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Hedging uncertainty with cryptocurrencies: Is bitcoin your best bet? *

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ABSTRACT

Are cryptocurrencies useful minimum-variance hedging instruments? This paper develops a two-step analytical framework to explore this question across time. First, it estimates dynamic optimal weights, calibrated when investing between the aggregate market and a respective sampled cryptocurrency. This is performed separately for 11 major cryptocurrencies using the dynamic conditional correlation (DCC) approach of Engle (2016). Second, using a fractional regression approach, it uncovers linkages between optimal weights in cryptocurrencies and sources of economic uncertainty. Overall, this paper makes the following important findings. First, optimal weights in cryptocurrencies all rose rapidly during the COVID-19 pandemic. In all, bitcoin showed to be the leading cryptocurrency in terms of hedging effectiveness during this recent time period. Second, most cryptocurrencies exhibit zero or negative betas consistently across time, thus making them natural hedging instruments for investors seeking to reduce their portfolio's comovement with the market. Finally, cryptocurrencies serve as better hedges for economic uncertainties arising from equity and commodity markets. They are relatively less effective for uncertainties arising from risks in the banking industry and firm default risk. This paper contributes broadly to the asset pricing literature since our two-step approach herein can tractably be extended to other asset classes or other econometric measures of systematic risk.

Keywords

Bitcoin; cryptocurrencies; fractional regression; dynamic conditional beta; minimum-variance optimization

JEL classification

C58; G12; G17

"You have to really stretch your imagination to infer what the intrinsic value of Bitcoin is...I have not been able to do it...Maybe somebody else can..."

– Alan Greenspan

1. INTRODUCTION

Policymakers and economists tend to take a cautionary stance towards cryptocurrencies and their viability as a reliable medium of exchange. As Greenspan skeptically states, it takes a stretch of the imagination to infer the intrinsic value of bitcoin.[1] Moreover, as argued by Yermack (2015), because time variation in the value of bitcoin appears uncorrelated with traditional fiat currencies or other asset classes, it may be more of a speculative investment rather than a viable currency. Despite such dire warnings, a growing number of market participants are embracing cryptocurrencies in quite imaginative ways and, with presently over 2,000 such currencies in circulation, are demonstrating their possible investment, speculative, and transactional uses in our economy.[2]

Broadly speaking, there are three budding strands of academic literature on this subject. The first strand attempts to statistically explain variations or shocks in cryptocurrency prices (Bouri et al., 2018; Bouri et al., 2021; Brauneis and Mestel, 2018; Cheah et al., 2018; Gkillas and Katsiampa, 2018; Khuntia and Pattanayak, 2018; King and Koutmos, 2021; Koutmos, 2018; Li and Wang, 2017; Phillip et al., 2018; Urquhart, 2017; Zhang et al., 2021). Studies in this strand generally find that cryptocurrency price changes are statistically detached from economic fundamentals, at least in the center of their distributions, and exhibit greater degrees of unexplainable volatility in relation to conventional assets. Motivated by the first strand of literature, the second strand argues that cryptocurrencies cannot perform the functions of fiat money and, given their decentralized nature, do not enjoy the protection of the state or central bank (Gandal et al., 2018; Lo and Wang, 2014; Velde, 2013; Yermack, 2015). The third strand is arguably the most nascent in this growing field and explores the diversification benefits associated with cryptocurrencies (Bouri et al., 2017a; Bouri et al., 2017b; Bouri et al., 2020;

[1] See the article in *Bloomberg* where Greenspan argues how bitcoin has no intrinsic backing and may be a bubble: *https://www.bloomberg.com/news/articles/2013-12-04/greenspan-says-bitcoin-a-bubble-without-intrinsic-currency-value*.

[2] There are presently over 2,000 cryptocurrencies in circulation (see *https://coinmarketcap.com*) and a multitude of websites and exchanges that help investors find and exploit arbitrage opportunities (see *https://coingap.org*). There is also a growing list of mature firms, such as Bloomberg, Expedia, Microsoft, Newegg, Subway, T-Mobile and Whole Foods, to name but a few, which accept bitcoin (see *https://99bitcoins.com/who-accepts-bitcoins-payment-companies-stores-take-bitcoins/*).

Chuen et al., 2017; Kurka, 2019; Mokni et al., 2020; Platanakis et al., 2018; Wang et al., 2019). These studies are motivated by cryptocurrencies' uncorrelated nature with the economy and posit whether they can serve as useful hedging vehicles for risk-minimizing investors.

This nascent third strand of literature, which to date almost exclusively focuses on bitcoin, offers inconclusive evidence (e.g., Bouri et al., 2017a; Bouri et al., 2017b; Wang et al., 2019; Kurka, 2019). On the one hand, a number of studies show that bitcoin offers useful hedging properties. Two such studies (Bouri et al., 2017a; Demir et al., 2018) consider whether bitcoin can hedge global uncertainty, as proxied by selected stock market indices, the VIX index (Bouri et al., 2017a), and the economic policy uncertainty index (EPU) index (Demir et al., 2018). They conclude that bitcoin can be a useful tool for hedging uncertainty under certain conditions. Dyhrberg (2016) adds that bitcoin can effectively hedge against the US dollar, albeit it may only be able to do so in the short-term. Urquhart and Zhang (2019) find that bitcoin represents a hedge for several currencies (CHF, EUR and GBP). Guesmi et al. (2019) and Bouri et al. (2017b) present evidence that bitcoin can be used as a diversifier to reduce portfolio risks. However, Corbet et al. (2018) show that the intensity of the volatility spillover between cryptocurrencies (bitcoin, ripple and litecoin) and traditional assets is significantly time-varying. This implies that diversification benefits may only be available to investors with specific investment horizons. Furthermore, Naeem et al. (2021) show evidence that the efficiency of cryptocurrencies can fluctuate across time periods and, specifically, the COVID-19 period adversely impacted the efficiency of several major cryptocurrencies.

Contrary to some of the aforementioned studies, others find little or no evidence that bitcoin can serve as a useful hedging instrument. For example, Wang et al. (2019) employ a large sample of cryptocurrencies but find little evidence that cryptocurrencies can present hedges against international stock indexes. Ji et al. (2019) test ten cryptocurrencies and present evidence suggesting dash may represent the most useful cryptocurrency for hedging and diversification within the cryptocurrency market since it depends more on its own volatility compared to other cryptocurrencies. Most recently, Antonakakis et al. (2019) provide a test of hedging properties across nine digital currencies using portfolios constructed using two cryptocurrencies. They show that constructing bivariate portfolios, using dynamic hedge ratios and dynamic portfolio weights, can yield potential hedging benefits to cryptocurrency investors.

Building on this nascent third strand of literature, the objective of our paper is to advance our understanding of cryptocurrencies' diversification properties. This area is important for future research because, first, there is mixed evidence as to whether cryptocurrencies can serve as hedging instruments and, second, it can help elucidate upon whether cryptocurrencies' seemingly detached behavior with other traditional asset classes can be useful in terms of portfolio allocation and risk hedging. This objective is especially topical given our current economic times as we try to recover our economies from the COVID-19 pandemic and governments around the world are constructing various economic stimulus packages. These stimulus packages, while well-intentioned, also have the capacity of exerting inflationary pressures on asset prices. In the words of asset manager Francesca Fornasari, who currently serves as head of currency solutions at Insight Investment, "...investment in assets with a limited supply such as bitcoin have become popular as a form of digital gold..."[3]

Other studies also argue that more work is needed to understand the hedging properties of cryptocurrencies (Antonakakis et al., 2019; Corbett et al., 2018). In particular, we explicitly address calls for research to consider "…the impact of the different functions and features that characterize each cryptocurrency on risk management…(and)…investigate whether other cryptocurrencies have similar (i.e., to bitcoin) diversification effects on investment portfolios..." (Antonakakis et al., 2019, p.14). Our paper also is motivated by the need to construct "...diversified cryptocurrency portfolio(s) that maximizes return and balances risk while accounting for the risk preferences of crypto-investors..." (Ji et al., 2019, p.15).

We address these calls for future research in the following important ways; first, we explicitly model the dynamic conditional betas of 11 of the most widely traded cryptocurrencies. Extant literature tends to conclude that cryptocurrencies are uncorrelated with the market. As shown herein, this is partially true. Although there are periods when betas oscillate below zero, indicating a detached correlation with the market, there are also periods when betas are actually positive and even higher than the sample betas observed for non-financial commodity futures.

From the dynamic conditional betas, minimum-variance optimal weights are estimated. These weights reflect the optimal weight, or fraction, of cryptocurrency to hold in combination with holding the aggregate market portfolio in order to achieve a minimum-variance portfolio.

[3] See *https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/for-uk-institutions-crypto-is-no-longer-the-wild-west-of-finance-62927482*.

As discussed later on, some cryptocurrencies (most notably bitcoin) serve as more powerful instruments for minimum-variance optimization than others. This finding accentuates when focusing on the most recent market volatility caused by the COVID-19 pandemic.

Second, this paper uses a fractional regression model to regress optimal weights against a set of risk factors that capture uncertainty across various dimensions of the economy. In doing so, we extend recent work by Fang et al. (2019) who stress the importance of time-varying economic uncertainty for considering the role cryptocurrencies can play in portfolio risk hedging. The economic uncertainty factors are developed as in Bali et al. (2014) and include uncertainty pertaining to the banking industry, commodities, credit conditions, foreign exchange, inflation, equity markets, the term spread and volatility expectations, respectively. Theoretically, our findings add to the important findings of Fang et al. (2019), who demonstrate that bitcoin may be able to hedge a single source of economic policy uncertainty. This is because we explicitly test the hedging capabilities of 11 of the largest cryptocurrencies and entertain a variety of measures which capture different facets of economic uncertainty.

