Should stock investors include cryptocurrencies in their portfolios after all?

Evidence from a conditional diversification benefits measure

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Abstract

Higher media coverage and stronger investor interest in cryptocurrency market may create closer linkages with traditional assets, leading to deteriorated diversification benefits. Cryptocurrencies have recently emerged as an alternative digital asset class; however, very little is known about their portfolio performances. In this study, we investigate the time-varying investment benefits of cryptocurrencies for stock portfolios using a correlation-based Conditional Diversification Benefits (CDB) measure. We construct six portfolios consisting of cryptocurrencies, developed and emerging equity markets and find that the time-varying correlations between cryptocurrencies and stock markets are generally low. However, the level of correlations significantly increases in turbulent periods, such as Brexit referendum and Coincheck hack. The dynamic CDB measures suggest that adding cryptocurrencies to equity market portfolios enhances portfolio diversification; however the benefits of diversification have diminished after late 2017. Our results offer significant insights and potential implications for market participants.

Keywords: Cryptocurrencies; Diversification; Portfolio Optimization; Dynamic conditional correlation (DCC); Dynamic equicorrelation (DECO)

JEL Codes: C32, G11

1. Introduction

Cryptocurrencies are decentralized digital assets designed to work as a medium of exchange based on blockchain technology.[1] Their main characteristics are the lack of central authority and physical representation. The crypto market has grown in popularity in recent years and become a part of the investment universe. A great attention has been paid by retail investors, traders as well as policy makers and other stakeholders. Bitcoin prices have climbed from few cents to nearly US$13,000, its market value have reached to US$235 billion and the total market value of cryptocurrencies has increased up to US$360 billion by June 2019. The rapid growth of cryptocurrencies, along with significant investor and media attention, has naturally attracted

[1] We use the terms 'cryptocurrencies', 'digital currencies' and 'virtual currencies' interchangeably in this paper.

interest from scholars. However, the existing literature on virtual currencies' empirical characteristics and possible benefits for market participants is still very scarce.

Roughly speaking, the literature on cryptocurrencies, mostly on Bitcoin, can be divided in two major strands. The first strand of the literature includes studies analyzing the empirical properties and stylized characteristics of virtual currency time series. As stated in Phillip et al. (2018), new researches provide evidence of many diverse stylized facts of Bitcoin including long memory and heteroscedasticity. Several papers investigate the informational efficiency of Bitcoin through a battery of statistical tests and find evidence of market inefficiency or weak efficiency (Urquhart, 2016; Bariviera, 2017; Nadarajah and Chu; 2017; Bouri et al., 2019). Some studies explore the volatility dynamics and show that Bitcoin volatility displays conditional heteroscedasticity and asymmetric effects (Chu et al., 2017; Katsiampa, 2017; Baur and Dimpfl, 2018).[2]

The second strand of the literature consists of papers that focus on safe haven potential, hedging and/or diversification abilities of cryptocurrencies. After devastating global financial crises witnessed over the last decade, investors have turned to alternative investments that can provide diversification benefits (Briere et al, 2015). The digital coins have increased investors' appetite due to their high returns and low correlation with traditional assets. A large amount of studies analyzes whether Bitcoin acts as a safe haven or hedge for different investment assets and finds that Bitcoin has hedge and safe haven properties depending on the market and time period (see among others, Dyhrberg, 2016a; Dyhrberg, 2016b; Bouri et al., 2017; Selmi et al., 2018; Urquhart and Zhang, 2019; Charfeddine et al., 2019; Stensas, 2019). Corbet et al. (2018) investigate the dynamic linkages between cryptocurrencies (Bitcoin, Ripple and Litecoin) and some financial assets. Their results show that the cryptocurrencies are isolated from financial assets and hence they may provide diversification benefits. However, the linkages are time-varying, reflecting external economic and financial shocks may adversely affect these benefits.

There is a voluminous body of theory and evidence on the portfolio performance of alternative investment vehicles. For instance, a large number of studies have been devoted to analyze diversification benefits of commodities and cited mixed results. Some studies suggest that adding commodities to conventional portfolios increases diversification benefits (Gorton and Rouwenhorst 2006; Conover et al., 2010; Demiralay et al., 2019) while some others find contrasting evidence mainly due to the increased financialization of commodity futures (Daskalaki and Skiadopoulos, 2011; Silvennoinen and Thorp, 2013; Büyüksahin and Robe, 2014). There is also growing research investigating the potential of artworks as an alternative investment asset. Renneboog and Spaenjers (2013) find that the risk-return profile of artworks is much less attractive than that of financial assets while Kraeussl and Logher (2010) and Skinner and Jackson (2019) highlight some possible benefits of investing in art markets.

[2] Note that the literature cites mixed results regarding the existence of asymmetric return-volatility relationship on cryptocurrencies. In a recent study, Charles and Darne (2019) show that more robust estimator proposed by Bollerslev and Wooldridge (1992) does not produce any statistically significant leverage parameter.

The low degree of co-movements between cryptocurrencies and conventional assets has been documented by some previous studies (see, for example, Ji et al., 2018; Corbet et al., 2018; Kurka, 2019). Given the low level of interlinkages and distinct characteristics of the digital currencies, investors may reap the potential benefits of diversification. Platanakis and Urquhart (2019a) examine the investment benefits of Bitcoin in a traditional portfolio, using different asset allocation strategies and find that it generates substantially high risk-adjusted returns. Symitsi and Chalvatzis (2019) assess the performance of Bitcoin within portfolios of different asset classes and provide evidence of significant diversification benefit from its inclusion. However, they further note that the benefits can deteriorate in non-bubble periods with less extreme market conditions. Using a CVaR model, Eisl (2015) and Kajtazi and Moro (2019) suggest that adding Bitcoin significantly improves the portfolio performance. Guesmi et al. (2019) show that Bitcoin can provide diversification and hedging benefits for investors. Note that the majority of prior researches focuses solely on Bitcoin, ignoring the other cryptocurrencies.

As suggested by Bouri et al. (2019), Bitcoin has lost most of its dominance in the cryptocurrency market and investors have started to consider other cryptocurrencies as digital investment vehicles. It is also important to note that there exist some considerable differences among cryptocurrencies in terms of usage and hash algorithms. For example, most cryptocurrencies make use of a different Proof-of-Work (POW) algorithm; Bitcoin is based on a hash algorithm called SHA-256, Monero uses CryptoNight, and Ethereum uses Ethash. Ripple is focused on cross-border payments while Ethereum is mostly used for smart contracts. In addition, their supply mechanism is different; currently around 18 million bitcoin and 20 billion stellar are in circulation. Given all these differences, it is important to analyze whether a single cryptocurrency is an ideal candidate for investors to achieve an optimal asset allocation strategy.

Some recent researches have begun to explore whether different cryptocurrencies add value to an investment portfolio. For example, Dorfleitner and Lung (2018) assess the diversification benefits of various cryptocurrencies, employing mean–variance spanning tests. Their results show that virtual currencies yield significant diversification benefits mostly due to an increase in portfolio returns, not a reduction of risk. In a more recent paper, Brauneis and Mestel (2019) examine risk-return benefits of cryptocurrency-only portfolios using data of the 500 most capitalized cryptocurrencies. They find substantial potential for risk reduction in mixed portfolios. Liu (2019) investigates portfolio diversification across ten major cryptocurrencies and shows that diversification among the cryptocurrencies considerably improves Sharpe ratio and utility.

