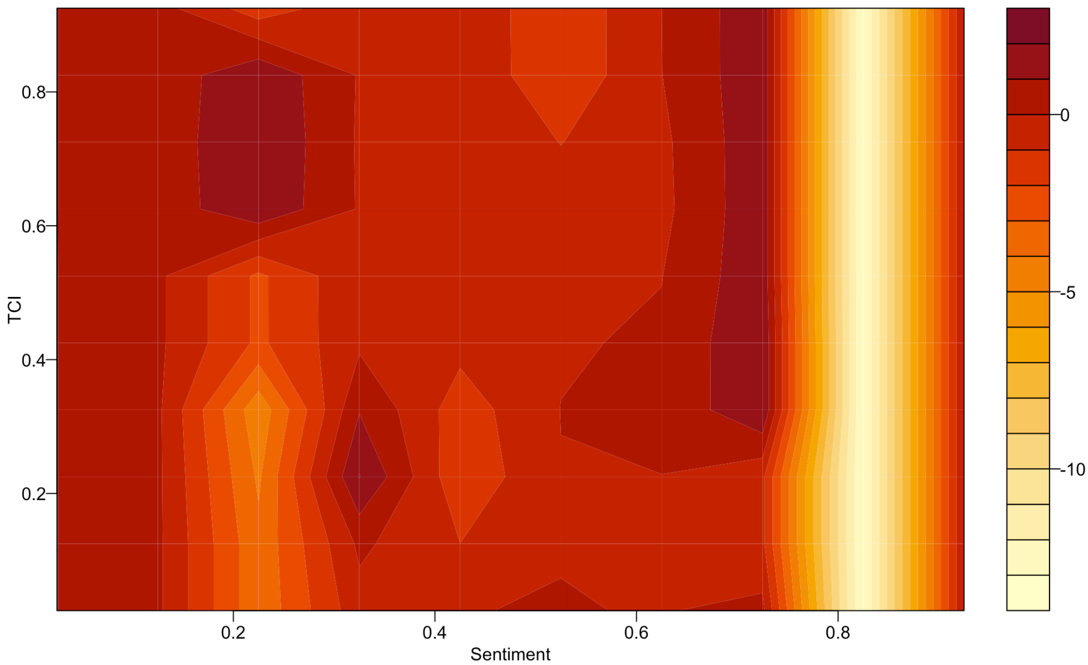


Figure 5: Common Market Volatility

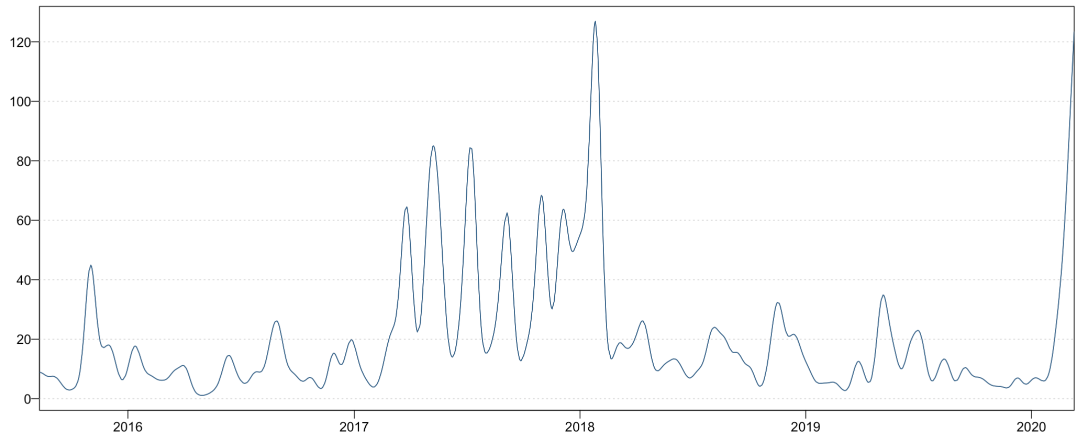


Figure 6: Quantile Slope Estimates of the Impact of Investor Happiness on Common Market Volatility