Coefficient estimates from our fractional regression model demonstrate some degree of heterogeneity between cryptocurrencies' usefulness as a hedging asset as well as their dynamic beta behaviors across time. However, it appears that rising economic uncertainty stemming from commodity markets, foreign exchange markets, equity markets, the TERM spread and volatility risk, respectively, are linked to rising optimal weights across most of the sampled cryptocurrencies.

The results have interesting implications for investors who want to diversify their portfolios using cryptocurrencies in the presence of economic uncertainty. From an investment point of view, the findings herein identify which of the cryptocurrencies serve as potentially more useful minimum-variance optimizers and how such optimal weights diffuse across time. From an asset pricing point of view, the two-step analytical framework implemented herein can be tractably applied to other asset classes and makes for useful cross-asset comparisons. Finally, from a market microstructure point of view, the findings carry implications when discussing whether cryptocurrencies are integrated or segmented.

The remainder of the paper proceeds as follows. Section 2 reviews the literature. Section 3 discusses the sampled cryptocurrencies and their return dynamics. Section 4 proceeds in three subsections: the first estimates betas and optimal weights. The second introduces the economic

uncertainty risk factors and how they are estimated. The third describes the fractional regression model. Section 5 discusses the findings. Finally, Section 6 concludes.

2. LITERATURE REVIEW

The ability to diversify risk is a fundamental concept within finance. Portfolio theory suggests that investors can construct portfolios that can successfully diversify idiosyncratic sources of risk by virtue of selecting different investable assets that are not perfectly correlated. This property allows investors to access higher returns for given levels of risk. A well-established fact is that while diversification can reduce idiosyncratic risk, it may not be able to protect one's portfolio from the various sources of economic risk. This is especially true during crises periods, when correlations between traditional asset classes increase (e.g., Boyson et al., 2010; Brunnermeier and Pedersen 2009; Gromb and Vayanos 2002; Platanakis et al., 2019; Shleifer and Vishny 1997). These observations also serve to highlight the dynamic nature in correlations between investable assets. In recent years, this property, as well as economic uncertainty arising from various market sources, such as equities and bonds, currencies, real estate and commodities, has incentivized investors to seek out alternative investable assets to diversify or hedge prevailing risks (Guesmi et al. 2019; Platanakis et al., 2019).

In particular, investors have explored various alternatives to equities and bonds including major commodities (Baur and McDermott, 2010; Kilian 2009) and real estate (Platanakis et al., 2019).[4] Since such alternative assets exhibit joint dependency with financial markets (Kilian, 2009), their roles as diversifiers in investors' optimal portfolios is important to analyze. For instance, low correlations between commodities and equities has shown to help reduce portfolio risk and improve returns in mixed-asset portfolios during specific sampling periods (Bekkers et al., 2009; Harvey and Erb, 2006; Hensel and Ankrim, 1993; Kim et al., 2011). A growing literature has considered such diversification effects using mixed asset portfolios (Jackwerth and Slavutskaya, 2016; Jacobs et al., 2014) or the additions of one alternative asset in mixed-asset portfolios (e.g., Belousova and Dorfleitner, 2012; Bessler and Wolf, 2015) and generally find that diversification opportunities are possible across specific sample periods. Baur and

[4] In an international survey of investors conducted by Barclays Capital, approximately half of surveyed investors cited portfolio diversification as a key motivation for investing in alternative assets. For example, see: *https://www.barcap.com/ about-barclays-capital/press-office/research-reports.html*.

McDermott (2010) suggest that precious metals, such as gold, may mitigate investor losses during extreme adverse market movements.

However, although such alternative assets have been shown to offer important portfolio diversification benefits, a number of studies have questioned their effectiveness – especially during adverse market conditions, such as the recent market declines caused by the COVID-19 pandemic. From one perspective, because correlations between commodities and equities are likely to increase during such periods, this constrains their ability to act as diversifiers in mixed-asset portfolios (Cheung and Miu, 2010; Silvennoinen and Thorp, 2013). For instance, Cheung and Miu (2010) argue that the often purported diversification benefits of commodity futures in the finance literature may be exaggerated given the dynamic nature of correlations across time. Platanakis et al. (2019) go further and demonstrate that since estimation errors are likely higher and transaction costs greater for alternative assets compared to equities and bonds, their inclusion in portfolios can induce harmful rather than beneficial diversification effects. They further find that this effect is especially pronounced during recent economic downturns.

Most recently, excited by the buzz surrounding cryptocurrencies, and aware of potential limitations of traditional alternative assets as diversifiers during adverse financial market conditions, some investors have begun to consider whether cryptocurrencies can offer portfolio diversification benefits. However, much of the emerging research has explored diversification within the context of multi-asset cryptocurrency-only portfolios; testing the performance of various portfolio optimization techniques rather than in the context of using cryptocurrencies with conventional assets, such as the aggregate market portfolio.[5]

Brauneis and Mestel (2019) employ daily data for a large sample of cryptocurrencies over a two-year period within a mean-variance framework and demonstrate multi-asset cryptocurrency portfolios outperform single asset cryptocurrency portfolios. Platanakis et al. (2018) construct portfolios of four major cryptocurrencies (bitcoin, litecoin, ripple and dash) to compare the performance of naïve (1/N) and optimal (Markowitz) diversification and find no meaningful differences in expected returns or risk-adjusted returns. Platanakis and Urquhart

[5] A number of studies also question whether bitcoin can represent a safe haven (e.g., Bouri et al., 2017b; Shahzad et al., 2019; Urquhart and Zhang, 2019). Shahzad et al. (2019) consider this with respect to extreme adverse market conditions but find only weak evidence in support of this. Specifically, any advantage bitcoin may have as a 'safe haven' property can vary significantly with both time and geography. Bouri et al. (2017b) also find that bitcoin's safe haven property exhibits significant temporal variation, with it being particularly effective during strong adverse movements in Asian stocks. Urquhart and Zhang (2019) find stronger support in relation to several currencies (CAD, CHF and GBP).

(2019) also compare with these portfolio construction techniques to an advanced Black–Litterman model, which they show outperforms the naïve and Markowitz approaches out-of-sample. Liu (2019) constructs portfolios containing only cryptocurrencies (bitcoin, ethereum, ripple, litecoin, stellar, monero, dash, tether, NEM and verge) and finds that while the minimum-variance portfolio serves to minimize sample volatility, the maximum utility model yields the highest return. However, no models are consistently better than a naïve model based on the Sharpe ratio.

This literature paves the motivation for trying to examine the wider potential of cryptocurrencies as diversifiers in mixed-asset portfolios. Relatively less is understood as to whether cryptocurrencies can be used to diversify risk in the context of mixed-asset portfolios. Guesmi et al. (2019) employ several models based on a DCC-GARCH framework to consider dynamics between bitcoin and several traditional assets. In particular, they construct portfolios that include traditional fiat currencies (euro and Chinese yen exchange rate), two world stock market indices, commodities (gold and oil), as well as bitcoin. Selmi et al. (2018) explore the effectiveness of bitcoin and gold, albeit in two-asset only portfolios to mitigate downside oil price movements. They show that while both bitcoin and gold can reduce portfolio risks, their relative influence depends on the prevailing economic conditions in each market. Finally, Kajtazi and Moro (2019), applying a mean-CVaR approach, construct portfolios containing several US, European and Chinese assets and test whether the addition of bitcoin influences portfolio risk-return characteristics. They find that while bitcoin can boost returns it does not effectively reduce volatility. Moreover, they demonstrate that the influence of bitcoin is significantly time-varying.

3. DATA SAMPLE & PRELIMINARY STATISTICS

3.1. Sampled cryptocurrencies

To contribute to our broader understanding of how cryptocurrencies can serve as hedging instruments, this paper samples 11 of the largest cryptocurrencies based on market capitalization. The sample range is from April 28, 2014 until May 15, 2020 for a total of 1,580 daily observations. As explained in the next section, since the paper estimates dynamic conditional covariances, correlations, betas and, finally, optimal weights using the market portfolio, it

excludes weekend cryptocurrency prices.[6] In addition to equity markets only being open on weekdays, the economic uncertainty risk factors used herein are also observable only on weekdays. The sample range is the same for all cryptocurrencies. There are some currencies, such as bitcoin cash which, despite their relatively high market capitalizations, are excluded given their rather small sample size (of only two or so years). Ensuring an equal sample size will allow for some cross-currency comparisons in the upcoming discussion.

Table 1 lists the 11 sampled currencies along with some descriptive statistics. Most striking is the price volatility these currencies have experienced. For example, bitcoin's minimum price was $171.51 for the sample period while its maximum price was $20,089.00. Despite some other currencies currently trading for prices much lower than bitcoin's (such as groestlcoin), they too have experienced large percentage changes in their prices over time – a perhaps alluring characteristic for the investors who trade them. Moreover, while bitcoin historically constitutes over half of the entire market capitalization of all cryptocurrencies in circulation, many other of the currencies, as shown in Table 1, are attracting significant and rising amounts of trade volumes.

[Table 1]

Finally, instead of relying on an individual cryptocurrency exchange for price data, this paper sources data for all 11 cryptocurrencies from *https://coinmarketcap.com*. These price data are advantageous for empirical testing (and arguably more representative) since they are calculated by the volume-weighted average of all prices reported in all the various exchange markets.[7]

3.2. Distributional and risk-return properties of cryptocurrency returns

Descriptive statistics for the sampled currencies' percentage logarithmic returns are shown in Table 2. These statistics indicate that their returns distributions are fat-tailed with excess kurtosis greater than what is commonly observed across the returns of conventional asset classes. These inferences from Table 2 are qualitatively consistent with the findings of Phillip et al. (2018) and Fry (2018).