As it is seen, the majority of previous scholarly work analyzes the investment characteristics and diversification benefits of Bitcoin; the existing literature on Bitcoin is even in its infancy though. The investment potential of other digital currencies is still understudied. As stated by Symitsi and Chalvatzis (2019), given the recent events, such as the growing number of crypto funds and increasing institutional investment in cryptocurrency markets, more extensive research is needed in the field. In this regard, we explore the time-varying diversification benefits of eight largest cryptocurrencies for developed and emerging market equity portfolios, using a novel method, called Conditional Diversification Benefits (CDB) measure proposed by Christoffersen et al. (2014). To the best of our knowledge, this is the first paper that quantifies the diversification benefits of various cryptocurrencies in a dynamic framework.

Our empirical methodology has several steps. First, we estimate the conditional correlations between cryptocurrencies and stock returns at equilibrium using the dynamic equicorrelation (DECO) model of Engle and Kelly (2012) which allows us to estimate the large variance–covariance matrices with ease. We construct six hypothetical portfolios consisting of virtual currencies and equity markets. We find low level of equicorrelations between cryptocurrencies and stock markets until late 2017; however, the co-movements have significantly increased thereafter, implying that the diversification benefits may diminish over time.

Secondly, we employ the dynamic conditional correlation (DCC) model of Engle (2002) to estimate the pairwise conditional correlations that are the inputs for the CDB quantification. Note that in both DECO and DCC estimations, we conduct the EGARCH model as the univariate volatility model. The DCC model enables the comparison of the correlation levels for individual asset pairs rather than portfolios. The overall results from the DCC model suggest that the bivariate conditional correlation are generally low fluctuating between -0.1 and 0.1, indicating possible diversification benefits of cryptocurrencies.

Finally, we quantify the diversification benefits of cryptocurrencies across both developed and emerging equity markets using the CDB measure based on the time-varying optimal portfolio weights and the correlations from the DCC model. The CDB results provide evidence of diversification benefits for portfolios including cryptocurrencies. However, the benefits are time-varying and highly responsive to external events, such as government bans on cryptocurrency operations. Our findings suggest that adding cryptocurrencies to a stock portfolio is still beneficial from the perspective of the correlation-based CDB measure despite of the increasing co-movements between digital currencies and equity markets. Therefore, cryptocurrencies can be regarded as alternative investment vehicles for portfolio optimization. Our results further indicate that NEM is always included in the optimal CDB portfolios with the highest average allocation among the cryptocurrencies.

Our study contributes to the growing literature of cryptocurrencies in several important ways. First, we provide an in-depth analysis of diversification benefits from adding cryptocurrencies to stock portfolios. The investor attention in cryptocurrency markets has significantly increased over the last years and our results provide potential insights and implications for investors. Second, we believe that it is of particular importance to analyze diversification benefits of single cryptocurrencies, as they differ in terms of size, usage and mining techniques. As stated earlier, a vast majority of the previous studies considers only Bitcoin and the portfolio performance of other cryptocurrencies remains extremely understudied. Third, we explore the diversification benefits in a dynamic framework, which gives further insights for investors. Given the cryptocurrency-related events and political turmoil witnessed in the last years, the investment performance of cryptocurrencies can exhibit state-dependent characteristics.

The rest of the paper is organized as follows: Part 2 explains the methodology, Part 3 presents the summary statistics, Part 4 presents and discusses the empirical results, and finally Part 5 concludes.

2. Methodology

Portfolio optimization requires a rigorous process of estimating the variance-covariance matrix of the assets. Constant covariance matrix calculated by using equally weighted historical returns has been widely used among researchers and practitioners for a long time. However, the assumption of constant variance-covariance matrix may be too restrictive to fit in with reality since time-varying volatility behavior of most financial time series challenges the simplicity of this approach. Dynamic multivariate volatility models produce variance-covariance matrices for portfolio optimization problem. In this study, we employ dynamic conditional correlation (DCC) and dynamic equicorrelation (DECO) models to capture the time-varying correlations among the cryptocurrency and stock market returns. We further assess diversification potential of cryptocurrencies in stock portfolios utilizing Conditional Diversification Benefits (CDB) measure introduced by Christoffersen (2014).

2.1. DCC-GARCH Model

The DCC-GARCH model of Engle (2002) is estimated in two steps. In the first step univariate GARCH models are fitted to each return series, and, in the second stage, residuals, transformed by their standard deviation, are used to estimate the coefficients of the dynamic correlations.

Let $r_{i,t}$ represents the colon vector of stock market and cryptocurrency returns in an n asset portfolio and follows an AR(1) process;

$$r_{i,t} = \mu_i + \kappa r_{i,t-1} + z_{i,t} \tag{1}$$

The AR(1) filtered returns, $z_{i,t}$, from the Eq.(1) are normally distributed with zero mean such that;

$$z_{i,t}|I_{t-1}\ N(0, H_t) \tag{2}$$

where H_t is the conditional variance matrix with I_t showing the information set up to time $t-1$.

The idea of the DCC-GARCH model is that the covariance matrix, H_t , can be decomposed into conditional standard deviations, D_t, and a correlation matrix, R_t, which are designed to be time-varying.

$$H_t = D_t R_t D_t \tag{3}$$

where, D_t is a nxn diagonal matrix having conditional standard deviations $\sqrt{h_{i,t}}$, on its diagonals, and R_t is dynamic correlation matrix (off-diagonal elements). To calculate the conditional variances, $h_{i,t}$ for assets we use EGARCH(1,1) model (Nelson,1991). The model is expressed as;

$$\ln(h_t) = \omega + \beta \ln(h_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \frac{2}{\pi}\right] \tag{4}$$

Since the logarithm of conditional variance $\ln(h_t)$ is modeled, even if the parameters are negative, h_t will be positive. The α parameter represents a magnitude effect or the symmetric effect of the model. β measures the persistence in conditional volatility. The γ parameter measures the asymmetry or the leverage effect, the parameter of importance so that the EGARCH model allows for testing of asymmetries. If $= 0$, then the model is symmetric. When < 0 , then negative shocks (bad news) generate more volatility than positive shocks (good news) of the same magnitude. When > 0 , it implies that positive shocks are more powerful on the conditional volatility than negative shocks.

The conditional standard deviations $\sqrt{h_i, t}$ is expressed by diagonal matrix D_t as:

$$D_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 \\ 0 & 0 & \cdots & \sqrt{h_{nn,t}} \end{bmatrix} \tag{5}$$

The standardized residuals from the Eq.(4), $\frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}$, are further used for estimating time-varying correlation matrix R_t. The correlation matrix R_t has to be positive definite in order to ensure the positive definiteness of H_t. Furthermore, all correlation coefficients must be bounded from -1 to 1. Thus the correlation matrix of the standardized residuals must be decomposed as;

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{6}$$

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 \\ 0 & 0 & \cdots & \sqrt{q_{nn,t}} \end{bmatrix} \tag{7}$$

where Q_t^* is the diagonal matrix of its diagonal elements as shown in Eq.(6). Q_t is a positive definite matrix that determines the construction of dynamics and Q_t^{*-1} normalizes the elements in Q_t.

In the formulation of DCC model, the dynamics of Q_t is characterized with the cross-products of the return shocks:

$$Q = (\mathbb{1} - a - b)\overline{Q} + a\varepsilon_{t-1} - \mathbb{1}\varepsilon'_{t-1} + bQ_{t-1} \tag{8}$$

with $\overline{Q}$ representing the unconditional covariance matrix of the standardized error terms and a and b are constant coefficients.