[6] Sample cryptocurrency betas using the E-mini S&P 500 futures quotes for Sundays beginning at 5:00pm (E-mini does not trade on Saturdays), along with other interesting statistics at various frequencies (not tabulated for brevity) are available upon request.

[7] See *https://coinmarketcap.com/faq/* for more explanations.

[Table 2]

Value-at-Risk (VaR), modified VaR (MVaR), Sharpe and modified Sharpe ratios, respectively, are also shown in Table 2 to provide a broader description of the currencies' risk-return properties and to allow for some comparisons.[8] Fatter tails and excess kurtosis relative to a normal distribution (skewness risk and kurtosis risk) can be integrated into the MVaR and modified Sharpe ratio (Gregoriou and Gueyie, 2003). The MVaR can be expressed as follows (using similar notation as the VaR in footnote (8)):

$$\text{MVaR} = W\left[\mu - \{z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2\}\sigma\right] \quad (1)$$

whereby W is the value of the invested portfolio; z_c is the critical value for the probability $(1-\alpha)$ and is -1.96 for a 95% probability; μ is the mean return; σ is the standard deviation of returns; S and K is the skewness and kurtosis, respectively, of cryptocurrency returns. The modified Sharpe ratio can thus be expressed as follows:

$$\text{Modified Sharpe Ratio} = (R_\text{t} - r_\text{f})/\text{MVaR} \quad (2)$$

whereby r_f is the risk-free rate (see footnote (8)).

From the estimations in Table 2, the potential for investment loss is relatively lowest for bitcoin in relation to the other currencies (based on the VaR and MVaR). It also yields the most desirable return per unit of risk when compared to the other currencies (based on the Sharpe ratio). XRP yields the most desirable return per unit of risk based on the modified Sharpe ratio. Of all the currencies, XRP (XRP), dash (DASH), digibyte (DGB), and reddcoin (RDD) show the most pronounced excess kurtosis. RDD, which has the highest degree of kurtosis relative to the other sampled cryptocurrencies, also shows a pronounced difference between its VaR and MVaR estimates. Finally, groestlcoin (GRS), which is currently the smallest cryptocurrency in the sample (based on total market capitalization), exhibits the highest level of downside risk.

Table 3 shows a correlation matrix between the pairwise logarithmic returns of all the 11 sampled cryptocurrencies. The average pairwise correlation is 0.3163 while the minimum is 0.1324 (between XRP and groestlcoin) and the maximum is 0.6236 (between bitcoin and litecoin). It is interesting to note that litecoin is a spinoff to bitcoin, with many fundamental

[8] The Sharpe ratio for the returns, r, of cryptocurrency i can be computed as $(r_{i,t} - r_f)/\sigma$ whereby r_f denotes the risk-free rate (estimated as the daily return on the 1-month Treasury bill) and σ denotes the standard deviation of returns. The VaR is calculated as follows: $\text{VaR} = W(\mu\Delta t - n\sigma\sqrt{\Delta t})$ whereby μ is the mean return; W is the value of the portfolio; n is the number of standard deviations depending on the confidence level; Δt is the time window. More discussion and derivations for VaR and MVaR can be found in Signer and Favre (2002).

technical similarities.[9] Overall, the pairwise correlations show that the sampled cryptocurrencies' prices do not move perfectly in tandem with one another and this has implications for how well they can serve as diversification instruments for investors across time.

[Table 3]

4. ANALYTICAL APPROACH

4.1. Dynamic conditional betas and minimum-variance optimal weights

To estimate dynamic conditional covariances, correlations, betas and, finally, minimum-variance optimal portfolio weights between a respective cryptocurrency and the market, the dynamic conditional beta (DCB) model of Engle (2014; 2016) is used. Using similar notation, suppose we have dependent variables y_t and k independent variables x_t. Each of the variables has a conditional mean and variance and, jointly, they have a conditional covariance matrix, which can be expressed as follows:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} \mid \Im_{t-1} \sim D\left(\begin{pmatrix} m_{y,t} \\ m_{x,t} \end{pmatrix}, \begin{pmatrix} h_{yy,t} & h_{yx,t} \\ h_{xy,t} & h_{xx,t} \end{pmatrix}\right) \tag{3}$$

Assuming that the joint distribution is normal, we then have

$$y_t|x_t, \Im_{t-1} \sim N\left(m_{y,t} + h_{yx,t}h_{xx,t}^{-1}\left(x_t - m_{x,t}\right), h_{ee,t}\right) \tag{4}$$

and whereby the conditional covariance matrix with the residuals can be shown as

$$h_{ee,t} = h_{yy,t} - h_{yx,t}h_{xx,t}^{-1}h_{xy,t} \tag{5}$$

The coefficient of x_t is the dynamic conditional beta shown as

$$\beta_t = h_{xx,t}^{-1}h_{xy,t} \tag{6}$$

From one period to the next, the matrix of coefficients changes whereby each row of β_t corresponds to the dynamic conditional beta of one equation. Like standard multivariate GARCH processes, the betas are conditional on past variances and covariances.

Figure 1 plots the time series movements of each respective sampled cryptocurrencies' betas, estimated from equations (3) through (6). Summary statistics are also provided and include the average, minimum, maximum, and the 25th, 50th and 75th percentiles, respectively, for each of the betas. We can observe visually from Figure 1 that cryptocurrencies display unique beta

[9] Litecoin was a fork of the Bitcoin Core client. More information on litecoin, along with a repository of other cryptocurrency whitepapers and relevant presentations, is publicly available here: *https://www.allcryptowhitepapers.com/litecoin-whitepaper/*.

behaviors that are uncommon among traditional asset classes. For prolonged periods, their betas can oscillate around zero. For example, bitcoin has an average beta of -0.0127 and groestlcoin, the smallest of all the sampled cryptocurrencies, has an average beta of -0.7707. While most of the sampled cryptocurrencies have low average betas, reddcoin displays a relatively high average beta of 1.2970.

[Figure 1]

Are cryptocurrencies useful hedging instruments? From a risk management point of view, they may provide risk reduction benefits by helping to minimize a portfolio's variance. If we let the variance in the returns of the CRSP value-weighted index be h_m, the variance of cryptocurrency's i returns be $h_{c,i}$, and the optimal weight of the cryptocurrency in a minimum-variance portfolio be w, the overall portfolio variance is

$$V_{t-1}(\pi_t) = w^2 h_{m,t} + (1-w)^2 h_{c,i,t} + 2w(1-w)\beta_t h_{m,t} \tag{7}$$

and the optimal weight in cryptocurrency i is

$$w = \frac{(1-\beta_t)h_{m,t}}{h_{c,i,t}+(1-2\beta_t)h_{m,t}} \tag{8}$$

These optimal weights are estimated for each weekday and are plotted in Figure 2. While some more discussion of these estimations follows in Section 4, it is important to note that optimal weights for all the sampled cryptocurrencies spiked significantly during the recent COVID-19 pandemic which has had a negative impact on stock market prices. This means that holding an optimal weight of the portfolio in cryptocurrencies can actually help reduce total portfolio variance. For bitcoin, we see that the optimal weight reached a peak value of 0.4912 on April 2, 2020. In particular, optimal weights in bitcoin remained relatively high from February through March of 2020 – a time period in which the S&P500 market index lost more than 30% of its market value. Based on this historical data, and compared to the remaining sampled cryptocurrencies, bitcoin is shown to be a better bet for minimum-variance hedging during unusual economic times, such as the recent global pandemic. While some cryptocurrencies show higher maximum optimal weights than others for the February through April 2020 period, all the sampled cryptocurrencies display maximum optimal weights that exceed 20%.

[Figure 2]

4.2. Economic uncertainty risk factors

Identifying how economic uncertainty is linked to fluctuations in optimal weights can give us a better sense of the usefulness of cryptocurrencies as hedging instruments in time periods of rising or declining uncertainty. Following Bali et al. (2014), among others, this paper uses risk factors that, when constructed, can proxy for economic uncertainty.

The financial and economic indicators used in this paper, and which are often used by academics and policymakers for forecasting purposes, are as follows: (1) BANK: This variable reflects uncertainty that stems from bank specific events and risks.[10] Following Anderson and Fraser (2000) and Chen et al. (2006), among others, this variable is calculated by extracting the time series residuals of a market model where returns on the banking industry are regressed against returns of the market portfolio. (2) COM: This variables reflects conditions stemming from commodity markets and is calculated as the logarithmic returns on the Thomson Reuters/CoreCommodity CRB Index. (3) DEF: This variable reflects firm default risk and is calculated as the spread between Moody's seasoned Baa and Aaa corporate bond yields. (4) FX: This variable reflects conditions in foreign exchange markets and the US dollar. The trade-weighted US dollar index is used as a proxy for this. (5) INF: This variable reflects inflation conditions. It is calculated as changes in the 5-year, 5-year forward inflation expectation rate. (6) MKT: This reflects market conditions and is the returns on the value-weighted NYSE/AMEX/NASDAQ Center for Research in Securities Prices (CRSP) equity market index. (7) TERM: This variable reflects economic and business cycle activity and is calculated as changes in the term spread (the spread between 10-year and 3-month treasuries). (8) VIX: This variable reflects volatility expectations in the market and is the CBOE Volatility Index.

Following Bali et al. (2014) and others, this paper thus estimates economic uncertainty for each of these variables using a multivariate asymmetric GARCH with a vector autoregressive (VAR) process:

$$\begin{bmatrix} Z_{i,t+1} \\ Z_{j,t+1} \end{bmatrix} = \begin{bmatrix} b_0^i \\ b_0^j \end{bmatrix} + \begin{bmatrix} b_1^i & b_2^i \\ b_1^j & b_2^j \end{bmatrix} \begin{bmatrix} Z_{i,t} \\ Z_{j,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t+1} \\ \varepsilon_{j,t+1} \end{bmatrix} \tag{9}$$

$$E\left[\varepsilon_{i,t+1}^2 \middle| \Omega_t\right] \equiv \sigma_{i,t+1}^2 = \gamma_0^i + \gamma_1^i \varepsilon_{i,t}^2 + \gamma_2^i \sigma_{i,t}^2 + \gamma_3^i \varepsilon_{i,t}^2 D_{i,t} \tag{10}$$

[10] The Dow Jones US Bank Index is used to calculate BANK. Various alternative measures (which use the Fama-French portfolios or other liquid bank sector ETFs) are also entertained (available upon request) and the reported findings are robust. Data for BANK, COM and VIX are obtained from Bloomberg while data for DEF, FX, INF and TERM are from FRED.

$$E\left[\varepsilon_{j,t+1}^2 \middle| \Omega_t\right] \equiv \sigma_{j,t+1}^2 = \gamma_0^j + \gamma_1^j \varepsilon_{j,t}^2 + \gamma_2^j \sigma_{j,t}^2 + \gamma_3^j \varepsilon_{j,t}^2 D_{j,t} \quad (11)$$

$$E_t\left[\varepsilon_{i,t+1}\varepsilon_{j,t+1} \middle| \Omega_t\right] \equiv \sigma_{ij,t+1} = \gamma_0^{ij} + \gamma_1^{ij} \varepsilon_{i,t}\varepsilon_{j,t} + \gamma_2^{ij} \sigma_{ij,t} + \gamma_3^{ij} \varepsilon_{i,t}\varepsilon_{j,t} D_{i,t} D_{j,t} \quad (12)$$

whereby $Z_{i,t+1}$ ($Z_{j,t+1}$) represents one of the eight variables which serves to proxy for the state of the economy in day $t+1$; $Z = [\text{BANK}, \text{COM}, \text{DEF}, \text{FX}, \text{INF}, \text{MKT}, \text{TERM}, \text{VIX}]$. Given that equations (9) through (12) define an asymmetric GARCH specification, the dummy variables, D, serve to capture such possible asymmetries in the time series dynamics of the variables:

$$D_{i,t} = 1 \text{ for } \varepsilon_{i,t} < 0 \text{ and } D_{i,t} = 0 \text{ otherwise} \quad (13)$$

$$D_{j,t} = 1 \text{ for } \varepsilon_{j,t} < 0 \text{ and } D_{j,t} = 0 \text{ otherwise} \quad (14)$$

Equation (9) is a VAR(1) process in order to account for serial correlation in the seven state variables as well as their cross-correlations simultaneously. The information set at time t which market participants use to form expectations about the state variables is denoted by Ω_t. Conditional variances are denoted by σ^2 for each of the Z variables. The threshold GARCH (TGARCH) of Glosten et al. (1993) is used to allow for asymmetries whereby D is equivalent to one when ε is negative and zero otherwise. Thus, if the coefficient γ_3 is estimated to be positive (negative), the TGARCH specification implies that negative shocks result in higher (lower) volatility than positive shocks of equal magnitude.

Equations (9) through (12) are estimated simultaneously using the maximum likelihood methodology. The residual vector, U_t and the conditional variance-covariance matrix, V_t, can be expressed, respectively, as

$$U_t = \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{bmatrix} = \begin{bmatrix} Z_{i,t} - b_0^i - b_1^i Z_{i,t-1} - b_2^i Z_{j,t-1} \\ Z_{j,t} - b_0^j - b_1^j Z_{i,t-1} - b_2^j Z_{j,t-1} \end{bmatrix} \quad (15)$$

$$V_t = \begin{bmatrix} \sigma_{i,t}^2 & \sigma_{ij,t} \\ \sigma_{ij,t} & \sigma_{j,t}^2 \end{bmatrix} \quad (16)$$

The log-likelihood function, assuming conditional multivariate normality, can be expressed as

$$\log L(\Theta) = -{}^1\!/_2 \sum_{t=1}^{N} [\ln(2\pi) + \ln|V_t| + U_t^T V_t^{-1} U_t] \quad (17)$$

whereby Θ denotes the vector of parameters in equations (9) through (12) and N denotes the number of daily observations for each of the data series.

Figure 3 displays the time series plots of the eight economic uncertainty measures. For visual purposes, all these series are normalized and bounded between zero and one (they do not enter as normalized variables when estimating our fractional regression model, which we discuss

in Table 4 and subsection 4.3). It is noteworthy that all the uncertainty measures experienced a spike during this recent COVID-19 pandemic. While the shock to these measures is somewhat decaying recently, as the market and economy begin to reopen slowly, we can see that these specific measures are sensitive to historical events which have impacted global markets. For example, uncertainty stemming from volatility expectations (VIX_U) spikes significantly in the beginning of February 2018. Around this time, the S&P500 dropped almost 10% within a few trading days. The financial press which covered this time period indicates that this was due to worries that the Fed will raise interest rates and because of computer-programmed trading.[11]

[Figure 3]

4.3. Fractional regression analysis of optimal weights

The time series of optimal weights, w, from equation (8) for each of the cryptocurrencies, respectively, are to be regressed against the eight aforementioned economic uncertainty variables. During periods when w rises, it signifies that the respective cryptocurrency is a more valuable hedging instrument for maintaining a minimum-variance portfolio. If w declines, it signifies that the currency is less valuable as a hedging instrument.

Establishing the linkages between the time path of w, for each respective cryptocurrency, and shifts in economic uncertainty is important because it will tell us how useful each of these currencies is as a hedging instrument during periods of oscillating economic uncertainty and which types of uncertainty are they a hedge for. The economic uncertainty measures are estimated from equations (9) through (17) and, just as in Bali et al. (2014), among others, are not transformed or normalized. Since w is expressed as a fraction, conventional regression methods (such as OLS) are inadequate to use. Nonlinear methodologies, such as logit and probit approaches or censored and truncated regressions are also inadequate for this purpose. This is because a nontrivial portion of observations lie near zero for the cryptocurrencies (i.e., there are prolonged periods where these currencies are not useful minimum-variance hedging instruments).

Consistent with Papke and Wooldridge (1996; 2008), fractional regression models overcome the limitations of conventional linear and non-linear models when working with bounded (fractional) data that is non-binary in nature and which can cluster heavily in one bound

[11] See *https://www.cnbc.com/2018/02/05/why-the-stock-market-plunged-today.html*.

or another. As is described by Gallani et al. (2015), fractional regression models are econometrically advantageous for four reasons. First, they do not require any correction or alteration of the values observed at the bounds. Second, they account for non-linearity in the data. Third, they are robust with generalized linear model assumptions. Finally, they permit for the discovery of the dependent variable's regression function for a given set of regressors.

Using similar notation to Papke and Wooldridge (1996) and Gallani et al. (2015), suppose the fractional variable of interest y, $0 \leq y \leq 1$, is to be estimated by a $1 \times k$ vector of explanatory variables $x \equiv (x_1, x_2, \dots, x_k)$, whereby $x \equiv 1$. The population model can be expressed as

$$E(y|x) = G(x_i b) \forall i \tag{18}$$

whereby $G(.)$ is a known function with $0 < G(z) < 1 \ \forall z \in \mathbb{R}$, and which satisfies the condition that the fitted values lie in the unit interval. Non-linear functional forms that can be used for G include the logistic function $G(x) \equiv \Lambda(z) \equiv [\exp(z)]/[1 + \exp(z)]$ and $G(x) \equiv \Phi(z)$, whereby $\Phi(.)$ is the standard normal cumulative density function.[12]

5. DISCUSSION OF FINDINGS

As mentioned, Figures 1 and 2 respectively show time series plots of the sampled cryptocurrencies' dynamic conditional betas and the optimal weights, w, calibrated when investing between the market and a sampled cryptocurrency. Several of the lesser known currencies, such as digibyte (DGB), vertcoin (VTC), and groestlcoin (GRS), have relatively higher systematic variations in betas. Conversely, bitcoin (BTC), which is the most well-known of all the currencies, exhibits relatively lower systematic variance in its betas (overall it has a wide sample range for betas with a minimum and maximum of -13.3906 and 1.4523, respectively, but the systematic day-to-day oscillations are not as pronounced as with some of the smaller cryptocurrencies).

To some extent, all the sampled currencies exhibit periods of negative or zero betas throughout their time paths. This indicates a negative or zero covariance with the market and is a

[12] Various maximization techniques are entertained to maximize the log-likelihood function. More details and untabulated results are available upon request. In addition, more details and application of fractional regression models can be found in Gallani et al. (2015). Unlike logit or probit regressions, which attempt to predict probabilities of the occurrence of some event, fractional regression models estimate the conditional expected value of the bounded dependent variable.

reason why many extant studies cannot explain their returns using market factors that have successfully been used to explain the returns of traditional asset classes, which tend to commove positively with the market. For example, in the case of bitcoin, and in untabulated results, approximately half of its betas lie below the mean, μ, of -0.0127. This finding echoes the conclusions by Li and Wang (2017, p.59), who argue that, when trying to model or explain bitcoin prices, "...it will be necessary to revisit the model (of bitcoin prices) at some future time and consider the possibility of multiple regime changes in exchange rate dynamics..."