The estimation of the parameters of H_t, $\theta = (a, b)$ can be achieved by maximizing the log-likelihood function given as:

$$\mathbb{L}(\theta) = -\frac{1}{2}\sum_{i=1}^{T}\{n\log(2\pi) + 2\log(|D_t|) + \log(|R_t|) + \varepsilon_t' R_t^{-1}\varepsilon_t\} \quad (9)$$

2.2. DECO-GARCH Model

Engle and Kelly (2012) introduced the DECO model as a special case of the DCC model. It also involves a two-step estimation process. Similarly, to the DCC model, conditional variances and standardized residuals are computed using a univariate GARCH model and then conditional correlations are obtained. Contrary to the DCC model, the DECO model assumes that all pairwise correlations are equal on a given time period. This hypothesis seems to be restrictive since some markets tend to have higher cross-correlations. However, equal correlation assumption also contributes strongly to ease the computational complexity for higher dimensional portfolios. Although, the correlations are assumed to be equal contemporaneously across all the assets, they are still time-variant. Therefore, in the equicorrelated model the conditional correlation matrix can be written as:

$$R_t = (1 - \rho_t)\mathbb{I}_n + \rho_t \mathbb{1}_n \quad (10)$$

where $\mathbb{I}_n$ is the n-dimensional identity matrix and $\mathbb{1}_n$ is a nxn matrix of ones. ρ_t represents the scalar equicorrelation computed as the average of the $n(n-1)/2$ DCC correlations at time t:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}(\mathbb{1}' R_t^{DCC}\mathbb{1} - n) = \frac{2}{n(n-1)}\sum_{i>j}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \quad (11)$$

where $q_{ij,t}$ is the $(i,j)^{th}$ element of the matrix Q from the DCC model. This assumption of equicorrelation leads to a much simpler and computationally inexpensive log-likelihood function:

$$\mathbb{L} = -\frac{1}{T}\sum_{t=1}^{T}\left\{\log([1-\rho_t]^{n-1}[1+(n-1)\rho_t) + \frac{1}{1-\rho_t}\left(\sum_{i=1}^{n}\varepsilon_{i,t}^2 - \frac{\rho_t}{1+(n-1)\rho_t}\left(\sum_{i=1}^{n}\varepsilon_{i,t}\right)^2\right)\right\}$$
(12)

Note that, when n increases, it is relatively easy to maximize the log-likelihood function corresponding to the correlation component of the DECO model.

2.3. Conditional Diversification Benefits

It is realistic to analyze time-varying diversification benefits given the dynamic correlations between assets. To this end, we follow the methodology introduced by Christoffersen et al. (2014). CDB measure allows us to compute optimal asset weights in portfolio optimization and to examine time-varying behavior of investment benefits. Quantifying the correlation-based diversification benefits offers a very realistic and practical approach. The CDB methodology given by Christoffersen et al. (2014) is outlined in the following stages:

The portfolio variance $V(r_p)$ is a combination of the equally weighted average covariance of the single asset returns.

$$V(r_p) = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,t}\, w_{j,t}\rho_{ij,t}\rho_{ij,t}\sqrt{h_{i,t}}\sqrt{h_{j,t}} \tag{13}$$

Let volatility is time-dependent and same across assets such that; $\sqrt{h_{i,t}} = \sqrt{h_{i,t}}\forall i, j$

Let $V(r_{A,t}) = V(r_{i,t})V(r_{j,t})$ represents asset volatility. Therefore:

$$V(r_p) = V(r_A)\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,t}\, w_{j,t}\rho_{ij,t} \tag{14}$$

and,

$$\frac{V(r_{p,t})}{V(r_{A,t})} = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,t}\, w_{j,t}\rho_{ij,t} \tag{15}$$

We minimize the variance ratio in Eq.(15) by changing dynamic weights $w_{i,t}^{*}$ subject to $\sum w_{i,t}^{*} = 1$ and $w_{i,t}^{*} \geq 0$. Dynamic conditional correlation based diversification benefits can be computed as;

$$CDB_t = 1 - \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,t}^{*}\, w_{j,t}^{*}\rho_{ij,t} \tag{16}$$

The CDB measure calculated by the correlations generated from the DECO model, where all pairwise correlations are identical, can be expressed as

$$CDB_t = 1 - \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,t}^{*}\, w_{j,t}^{*}\rho_{ij,t} = 1 - \rho_t \tag{17}$$

3. Summary Statistics

The dataset used in our study includes daily closing prices from eight developed countries (Australia, Canada, France, Germany, Italy, Japan, UK, and U.S), eight emerging countries (Brazil, China, India, Indonesia, Mexico, Russia, South Korea and Turkey), and eight cryptocurrencies (Bitcoin, DASH, Ethereum, Litecoin, Monero, NEM, Stellar and Ripple).[3] The stock market data is retrieved from investing.com and the data for cryptocurrencies is downloaded from https://coinmarketcap.com/. The study period is from August 7, 2015 to June 21, 2019.[4] The returns for both stock markets and cryptocurrencies, ri_t, are the continuously compounded rate of return and calculated as $r_t = 100 \times \log(P_t / P_{t-1})$, where Pt is price at time t.

Table 1 presents the summary statistics for the daily returns. The relevant statistics demonstrate that the average return is quite low for equity markets. It ranges between -0.014% and 0.035% for the developed markets and between -0.007% and 0.084% for the emerging markets. The daily mean return for cryptocurrencies ranges from 0.159% to 0.685%, indicating that the average returns of the cryptocurrencies are much higher than those of the equity markets. The standard deviation statistics show similar risk profiles in stock markets over the sample period with the highest value of 1.611% for Russia and the lowest value of 0.724% for Canada. The standard deviations are much higher for cryptocurrencies ranging from 4.175% for bitcoin to

[3] We use the national stock indices prices in USD currency for both developed and emerging markets.
[4] The selection of the data period is based on the data availability for Ethereum.

9.207% for NEM. Therefore, based on the risk-return profile, cryptocurrencies provide higher returns but possess higher risk.

Skewness and kurtosis statistics imply leptokurtic distribution of the daily returns for all the markets. The skewness values are negative for stock markets, showing a high likelihood of having negative returns during the study period. The cryptocurrencies exhibit positive skewness, except for Bitcoin. The kurtosis statistics are all greater than three, suggesting that the distributions display tails exceeding the tails of the normal distribution. The non-normality is also confirmed by Jarque-Bera test statistics.

We compute Box-Pierce statistics for both return and squared return series to test for serial correlation. The BP statistics on return series suggest autocorrelated returns in most of the cases. The serial correlation of the squared returns exhibits high dependence and shows potential presence of ARCH effects. The existence of conditional heteroskedasticity is also verified from the ARCH LM statistics. We also perform unit-root tests to check for stationarity. The ADF tests fail to reject the null hypothesis of non-stationarity for all return series. In overall, our initial analysis shows that market returns display some stylized facts of financial time series including non-normality, serial correlation and conditional heteroscedasticity. These statistical properties imply the appropriateness of GARCH-class modeling to investigate time-varying volatility for both equity markets and cryptocurrencies.