Those currencies that experience the most extreme variance in their betas may also be the least useful, relatively speaking, as minimum-variance hedging instruments. For example, vertcoin (VTC) and groestlcoin (GRS) have maximum optimal weights of 23.31% and 22.40%, respectively. Consistent with this observation, it appears that these currencies are generally most useful when their betas oscillate near zero (or are negative). It is during these ('zero beta') periods when optimal weights tend to have a possibility of rising. During periods of high volatility in betas (especially when betas oscillate greatly and take large positive values), we see declines in optimal weights. Overall, while the average optimal weights tend to be low for the respective cryptocurrencies over the entire sample period, there are instances when they do serve as useful hedging instruments. For example, bitcoin (BTC), XRP (XRP), litecoin (LTC), dash (DASH), digibyte (DGB), and NXT (NXT) have maximum optimal weights of 49.12%, 33.71%, 35.89%, 29.20%, 30.02% and 31.85%, respectively. All these maximum optimal weights are witnessed during the unprecedented market volatility we are currently experiencing as a result of the COVID-19 pandemic.

Our finding that optimal portfolio weights of cryptocurrencies are time varying is interesting and worthy of further investigation for future research. This is because it implies that cryptocurrencies can potentially serve as useful hedging instruments during some periods but not during others. This is consistent with Fang et al. (2019) who argue that the hedging abilities of bitcoin vary with underlying economic uncertainty. It is also related to the findings of Naeem et al. (2021) who show that the efficiency of cryptocurrencies can vary across economic periods. Our paper, however, shows how these hedging abilities explicitly shift in relation to such economic uncertainty (we show this in Table 4). In addition, our findings of time variability in optimal portfolio weights extend the work of Antonakakis et al. (2019) who explore the hedging possibilities of leading cryptocurrencies in the context of bivariate cryptocurrency-only

portfolios. It also extends the work of Guesmi et al. (2019) who show that bitcoin can help reduce risk in mixed-asset portfolios.

Table 4 shows findings of the empirical linkages between the optimal weights and the aforementioned economic uncertainty measures. The economic uncertainty measures are estimated using equations (9) through (17) and represent uncertainty regarding the various states of the economy. The fractional regression model is shown in equation (18). As mentioned, optimal weights, w, are expressed as a fraction. Thus, conventional regression methods are inadequate to use. Given that w is time-varying for each of the respective cryptocurrencies, we can now see to what extent sources of economic uncertainty are statistically linked with fluctuations in w. If w rises along with rises in uncertainty, it suggests that the underlying cryptocurrency becomes more valuable as a diversification instrument during turbulent economic times. If there is no such relation, it suggests that the underlying cryptocurrency affords little or no benefit as a diversification instrument.

The findings in Table 4, which explicitly model linkages between optimal weights and sources of economic uncertainty, show that rises in uncertainty stemming from commodity markets (COM_U), equity markets (MKT_U), the term spread (TERM_U) and volatility expectations (VIX_U), respectively, are most consistently linked with rises in optimal weights for most of the sampled cryptocurrencies. For example, in 100% of cases (eleven out of eleven of the cryptocurrencies where estimated test statistics are greater than or equal to 1.96), optimal weights rise during periods of increases in MKT_U. Among all these economic uncertainty measures, uncertainty stemming from firm default risk and inflation risk (DEF_U and INF_U, respectively) have the lowest success rate in explaining optimal weights – none of the sampled cryptocurrencies show statistically significant changes in their optimal weights in response to shifts in DEF_U or INF_U. This is particularly interesting since inflation uncertainty has been one of the main theoretical drivers for holding cryptocurrencies (Li and Wang, 2017). For example, proponents for bitcoin argue that it may protect against inflation (see footnote (3)), which afflicts fiat monetary systems, since coin generation is determined by an equation that is transparent to all market participants.

[Table 4]

Overall, there appears to be some heterogeneity in coefficient significance across the currencies. These findings provide a unique lens from which to view the recent findings by Fang

et al. (2019), who show that the long-term price behavior of bitcoin is impacted by economic uncertainty. In our paper, however, we demonstrate that the influence of economic uncertainty on the effectiveness of cryptocurrencies in reducing risks in dynamic portfolios further varies with respect to the specific underlying sources of economic uncertainty.

6. CONCLUSION

In this paper, we develop and implement a novel two-step analytical framework for gauging the extent to which cryptocurrencies can serve as useful hedging instruments. The framework shown herein can be applied to other assets, thus making for useful cross-asset comparisons. Applying this framework, we explicitly model dynamic conditional betas for eleven of the most widely traded cryptocurrencies to explore whether cryptocurrencies can represent useful hedging instruments. First, we estimate optimal weights for each cryptocurrency using a DCC approach. We then apply a fractional regression approach to regress optimal weights against a set of economic uncertainty factors. These uncertainty factors are constructed using a multivariate asymmetric GARCH with a VAR process and serve to represent different economic states and sources for uncertainty.

The objective here is to see the extent to which optimal weights relate to specific sources of economic uncertainty. We present several interesting findings that have implications for investors, regulators and policy makers seeking to better understand the diversification and hedging properties of major cryptocurrencies.

We demonstrate that although cryptocurrencies can serve effectively as hedging instruments for constructing minimum-variance portfolios, this role is largely constrained to periods when they exhibit zero (or negative) beta behavior. Moreover, we observe some degree of heterogeneity in optimal weights across our sampled cryptocurrencies, implying that they perform differently with one another as hedging instruments. During the COVID-19 pandemic, we show a significant rise in the optimal weights of all the sampled cryptocurrencies. This happened during a period when the stock market declined and fear spread among investors as to the future of the economy. While some cryptocurrencies (such as bitcoin) appear to generally be better hedging instruments, more future investigation is needed in understanding the reasons,

behavioral, investment or otherwise, investors are drawn to these currencies and what other useful features they have.

Our paper also shows how optimal weights within portfolios can vary significantly with respect to underlying economic conditions and sources for economic uncertainty. While existing literature tends to conclude that cryptocurrencies are uncorrelated with the market, we show that there are periods in which betas are higher than what is observed even for non-financial commodity futures. From an asset allocation perspective, our results show which cryptocurrencies can serve as potentially more useful minimum-variance optimizers and how the time dynamics of such optimal weights shifts in response to changes in economic uncertainty. From a market microstructure point of view, our findings contribute to the ongoing discussion as to whether cryptocurrencies are integrated or segmented. In our correlation matrix in Table 3 we show that these eleven currencies do not move perfectly in tandem with one another. In Table 4 of our results, we show explicitly that they have the capacity to hedge against certain sources of economy uncertainty but not others.

It is left to future research to determine, both theoretically and empirically, *which* market risk factors do cryptocurrencies hedge against and under what circumstances. Our econometric approach herein has provided a starting point for linking cryptocurrencies' hedging usefulness to various sources of economic uncertainty. Once some understanding has been established as to what risk factors can be hedged with cryptocurrencies, a next step would be to investigate whether cryptocurrencies' technological infrastructures, such as their respective mining protocols or rules which govern their money supplies, also play roles in determining hedging effectiveness.

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Figure 1
Dynamic conditional betas

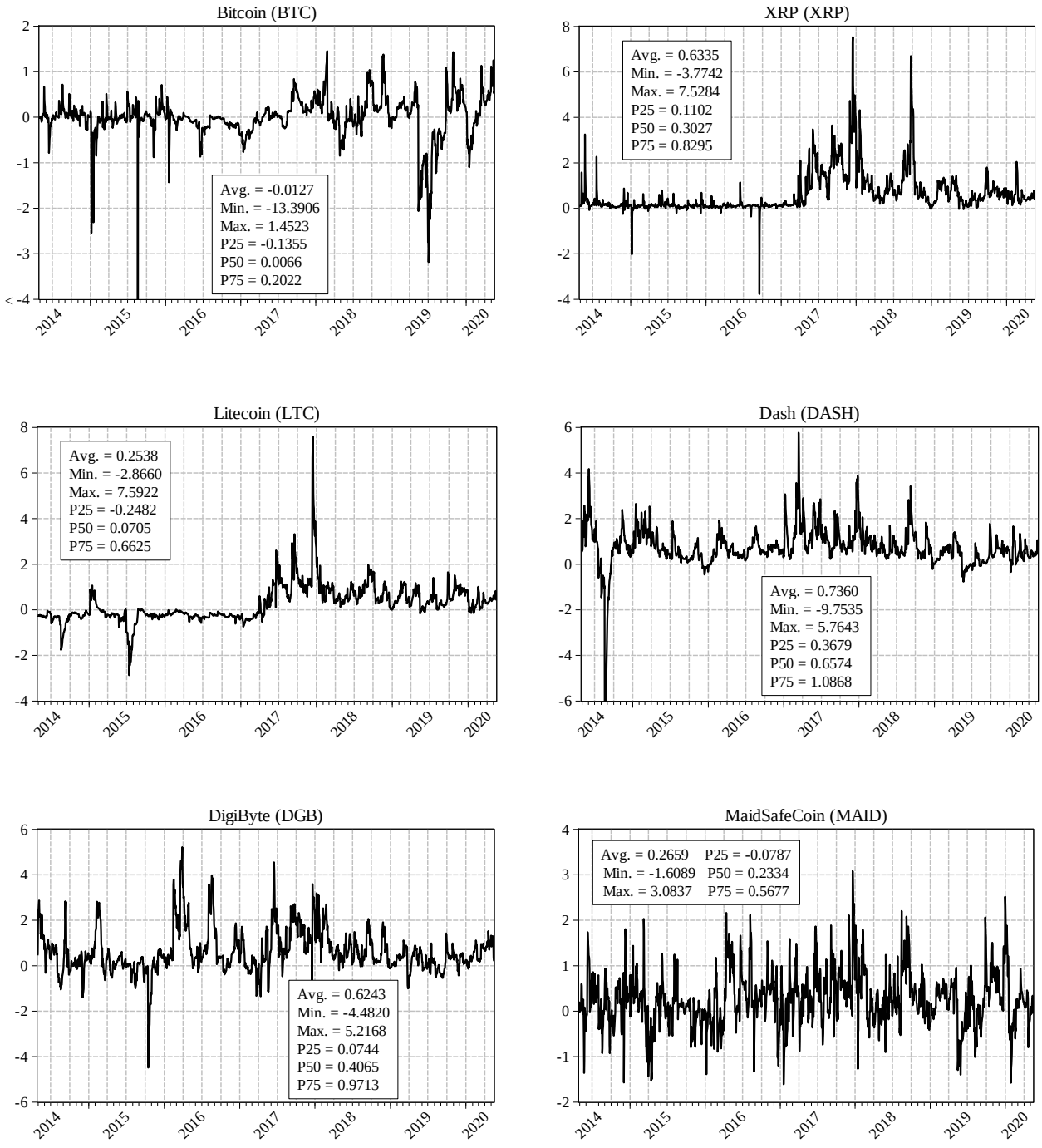
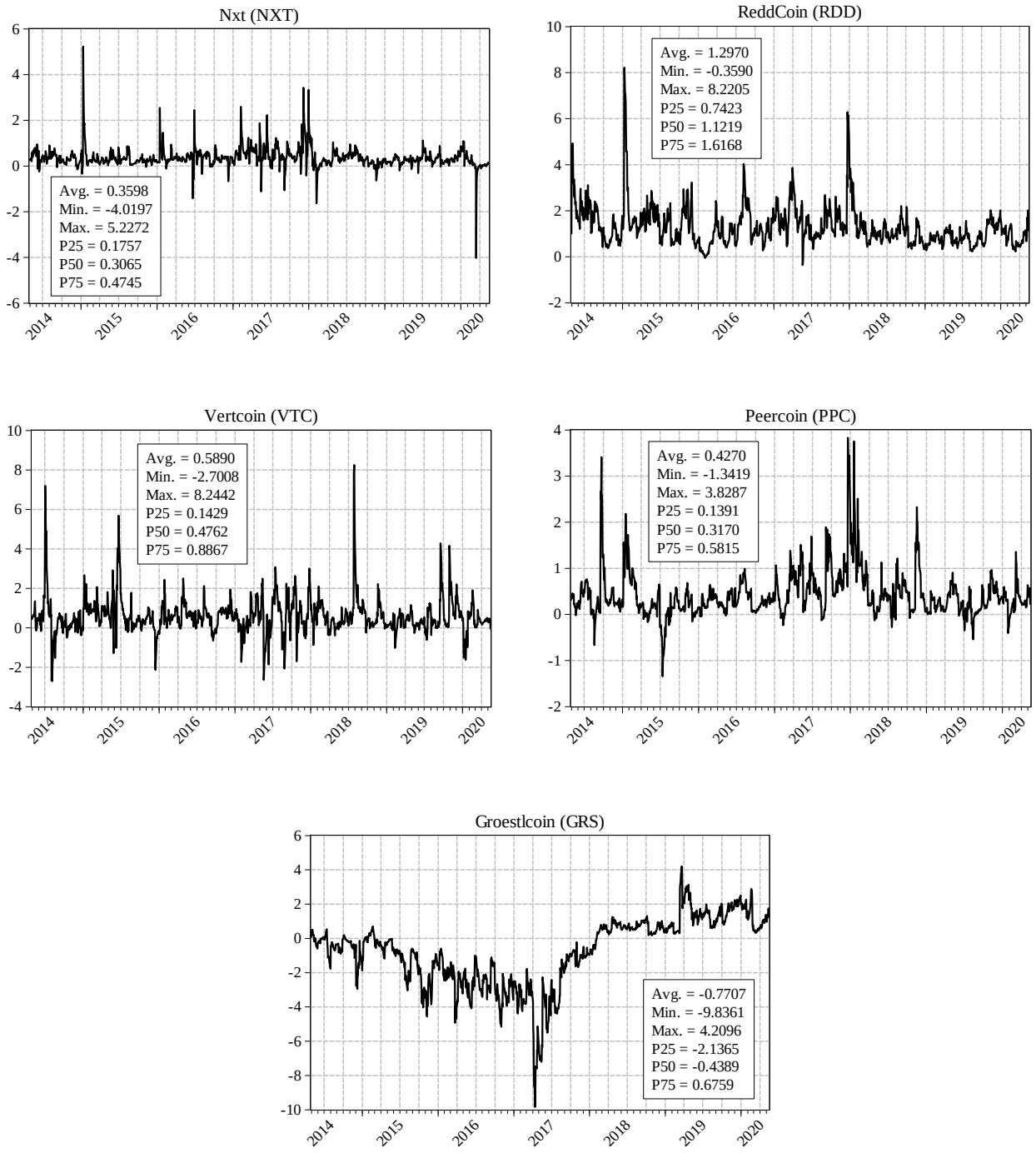


Figure 1
Dynamic conditional betas (Cont.)



This figure shows time series plots of each sampled cryptocurrencies' dynamic conditional betas, estimated using equations (3) through (6). Summary statistics for each of the cryptocurrencies' betas are also provided (average, minimum, maximum and the 25th, 50th and 75th percentiles, respectively). The sample period is from April 28, 2014 until May 15, 2020 (1,580 daily observations) for all the sampled cryptocurrencies.

Figure 2
Dynamic optimal weights

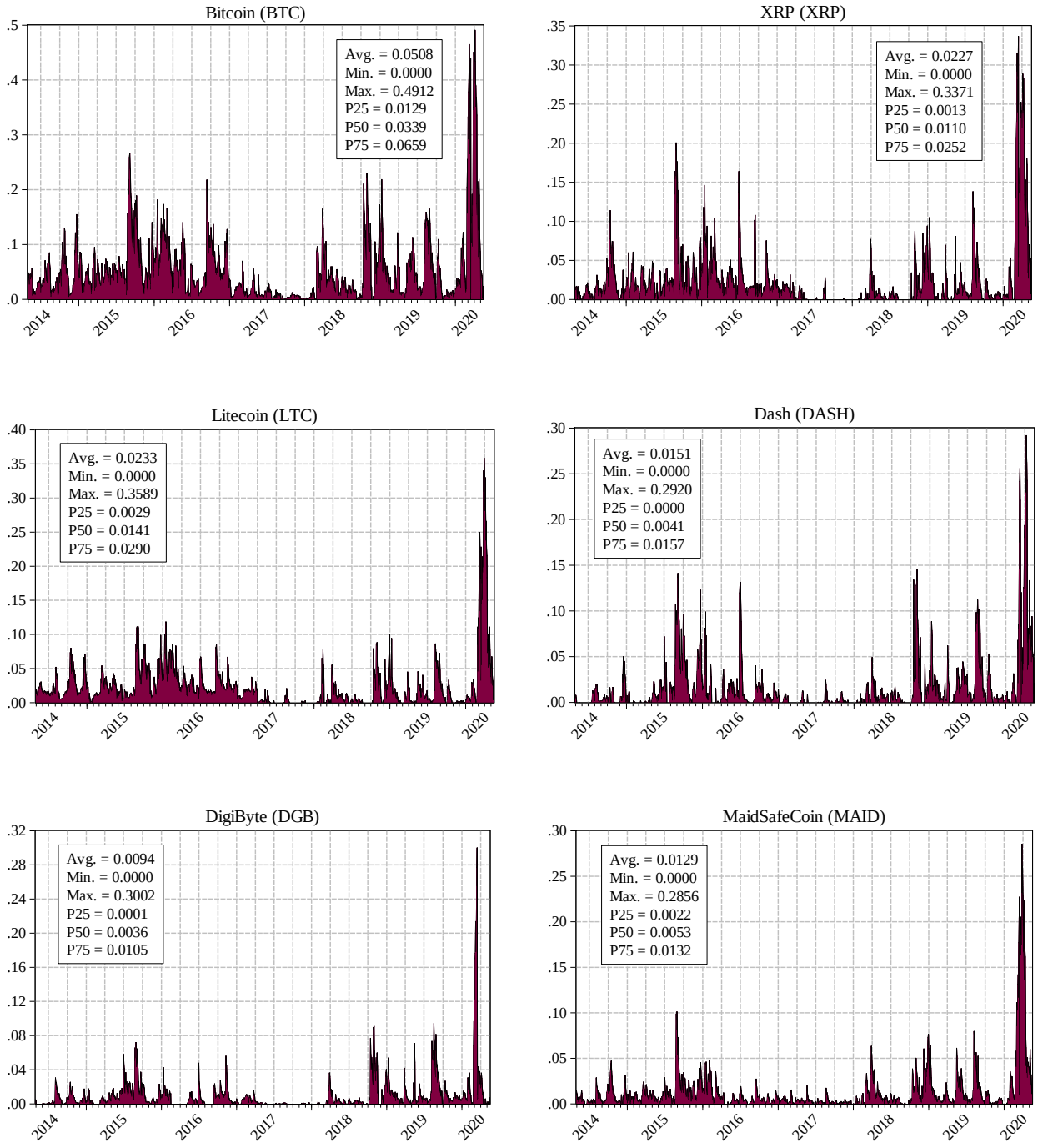
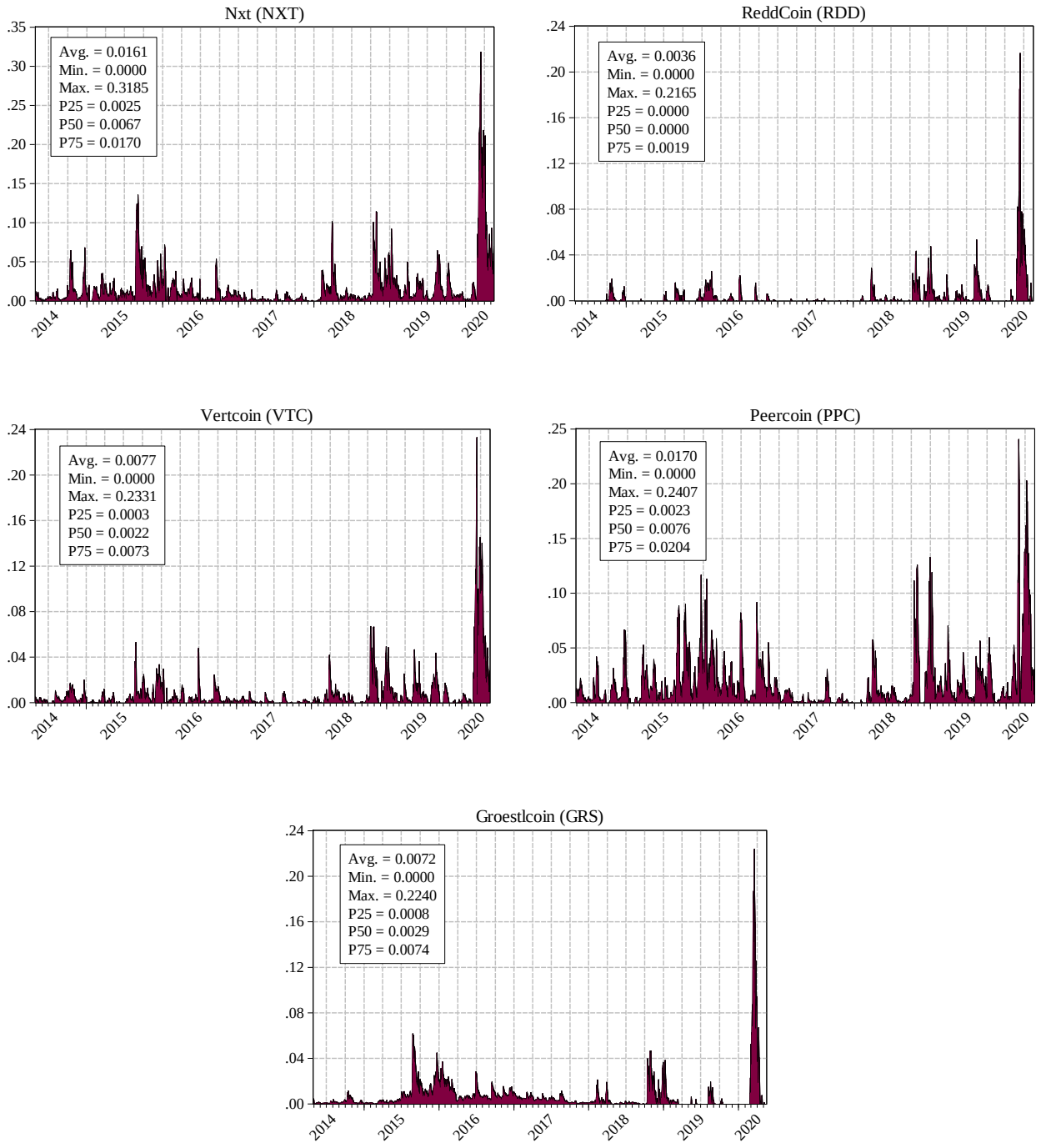