Table 1. Descriptive Statistics

	Mean	Median	Max.	Min.	Std. D.	Skew.	Kurt.	JB	BP	BP^2	ARCH	ADF
Developed Markets												
Australia	0.019	0.056	3.285	-4.176	0.828	-0.412	5.373	244.9[a]	26.229[a]	226.34	4.997[a]	-10.236[a]
Canada	0.021	0.063	2.897	-3.844	0.724	-0.418	5.74	318.4[a]	33.090[b]	708.660[a]	15.050[a]	-10.414[a]
France	0.006	0.037	4.232	-8.384	1.09	-0.697	8.948	1448.0[a]	17.249	162.382[a]	3.319[a]	-10.457[a]
Germany	0.013	0.065	4.852	-7.067	1.103	-0.454	6.141	436.055[a]	40.247[a]	269.356[a]	4.278[a]	-17.128[a]
Italy	-0.014	0.066	5.699	-13.331	1.416	-1.038	13.515	4456.2[a]	39.553[a]	99.262[a]	2.890[a]	-8.894[a]
Japan	-0.014	0.017	7.426	-8.253	1.332	-0.245	8.163	1043.5[a]	18.555	156.997[a]	4.283[a]	-10.017[a]
UK	0.014	0.047	3.515	-4.779	0.911	-0.203	5.767	303.4[a]	30.025[c]	498.899[a]	9.180[a]	-10.483[a]
US	0.035	0.049	4.777	-4.184	0.897	-0.528	6.821	609.5[a]	33.700[b]	328.069[a]	6.278[a]	-9.248[a]
Emerging Markets												
Brazil	0.084	0.102	6.387	-9.211	1.465	-0.203	5.339	218.6[a]	23.599	29.636[c]	1.167	-8.861[a]
China	-0.004	0.076	5.449	-8.873	1.384	-1.353	10.866	2684.1[a]	39.293[a]	318.513[a]	8.556[a]	-10.265[a]
India	0.042	0.048	3.625	-6.097	0.851	-0.469	6.758	581.9[a]	26.383	71.688[a]	3.802[a]	-9.243[a]
Indonesia	0.031	0.079	4.451	-4.088	0.907	-0.379	5.574	279.3[a]	37.071[b]	181.674[a]	3.269[a]	-11.141[a]
Mexico	-0.007	0.022	3.366	-5.988	0.89	-0.511	7.477	818.1[a]	55.624[a]	311.702[a]	8.560[a]	-9.637[a]
Russia	0.051	0.083	8.964	-12.153	1.611	-0.255	8.103	1020.4[a]	38.477[a]	121.213[a]	2.861[a]	-9.757[a]
S. Korea	0.03	0.072	3.536	-4.453	0.924	-0.41	4.681	135.7[a]	25.42	25.565	1.233	-9.532[a]
Turkey	0.019	0.027	5.255	-7.348	1.341	-0.267	5.142	189.0[a]	36.476[b]	50.136[a]	2.161[a]	-9.166[a]
Cryptocurrencies												
Bitcoin	0.265	0.278	22.512	-20.753	4.175	-0.212	7.969	964.6[a]	35.970[b]	118.571[a]	4.494[a]	-9.769[a]
DASH	0.21	-0.14	28.772	-24.323	5.896	0.348	6.6	521.6[a]	20.66	96.203[a]	3.068[a]	-8.628[a]
Ethereum	0.526	-0.149	41.234	-29.174	7.101	0.814	7.852	1016.0[a]	42.086[a]	218.578[a]	3.701[a]	-8.633[a]
Litecoin	0.159	-0.244	51.035	-39.515	6.144	1.268	15.238	6059.5[a]	30.641[c]	79.557[a]	3.475[a]	-9.523[a]
Monero	0.211	-0.126	45.163	-29.318	7.043	0.602	8.012	1030.7[a]	22.286	48.797[a]	2.024[a]	-8.559[a]

NEM	0.685	0.008	99.558	-35.316	9.207	2.147	21.285	13684.7[a]	24.867	29.294[c]	1.362	-8.098[a]
Stellar	0.176	-0.46	66.678	-36.636	8.045	1.46	14.549	5504.3[a]	42.369[a]	97.280[a]	3.720[a]	-9.005[a]
Ripple	0.334	-0.365	60.689	-61.627	7.463	1.266	19.498	10807.2[a]	45.842[a]	292.569[a]	11.572[a]	-7.994[a]

Notes: JB is the Jarque-Bera normality test. BP and BP^2 represent the Box-Pierce test statistics for serial correlation of 20^{th} lag on the raw and squared residuals, respectively. ARCH (20) is the Lagrange multiplier test of order 20 for heteroscedasticity. ADF is the augmented Dickey Fuller statistics to test for the presence of unit-root; it is tested with trend and intercept. (a), (b) and (c) denote the statistical significance at the 1, 5 and 10 per cent levels, respectively.

4. Empirical Results

4.1. DECO Model Results

As discussed earlier, the DECO model allows us to obtain a single dynamic correlation coefficient for a group of assets. The correlations derived from the DECO model can also reflect the integration process among different markets. In order to measure the level of equicorrelations, we form six hypothetical portfolios from a set of 8 cryptocurrencies, 8 emerging markets and 8 developed markets. Portfolio 1 only includes the developed markets (DM only), Portfolio 2 only has emerging markets (EM only) and Portfolio 3 only consists of cryptocurrencies (CC only). The other portfolios are mixed: Portfolio 4 combines both developed and emerging markets (DM & EM), Portfolio 5 incorporates cryptocurrencies and developed markets (CC & DM), and lastly, Portfolio 6 includes cryptocurrencies and emerging stock markets (CC & EM).

Table 2 reports the parameter estimates of the DECO model.[5] The autoregressive equicorrelation parameters *b* are all statistically significant at the 1% level, confirming that the equicorrelations display a dynamic behavior. The sum of the coefficients *a* and *b* is very close to unity in each portfolio, suggesting highly persistent correlations and very slow mean reversion. The average DECO coefficients, ρ_{DECO}, show that the developed markets have the highest level of co-movement. The inclusion of cryptocurrencies into the developed market portfolio substantially reduces the level of equicorrelations. It is also clear that emerging markets are potential diversifiers for developed market portfolios as the equicorrelation level decreases from 0.466 for Portfolio 1 to 0.309 for Portfolio 4. Furthermore, the combination of emerging markets and cryptocurrencies results in lower degree of equicorrelations. Overall, our DECO results suggest that including cryptocurrencies in stock portfolios can add value for equity investors.

Table 2. DECO Model Results

	ρ_{DECO}		a		b		Persistence
Portfolio 1: DM only	0.466[a]	(0.026)	0.029[a]	(0.011)	0.936[a]	(0.013)	0.965
Portfolio 2: EM only	0.244[a]	(0.021)	0.043[b]	(0.018)	0.873[a]	(0.057)	0.915
Portfolio 3: CC only	0.310	(0.191)	0.129[a]	(0.020)	0.869[a]	(0.022)	0.998
Portfolio 4: DM & EM	0.309[a]	(0.020)	0.040[a]	(0.014)	0.894[a]	(0.037)	0.934
Portfolio 5: DM & CC	0.155	(0.373)	0.022	(0.073)	0.978[a]	(0.095)	1.000
Portfolio 6: EM & CC	0.179[a]	(0.040)	0.035[b]	(0.015)	0.956[a]	(0.022)	0.991

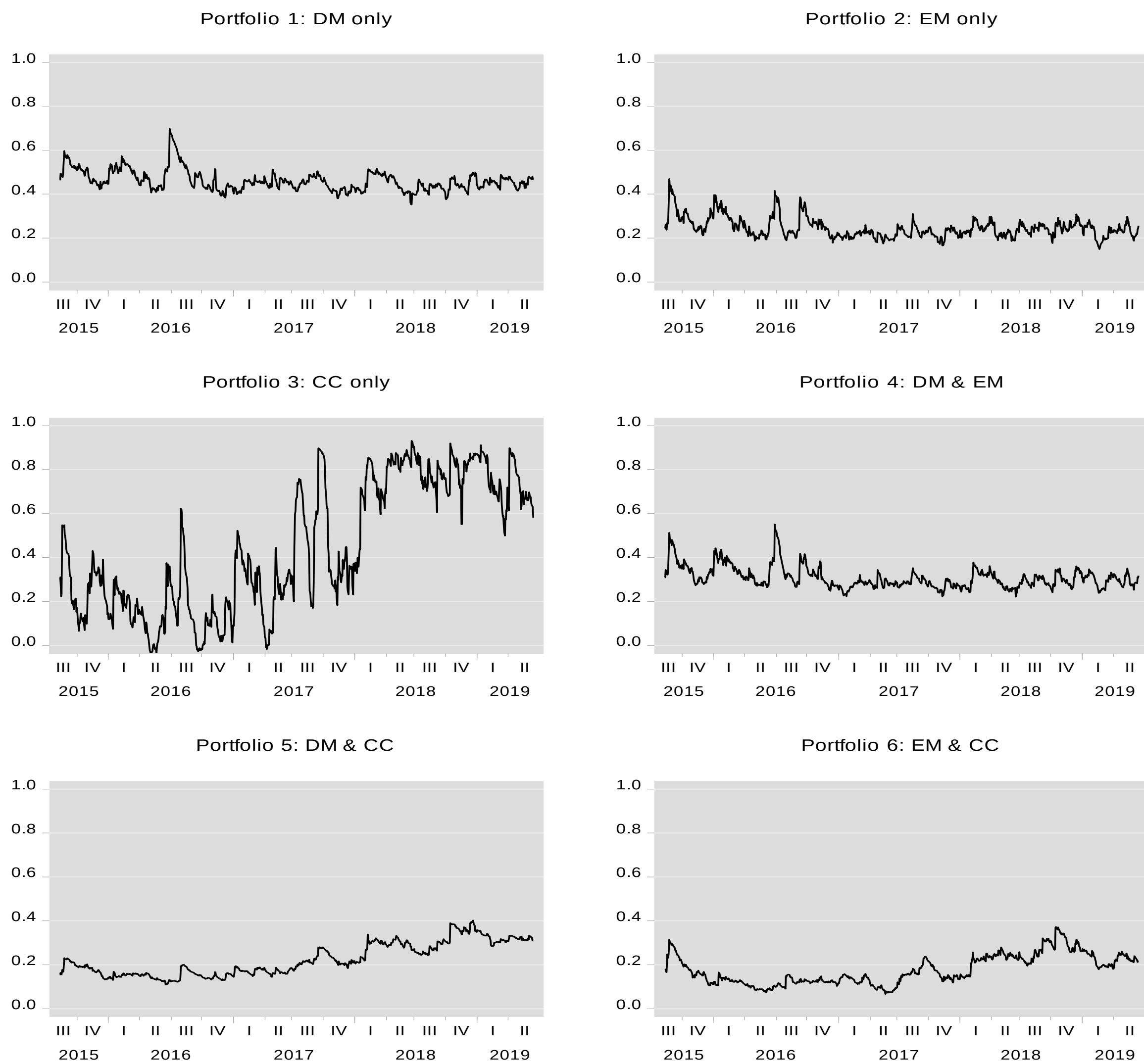
Notes: The values in the parentheses are robust standard errors. (a), (b) and (c) denote the statistical significance at the 1, 5 and 10 per cent levels, respectively.

Figure 1 displays the DECO levels over time for each hypothetical portfolio. The plots suggest a stable pattern in equicorrelations for developed (Portfolio 1) and emerging (Portfolio 2) market

[5] We applied Portmanteau tests of Li and McLeod and Hoskings on both raw and squared standardized residuals to check for autocorrelation. The tests suggest that the DECO models are correctly specified. For the sake of brevity, we do not include the test results in the paper, however they are available upon requests.

portfolios. For cryptocurrency portfolio (Portfolio 3), the estimated equicorrelations are highly volatile and display an upward trend over time. Portfolio 3 has the highest variation in the equicorrelations, ranging from a minimum of -0.04 to a maximum of 0.93. The strengthened equicorrelations imply increased integration of cryptocurrency markets over the last years, which confirms the recent findings of Ji et al. (2019), Kumar and Anandarao (2019) and Antonakakis et al. (2019).

Figure 1. Dynamic equicorrelations



Some news and events seem to have a strong impact on the equicorrelations among cryptocurrencies. The equicorrelations exhibit a sudden increase in June 2016 with Brexit referandum that caused rising global risk aversion. In addition, it is clear that hacker attacks, such as Bitfinex hack in August 2016 and Coincheck hack in January 2018, bring exogenous shocks to the cryptocurrency market, which raises security concerns and damages public confidence. The equicorrelations also display abrupt increases with Chinese and Indian governments' bans on cryptocurrency operations, sending negative information shocks to the market.

The co-movements in cryptocurrency markets are highly responsive to major events and news, confirming the studies of Yi et al. (2018), Katsiampa et al. (2019) and Antonakakis et al. (2019). We observe that the equicorrelations reach their peak during uncertainty periods, which can be explained by herding behavior among cryptocurrency traders. As stated by Baur and Dimpfl (2018) and Bouri et al. (2019), uninformed noise traders are very active in the cryptocurrency market. When uncertainty is high, traders tend to imitate trading strategies of other market participants, which leads to stronger market interlinkages (Ji et al., 2019). Thus, our results provide potential evidence of contagion as the equicorrelations significantly increase under market stress, which is in line with Kumar and Anandarao (2019). Furthermore, the equicorrelations considerably increase and stay at high levels after 2017. We argue that, apart from external shocks and events, surmounted trading activity in cryptocurrencies after 2017 has significantly contributed to stronger linkages across digital currencies.

The graphs for Portfolio 5 and 6 show heightened equicorrelations over time, suggesting increasing interlinkages between stock market and cryptocurrencies. The equicorrelations are higher during the aforementioned events. Nevertheless, it is clear that the level of equicorrelations for Portfolios 5 and 6 is lower than that of Portfolio 1 and 2 particularly from August 2015 till late 2017. This suggests that including cryptocurrencies in equity portfolios might provide diversification benefits; however, these benefits might have lessened for stock investors since early 2018.

4.2. DCC Model Results

Although the DECO modeling gives us a general picture of how the equicorrelations evolve over time for the asset combinations, analyzing the bivariate correlations between cryptocurrencies and equity markets is of pivotal importance for measuring diversification benefits since the bivariate correlation coefficient is a key input in portfolio optimization. In this section, we analyze the pairwise time-varying correlations between each cryptocurrency and equity market to have a further insight on the co-movement dynamics and hence potential diversification benefits. For this reason, we employ AR(1)-EGARCH-DCC (1,1) model to compute the cross-sectional differences in correlations.

Table 3 reports the average conditional correlations of each cryptocurrency with emerging and developed equity markets.[6] The average correlations are quite low and virtually zero, providing evidence of possible diversification benefits of cryptocurrencies for stock portfolios. Most of the

[6] Since presenting the bivariate correlation parameters is not feasible due to the large number of markets included in the study, we do not include the relevant results in the paper. Due to the same reason, we aggregate the correlation information and report only the average of the DCCs following Christoffersen et al. (2014). All the relevant findings are available upon request.

cryptocurrencies, except for Stellar and NEM, have higher average correlations with the developed markets, showing that cryptocurrencies are mostly better diversifiers for emerging market portfolio. DASH and Monero exhibit the highest correlation with developed and emerging markets, respectively, while NEM and Bitcoin have the lowest average correlations, correspondingly. This result shows heterogeneity of the cryptocurrencies in terms of co-movements with traditional equity investments, which is consistent with Corbet et al. (2018) and Bouri et al. (2019).