Figure 2
Dynamic optimal weights (Cont.)



This figure shows time series plots of each sampled cryptocurrencies' optimal weights, estimated using equations (7) and (8). Summary statistics for each of the cryptocurrencies' optimal weights are also provided (average, minimum, maximum and the 25th, 50th and 75th percentiles, respectively). The sample period is from April 28, 2014 until May 15, 2020 (1,580 daily observations) for all the sampled cryptocurrencies.

Figure 3
Normalized economic uncertainty measures

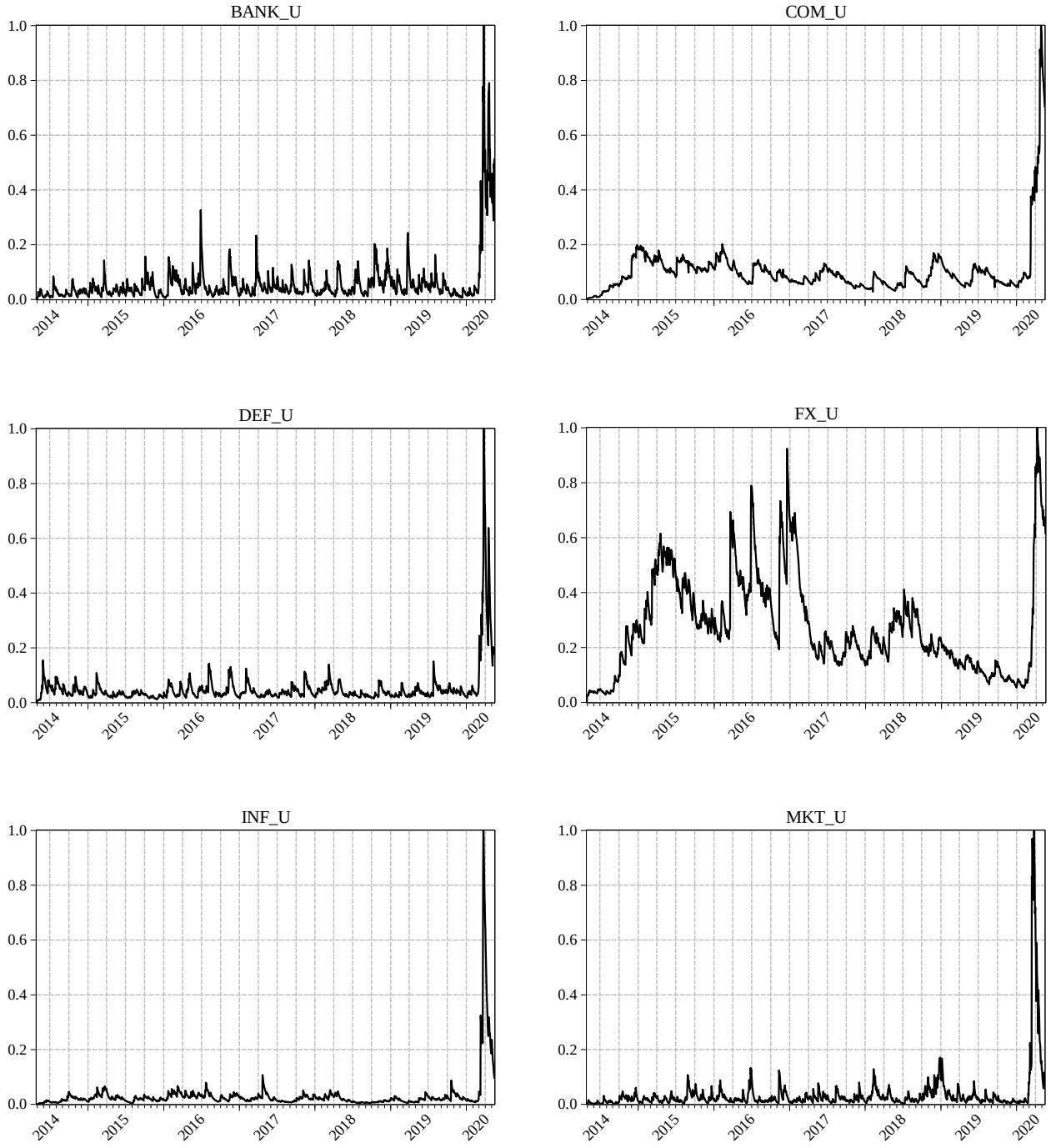
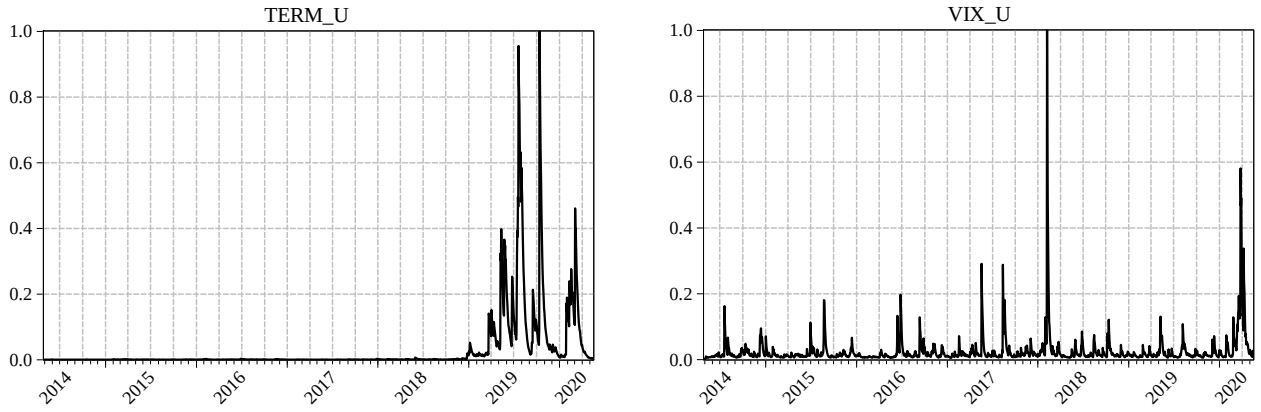


Figure 3
Normalized economic uncertainty measures (Cont.)



This figure shows time series plots of each of the economic uncertainty risk factors, estimated using equations (9) through (17). These risk factors are normalized and bounded between zero and one for visual purposes in this figure. The sample period is from April 28, 2014 until May 15, 2020 (1,580 daily observations) for all the sampled cryptocurrencies.