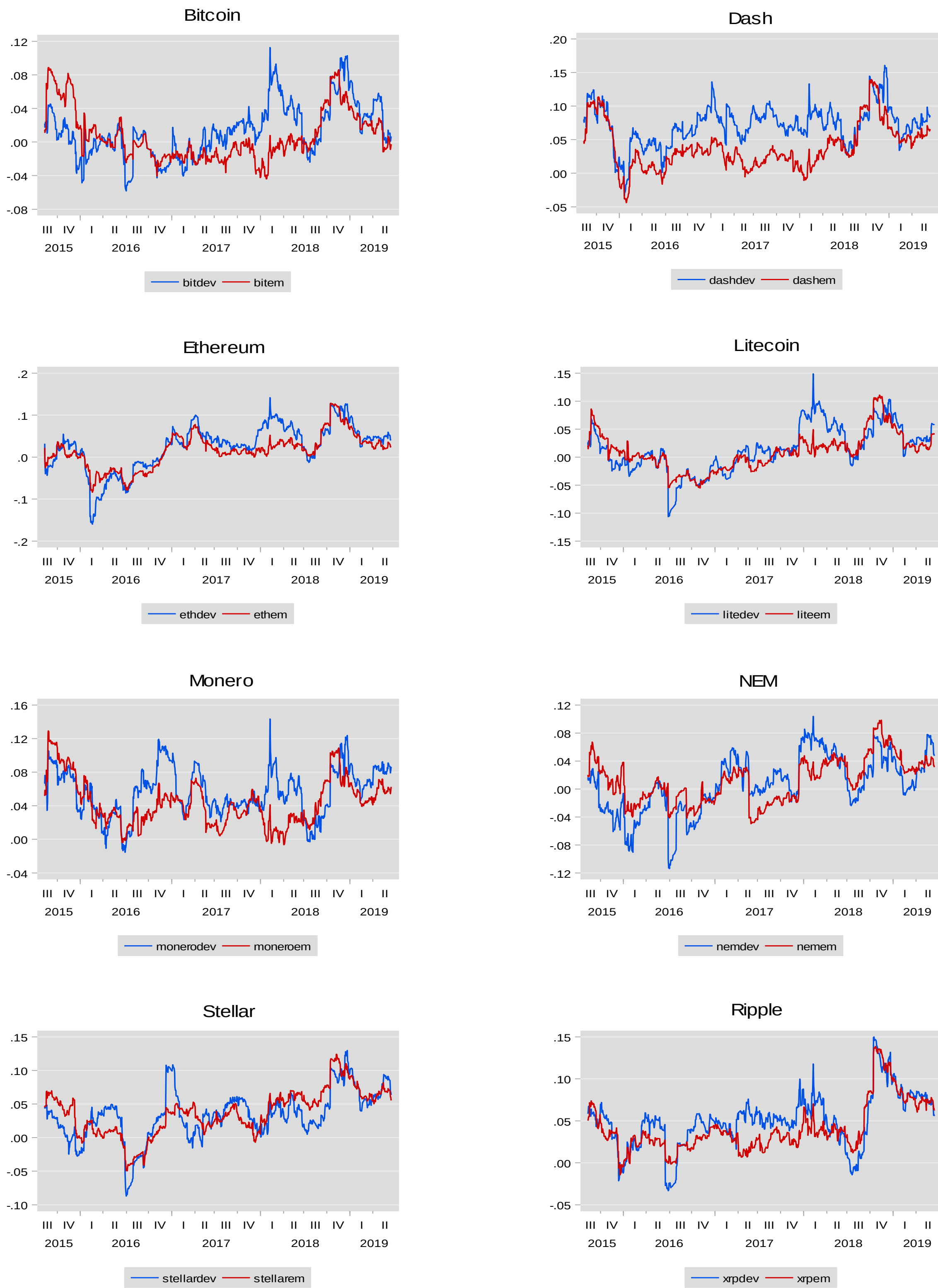
Table 3. Average Dynamic Conditional Correlations

	With Developed Markets	With Emerging Markets
Bitcoin	0.0129	0.0069
Dash	0.0727	0.0385
Ethereum	0.0251	0.0156
Lite Coin	0.0140	0.0097
Monero	0.0580	0.0435
NEM	0.0092	0.0119
Stellar	0.0353	0.0369
Ripple	0.0519	0.0411

The average conditional correlations give us an idea of the co-movements over the full sample period. However, it ignores the dynamic behavior of cross-correlations. Given the important news and incidences witnessed during the study period, it is vital to analyze cyclical movements in the dynamic correlations. Accordingly, Figure 2 plots the average dynamic correlations between cryptocurrencies and stock markets at each point in time. The blue and red lines represent the dynamic correlations of each cryptocurrency with developed and emerging markets, respectively.

The graphs yield some interesting conclusions. The correlations seem to be volatile and alternate between positive and negative values. This suggests that traders in cryptocurrency markets should not rely on the assumption of constant correlations when evaluating diversification benefits. Moreover, the average correlation with developed markets is higher than the average correlation with emerging markets, particularly after 2016, showing that cryptocurrencies and developed markets are more integrated.

Figure 2. Average Dynamic Conditional Correlations



We also notice different patterns in the average correlations in sub-periods. From the beginning of the sample period to March 2016, the market returns mostly decouple, leading to the loosening of the linkages between cryptocurrency and equity markets. In the second half of 2016, the levels of co-movement start increasing with Brexit. Afterwards, we observe heightened average correlations in the dependence structure. The dynamic average correlations display significant increases during 2017-2018, which coincides with cryptocurrency-related events, such as Chinese government cryptocurrency crackdown and Bitfinex's shutdown to fiat deposits. The correlations display a distinct spike in January 2018 when the biggest heists in history occurred; the Japanese exchange, Coincheck, suffered an attack, which costed it nearly 500 million NEM coins valued at about $550 million. This shows that cryptocurrency and stock markets recouple during stressful events, suggesting that diversification benefits offered by cryptocurrencies may deteriorate when the cryptocurrency market is exposed to negative shocks.

4.3. The CDB Results and Portfolio Statistics

This section documents and discusses the empirical findings from the CDB measure.[7] The plots in Figure 3 show the time-varying CDBs quantified with the optimal portfolio weights using the correlations generated from the DCC models. Comparing Portfolio 1 and 2, emerging markets offer higher diversification benefits than developed markets. Both portfolios give almost stable diversification benefits over the sample period. The benefits sharply decrease in Portfolio 1 in June 2016 when the Brexit referendum was voted upon. The benefits also decline in emerging markets but the level of benefits is still higher than in developed markets. The negative effect of Brexit on financial markets is also documented in Smales (2017), Ramiah et al. (2017) and Aristeidis and Elias (2018). When we combine emerging and developed markets in Portfolio 4, the level of diversification benefits is higher than Portfolio 1 and 2. Therefore, emerging markets still provide diversification benefits for stock investors.

Looking at cryptocurrency-only portfolio, Portfolio 3 indicates a decreasing trend in CDBs, consistent with the significantly increasing trend observed in DECOs in figure 1. The DECOs among cryptocurrencies have been increasing rapidly and as a result the CDBs have been decreasing over the last four years. The CDBs substantially decline after late 2017. We previously argued that increased trading activity in cryptocurrencies and external shocks, such as government bans on cryptocurrency operations, have significantly contributed to stronger linkages and deteriorated diversification benefits, as also stated by Antonakakis et al. (2019) and Yi et al. (2019). Portfolios 5 and 6 have a similar pattern like Portfolio 3; the benefits increase until late 2017 and then sharply decline until the end of the sample period. However, when adding cryptocurrencies into stock market portfolios, the diversification benefits are much higher than developed or emerging markets alone. This suggests that including cryptocurrencies in

[7] We test the robustness of the CDB results by estimating different multivariate GARCH models. More specifically, we conduct the BEKK-GARCH and the asymmetric DCC models and find that the patterns and trends in the time-varying correlations are very similar. We used the dynamic correlations generated from these MGARCH models in the CDB analysis. The qualitative results stay similar, which shows the robustness of our CDB findings. For the sake of brevity, we do not include the relevant results here; however, they are available upon request.

equity market portfolios significantly enhances portfolio diversification; however the benefits of diversification have lessened after late 2017.

Figure 3. Conditional diversification benefits

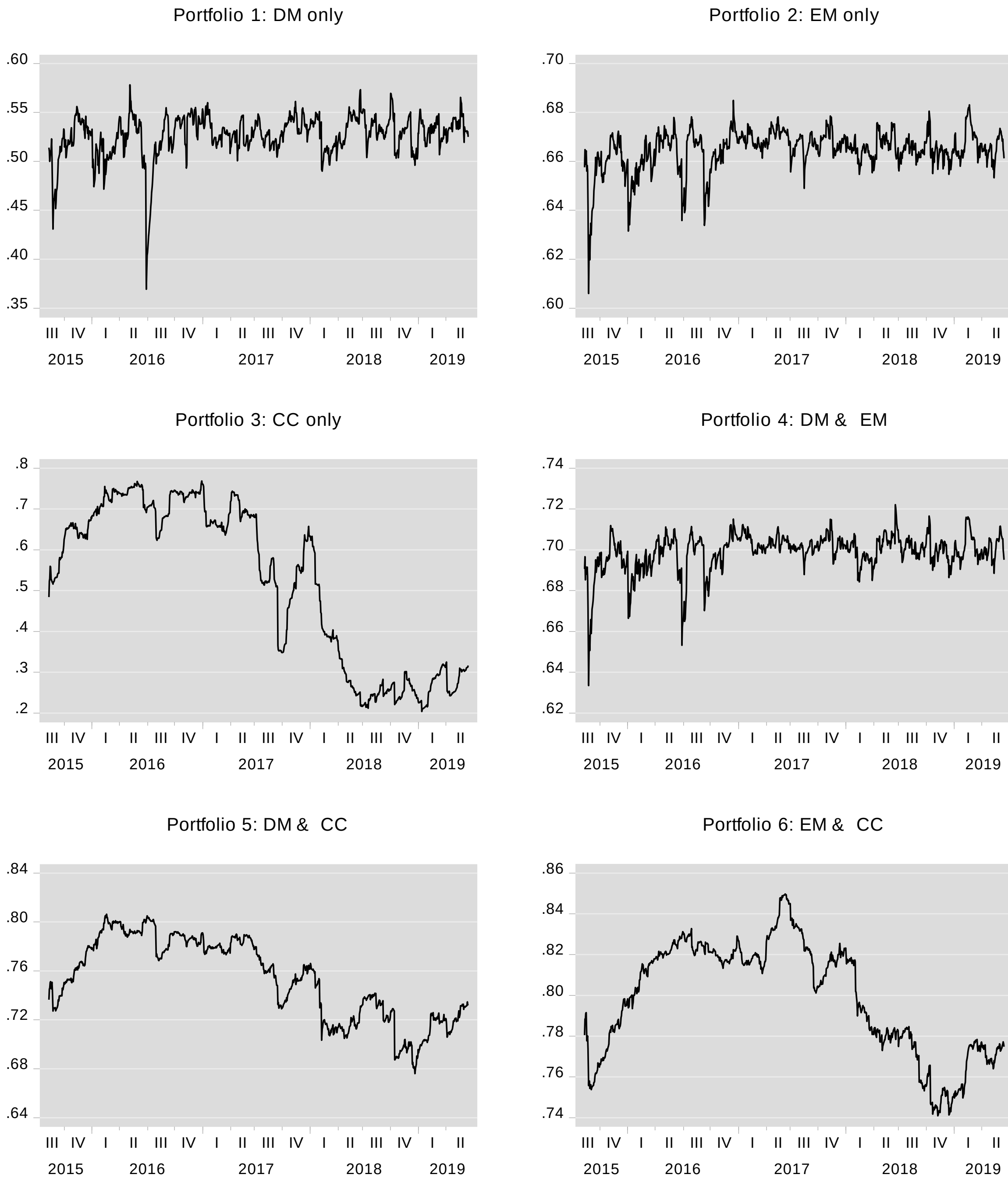


Table 4 reports the key statistics from the distribution of optimal weights for each market used to build the optimal portfolios. As suggested by Christoffersen et al. (2014), we allow for daily optimal weights changes; hence we create a distribution of weights over time for each market. Table 5 presents the average, minimum, maximum optimal weights over time and the fraction of days in which each asset has no allocation. In developed market portfolio (Portfolio 1), Italy and UK have zero allocation in at least 1 day over the sample period and France has almost zero allocation. Australia has the highest average allocation. Looking at Portfolio 2, emerging markets are very good investments from a correlation-based CDB perspective as they have no zero allocation. China has the highest mean allocation followed by Brazil. When we combine emerging and developed markets in Portfolio 4, UK and France have zero allocation virtually for the whole sample. The results for Portfolio 3 show that Bitcoin, Ethereum and Litecoin are not included in the cryptocurrency-only portfolio nearly in one-fourth of the sample period. NEM and Ripple have the highest average portfolio allocations.

Table 5. Statistics for CDB portfolio weights

	Mean	Min	Max	Fraction of zeros (%)
Portfolio1: DM Portfolio				
Australia	25.573%	20.616%	31.528%	0.000%
Canada	15.970%	10.967%	25.040%	0.000%
France	0.051%	0.000%	6.291%	97.637%
Germany	11.502%	3.384%	22.194%	0.000%
Italy	6.329%	0.000%	15.542%	1.504%
Japan	19.946%	14.234%	28.022%	0.000%
UK	7.134%	0.000%	16.063%	1.182%
US	13.495%	6.451%	20.465%	0.000%
Portfolio2: EM Portfolio				
Brazil	15.665%	13.101%	22.081%	0.000%
China	19.394%	17.318%	22.791%	0.000%
India	9.278%	6.225%	14.686%	0.000%
Indonesia	13.434%	11.124%	16.929%	0.000%
Mexico	9.158%	5.101%	13.792%	0.000%
Russia	9.903%	7.591%	15.278%	0.000%
South Korea	7.761%	4.795%	10.599%	0.000%
Turkey	15.407%	12.822%	18.861%	0.000%
Portfolio3: CC Portfolio				
Bitcoin	9.457%	0.000%	33.406%	25.564%
Dash	13.618%	0.000%	30.632%	2.256%
Ethereum	11.085%	0.000%	32.400%	22.986%
Litecoin	8.871%	0.000%	27.185%	22.986%
Monero	11.563%	0.000%	25.446%	2.900%
NEM	18.650%	4.027%	35.179%	0.000%

Stellar	10.268%	0.000%	30.824%	5.693%
Ripple	16.488%	1.786%	28.433%	0.000%
Portfolio4: DM & EM Portfolio				
Australia	12.505%	9.892%	16.965%	0.000%
Canada	3.428%	0.031%	8.862%	0.000%
France	0.008%	0.000%	3.431%	99.570%
Germany	3.388%	0.000%	8.249%	0.537%
Italy	3.827%	0.295%	9.195%	0.000%
Japan	6.847%	3.275%	11.509%	0.000%
UK	0.008%	0.000%	1.407%	98.067%
US	1.054%	0.000%	4.427%	18.475%
Brazil	13.928%	11.887%	20.129%	0.000%
China	15.448%	13.212%	19.342%	0.000%
India	2.797%	0.000%	6.325%	0.859%
Indonesia	11.236%	8.609%	14.961%	0.000%
Mexico	5.140%	0.434%	8.777%	0.000%
Russia	4.964%	1.986%	11.317%	0.000%
South Korea	1.170%	0.000%	4.973%	11.493%
Turkey	14.253%	12.001%	18.101%	0.000%
Portfolio5: DM & CC Portfolio				
Australia	14.057%	8.235%	23.267%	0.000%
Canada	7.521%	3.342%	13.261%	0.000%
France	0.353%	0.000%	6.633%	78.518%
Germany	4.645%	0.000%	13.686%	14.501%
Italy	3.308%	0.000%	13.412%	12.675%
Japan	10.663%	3.766%	14.642%	0.000%
UK	4.080%	0.000%	13.116%	9.989%
US	6.108%	0.000%	12.121%	0.215%
Bitcoin	5.350%	0.000%	15.806%	5.693%
Dash	2.716%	0.000%	8.856%	19.871%
Ethereum	7.928%	0.000%	19.978%	1.504%
Litecoin	5.956%	0.000%	12.464%	5.156%
Monero	5.269%	0.088%	9.592%	0.000%
NEM	9.626%	4.422%	14.818%	0.000%
Stellar	5.744%	1.181%	12.530%	0.000%
Ripple	6.675%	0.000%	12.144%	0.859%
Portfolio6: EM & CC Portfolio				
Brazil	8.235%	1.947%	14.209%	0.000%
China	11.161%	5.883%	16.125%	0.000%
India	6.911%	1.941%	14.659%	0.000%
Indonesia	8.273%	4.317%	13.425%	0.000%
Mexico	6.882%	3.170%	12.335%	0.000%
Russia	4.922%	0.494%	10.758%	0.000%