Table 1
Sampled cryptocurrencies

Cryptocurrency	Abbrev.	Avg. Price (in USD)	Min. Price (in USD)	Max. Price (in USD)	Avg. Volume (in USD)	Avg. Market Cap. (in USD)
1. Bitcoin	BTC	$3,826.5452	$171.5100	$20,089.0000	$6,535,378,449	$66,083,836,186
2. XRP	XRP	$0.2116	$0.0028	$3.8400	$539,711,510	$8,469,796,718
3. Litecoin	LTC	$42.2383	$1.1100	$375.2900	$862,289,980	$2,418,082,892
4. Dash	DASH	$120.2342	$1.0500	$1,642.2200	$128,548,462	$963,471,536
5. DigiByte	DGB	$0.0095	$0.0000	$0.1429	$4,008,055	$98,859,832
6. MaidSafeCoin	MAID	$0.1655	$0.0041	$1.2000	$893,334	$74,888,669
7. Nxt	NXT	$0.0560	$0.0051	$2.1600	$5,274,056	$55,907,205
8. ReddCoin	RDD	$0.0014	$0.0000	$0.0324	$1,992,706	$40,175,804
9. Vertcoin	VTC	$0.6610	$0.0053	$10.5300	$1,468,818	$27,110,793
10. Peercoin	PPC	$0.9288	$0.0949	$9.9200	$408,973	$22,265,955
11. Groestlcoin	GRS	$0.2142	$0.0001	$2.6900	$2,941,453	$15,141,491

This table lists by average market capitalization (in descending order) all the eleven sampled cryptocurrencies. While the second column shows their abbreviations (currency ticker), the remaining columns report statistics (in US Dollars) of the cryptocurrencies' average, minimum and maximum prices, respectively, along with average trade volumes and market capitalizations. The sample period is from April 28, 2014 until May 15, 2020 (1,580 daily observations) for all the sampled cryptocurrencies.

Table 2

Distributional and risk-return properties of cryptocurrency returns

Cryptocurrency	Mean	Med.	Min.	Max.	S.D.	Skew.	Kurt.	VaR	Mod. VaR	Sharpe	Mod. Sharpe
1. BTC	0.1932	0.1904	-46.4729	22.5119	4.5376	-0.7738	13.9209	-8.7005	-14.3080	0.0426	0.0135
2. XRP	0.2313	-0.3164	-51.2927	75.0830	7.3094	1.7497	20.3706	-14.0951	-15.0029	0.0316	0.0154
3. LTC	0.0912	0.0000	-51.3925	53.9797	6.6832	0.6915	16.2106	-13.0079	-17.7985	0.0136	0.0051
4. DASH	0.2386	-0.2844	-86.0201	76.8182	7.8733	0.1965	21.0193	-15.1931	-25.7903	0.0303	0.0093
5. DGB	0.3204	-0.3542	-53.7188	116.5601	11.1822	2.0342	20.7900	-21.5967	-20.0426	0.0287	0.0160
6. MAID	0.1022	-0.1511	-57.5271	53.8758	8.1081	0.1088	8.8742	-15.7897	-20.3032	0.0126	0.0050
7. NXT	-0.0447	-0.5224	-65.0424	71.1064	8.4784	0.9007	17.5328	-16.6624	-22.2577	-0.0053	-0.0020
8. RDD	0.3169	0.0000	-155.6445	146.4072	14.3832	0.9445	25.3885	-27.8742	-44.6642	0.0220	0.0071
9. VTC	-0.0690	-0.4237	-59.7069	98.1012	11.4720	1.2310	13.2810	-22.5541	-23.7981	-0.0060	-0.0029
10. PPC	-0.1324	-0.2233	-52.1184	46.4305	7.7628	0.1161	10.9831	-15.3475	-20.7653	-0.0171	-0.0064
11. GRS	0.2656	-0.6084	-86.8552	138.1051	15.4041	1.4635	14.4054	-29.9264	-29.6813	0.0172	0.0089

This table reports summary statistics for the eleven sampled cryptocurrencies' returns (expressed in percentages). The last four columns report value-at-risk (VaR), modified VaR, Sharpe and modified Sharpe ratios, respectively, for each of the cryptocurrencies. Both VaR measures are expressed as percentages. The sample period is from April 28, 2014 until May 15, 2020 (1,580 daily observations) for all the sampled cryptocurrencies.

Table 3

Correlation matrix between cryptocurrency returns

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. BTC	---	0.3751	0.6236	0.4934	0.3969	0.4653	0.5059	0.3245	0.3501	0.4995	0.2344
2. XRP	0.3751	---	0.3779	0.2557	0.3296	0.3095	0.3244	0.2170	0.2599	0.3057	0.1324
3. LTC	0.6236	0.3779	---	0.4455	0.3116	0.3706	0.4044	0.2326	0.3075	0.5367	0.2282
4. DASH	0.4934	0.2557	0.4455	---	0.2638	0.3517	0.3551	0.2244	0.2866	0.3782	0.1787
5. DGB	0.3969	0.3296	0.3116	0.2638	---	0.3314	0.3466	0.3026	0.2861	0.2878	0.1989
6. MAID	0.4653	0.3095	0.3706	0.3517	0.3314	---	0.3566	0.2532	0.3069	0.3631	0.1833
7. NXT	0.5059	0.3244	0.4044	0.3551	0.3466	0.3566	---	0.2876	0.3510	0.3799	0.2036
8. RDD	0.3245	0.2170	0.2326	0.2244	0.3026	0.2532	0.2876	---	0.2071	0.2602	0.1464
9. VTC	0.3501	0.2599	0.3075	0.2866	0.2861	0.3069	0.3510	0.2071	---	0.3251	0.1726
10. PPC	0.4995	0.3057	0.5367	0.3782	0.2878	0.3631	0.3799	0.2602	0.3251	---	0.1920
11. GRS	0.2344	0.1324	0.2282	0.1787	0.1989	0.1833	0.2036	0.1464	0.1726	0.1920	---

This table reports the pairwise correlations between all the sampled cryptocurrencies' returns. The average pairwise correlation is 0.3163, while the minimum and maximum is 0.1324 and 0.6236, respectively. The sample period is from April 28, 2014 until May 15, 2020 (1,580 daily observations) for all the sampled cryptocurrencies.

Table 4
Fractional regression estimates

Cryptocurrency	Economic uncertainty factors (explanatory variables)							
	BANK_U	COM_U	DEF_U	FX_U	INF_U	MKT_U	TERM_U	VIX_U
1. BTC	-0.0202 (-0.33)	0.0796** (2.66)	0.0108 (0.69)	2.5519** (4.62)	-0.0018 (-0.19)	0.4030** (2.54)	0.0878** (4.42)	0.0938 (1.51)
2. XRP	0.0540 (0.90)	0.1270** (4.76)	0.0010 (0.06)	5.0050** (6.77)	-0.0090 (-1.07)	0.4581** (4.15)	0.1253** (5.06)	0.1526** (2.23)
3. LTC	-0.0341 (-0.73)	0.0990** (4.52)	0.0067 (0.65)	4.1929** (8.13)	-0.0002 (-0.02)	0.4647** (5.04)	0.0775** (3.13)	0.1891** (5.19)
4. DASH	0.0920 (1.03)	0.1283** (3.73)	-0.0022 (-0.13)	4.5785** (4.15)	-0.0152 (-1.34)	0.4439** (3.05)	0.1558** (6.89)	0.2418** (3.04)
5. DGB	0.4025** (3.31)	-0.0205 (-0.30)	0.0108 (0.26)	-3.4376** (-2.02)	-0.0438 (-1.64)	0.4266** (2.03)	0.1480** (6.48)	0.2162** (2.72)
6. MAID	0.0314 (0.56)	0.1844** (7.42)	-0.0071 (-0.58)	-0.3676 (-0.40)	0.0064 (0.91)	0.5481** (5.16)	0.1160** (5.37)	0.1796** (2.69)
7. NXT	0.0936 (1.40)	0.2034** (7.69)	-0.0103 (-0.72)	-1.2163 (-1.36)	-0.0069 (-0.89)	0.6208** (7.51)	0.1146** (5.34)	0.1920** (4.46)
8. RDD	0.3981** (3.07)	0.1705** (2.24)	-0.0206 (-0.80)	-6.7560** (-2.20)	-0.0129 (-0.99)	0.6044** (3.95)	0.1693** (7.07)	0.2337** (2.40)
9. VTC	0.2738** (3.24)	0.1475** (4.35)	-0.0182 (-1.03)	-0.1487 (-0.10)	-0.0067 (-0.70)	0.4704** (3.94)	0.1414** (6.04)	0.0024** (3.05)
10. PPC	0.2002** (3.41)	0.0654** (2.46)	-0.0310** (-2.50)	3.6695** (5.81)	-0.0122 (-1.65)	0.5678** (4.68)	0.0692** (3.65)	0.1703** (2.55)
11. GRS	0.1033 (1.39)	0.0092 (0.16)	-0.0402** (-2.45)	3.4037** (3.10)	-0.0103 (-1.27)	1.0134** (9.10)	0.0681 (1.71)	0.1982** (3.89)
% of $t \geq 1.96$	36%	82%	0%	55%	0%	100%	91%	91%
% of $t \leq -1.96$	0%	0%	18%	18%	0%	0%	0%	0%
% insignificant	64%	18%	82%	27%	100%	0%	9%	9%

This table reports coefficient estimates of the fractional regression model whereby, for each respective cryptocurrency, optimal minimum-variance weights serve as the dependent variable and each of the aforesaid economic uncertainty factors serve as explanatory variables. For the sake of brevity, the intercept term is not reported. Parameter estimates for TERM_U and VIX_U are dilated by (×1,000) and (×100), respectively, for presentation purposes. Test statistics are in parentheses while (*) and (**) denote significance at the 5% and 1% levels, respectively. The last three rows summarize the percentage of cases where coefficients are significantly positive or negative, or statistically insignificant, respectively. The sample period is from April 28, 2014 until May 15, 2020 (1,580 daily observations) for all the sampled cryptocurrencies.