South Korea	3.537%	0.000%	7.311%	8.485%
Turkey	9.597%	6.268%	12.085%	0.000%
Bitcoin	5.215%	0.000%	14.549%	3.652%
Dash	3.701%	0.000%	11.336%	7.734%
Ethereum	6.565%	0.000%	16.890%	0.537%
Litecoin	4.945%	0.000%	11.710%	5.371%
Monero	3.200%	0.000%	6.868%	8.485%
NEM	8.595%	4.163%	12.383%	0.000%
Stellar	3.467%	0.000%	7.787%	4.082%
Ripple	4.795%	0.000%	9.607%	2.793%

The portfolio statistics for the combination of cryptocurrencies and developed markets in Portfolio 5 demonstrate that France is not included in the CDB portfolio in almost eighty percentage of the sample period. Germany, Italy, the US and the UK from the developed markets have a zero allocation in at least one day in the sample. From the cryptocurrency group, NEM and Monero are always added in the portfolio while the others have zero allocation in some part of the sample. Australia has the highest maximum allocation at 23.2%, followed by Ethereum (19.9%) and Bitcoin (15.8%). NEM has the highest average portfolio allocation. In Portfolio 6, South Korea, Monero and DASH have the largest fractions of days with zero weights in the sample. Ethereum has the highest maximum allocation and China has the highest average allocation. It is also clear that NEM is the best diversifier for both developed and emerging markets as it is always included in the CDB portfolios and has the highest average allocation among the cryptocurrencies.

In a nutshell, our results reveal that cryptocurrencies provide diversification benefits for equity markets despite of external shocks and market turmoil witnessed in recent years. However as seen in Figure 3, the benefits of diversification have declined after late 2017. The results reveal that the cryptocurrencies are heterogeneous digital coins in terms of diversification benefits; NEM seems to be the best diversifier with the highest average allocation and no fraction of days with zero weights while DASH (Monero) produces the least diversification benefits for emerging (developed) markets. The heterogeneity of cryptocurrencies as an investment class can be explained by their technical differences and unique usage characteristics as discussed before. The existence of diversification benefits offered by cryptocurrencies is consistent with the low correlation levels found in the bivariate DCC analysis. The low correlations mostly fluctuating between -0.1 and 0.1 can be related to the distinct factors that drive the equity and cryptocurrency prices apart. Standard equity pricing models suggest that stock prices are determined by future earnings (or dividends) and the discount rate. Unlike companies, cryptocurrencies neither have future earnings nor bear dividends. In one of the recent studies, Cong et al. (2019) show that the equilibrium value of digital coins can be determined by users' transactional demand rather than cash flows as in standard valuation models. Another study by Hayes (2017) finds three main determinants for the valuation of virtual currencies: the level of competition in the producer network, the rate of unit production, and the difficulty of algorithm. Therefore, cryptocurrency returns seem to be mostly related to idiosyncratic factors rather than exogenous factors. Taken together, distinct price dynamics of cryptocurrencies can reflect their diversification potential for stock portfolios.

As stated earlier, relevant studies mostly focus on the diversification benefits of bitcoin. This is one of the very few studies that explore the additional value of eight different cryptocurrencies for stock portfolios. Nevertheless, we compare our results with previous related works. The empirical results seem to be in line with the recent findings of Platanakis and Urquhart (2019b) and Platanakis et al. (2018) who show diversification potential of cryptocurrency portfolios. Platanakis and Urquhart (2019a) further find that the portfolio with Bitcoin performs much better than the traditional stock-bond portfolio even during the downturn in its price from January 2018, implying Bitcoin still offers diversification during price falls. This is consistent with our empirical finding that even if the diversification benefits provided by the digital coins have reduced since early 2018, portfolios including cryptocurrencies still offer higher benefits compared to the traditional stock portfolios as can be seen from the CDB plots. We further provide evidence of time-dependent diversification benefits of the digital currencies, which partly supports the results from Bouri et al. (2017) and Symitsi and Chalvatzis (2019) that document diversification potential of Bitcoin differed across time horizons.

5. Conclusion

According to the portfolio management theory, asset correlation is a key metric in portfolio optimization and it provides significant implications regarding asset allocation, hedging practices and risk management. The cross-correlation levels between financial markets have substantially increased over the last two decades, due to the extant crises, contagion effects and herding behavior of investors. Consequently, global investors have turned to alternative assets with a focus on cryptocurrencies as they usually exhibit lower linkages with conventional assets. In this paper, we examine whether the digital currencies are alternative investments for portfolio diversification. Our purpose is to better understand the performance of cryptocurrencies in terms of portfolio allocation and diversification benefits. In this regard, we analyze the time-varying diversification benefits of cryptocurrencies for equity portfolios, using a correlation-based CDB measure.

Our results address to several important points. First, employing the DECO model for the six hypothetical portfolios, we find that adding cryptocurrencies to equities decreases the level of the equicorrelations. However, some news and dramatic events, such as hacker attacks and governments bans on cryptocurrencies, seem to cause strengthened linkages. Second, analyzing the cross-sectional differences in the bivariate conditional correlations, we document that DASH and Monero (NEM and Bitcoin) exhibit the highest (lowest) correlations with developed and emerging markets, respectively, suggesting the heterogeneity of the cryptocurrencies in terms of interlinkages with stocks. Lastly, we examine the investment benefits of cryptocurrencies using a correlation-based CDB measure and show that the inclusion of virtual currencies in equity portfolios provides higher benefits than stock-only portfolios. However, the benefits from diversification have lessened after late 2017 with the increasing trading activity and some dramatic events. Our results suggest that NEM is always included in the optimal portfolios and it has the highest average allocation among the cryptocurrencies, therefore it should be always added in stock portfolios.

Although our findings provide significant insights and potential implications for investors, we note that the results should be interpreted with caution. First, as known, cryptocurrencies are far less liquid than stocks and the accessibility of cryptocurrencies to investors is still improving. Second, it is important to note that the CDB model is based on the conditional correlations computed from the daily historical correlations. We do not have an out-of-sample exercise, which would give further insights for market participants. Third, our results are only valid for stock portfolios and it would be interesting to explore the performance of the virtual currencies in portfolios consisting of bonds and commodities. All these open the doors for future studies. Despite some limitations, our study shows that cryptocurrencies constitute an emerging alternative asset class and their inclusion in portfolio allocation is beneficial to stock investors.

Data Availability Statement: The data that support the findings of this study are publicly available. These data were derived from the following resources available in the public domain:

For cryptocurrencies: https://coinmarketcap.com

For equity markets: https://www.investing.com/

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