Emerging Markets Review 56 (2023) 101054

Contents lists available at ScienceDirect

Emerging Markets Review

journal homepage: www.elsevier.com/locate/emr

Multivariate dynamics between emerging markets and digital asset markets: An application of the SNP-DCC model

Inés Jiménez [a,*], Andrés Mora-Valencia [b], Javier Perote [a]

[a] Department of Economics and Economic History and IME, Faculty of Economics and Business, Universidad de Salamanca, Campus Miguel de Unamuno (Edif. F.E.S.), 37007 Salamanca, Spain

[b] School of Management, Universidad de los Andes, Calle 21 No. 1-20, Bogotá 111711, Colombia

ARTICLE INFO

JEL classification:
C14
C58
F62
G15

Keywords:
Emerging markets
Digital markets
High-order moment spillover
SNP-DCC model

ABSTRACT

As crypto markets become more integrated, measuring their spillovers with financial markets becomes fundamental for portfolio choice and risk management. We investigate high-order moment transmission between emerging/developed and digital asset markets through a flexible semi-nonparametric approach that accounts for dynamic conditional correlation and spillover effects, not only in conditional volatility but also in conditional skewness and kurtosis. The results show a (positive) transmission of volatility from emerging and developed markets to digital asset markets, as a signal of market integration, but also some positive/negative skewness and kurtosis spillovers (remarkably from Crypto and Blockchain indices to Emerging Asia and Latin America indices) detected at daily and weekly basis.

1. Introduction

At the start of the 2008 financial crisis, Satoshi Nakamoto (Nakamoto, 2008) published the first article introducing a fully developed virtual currency: Bitcoin (BTC). It was no coincidence that the collapse of the world's banks would lead to this new paradigm where no central banks and financial institutions, which had played a controversial role during the crisis, are required. That was the beginning of a fast-growing burgeoning industry in market capitalization and countless new concepts that its development entails. Given its nature, through the Internet, this brand-new market appeared as a global one, accessible to anyone regardless of geographical location.

Bitcoin was launched as a new decentralized means of payment (no central banks or financial institutions are required to attest to the transactions replacing them with a blockchain platform). Other new cryptocurrencies have followed their lead. But the rapid growth of this industry not only led to consider 'the new digital money' but also its development has provided the inception of new technologies that go beyond means of payment.

In 2015, Ethereum (ETH) emerged as a cryptocurrency and an appealing new technology, enabling blockchain-based contracts including applications for non-financial and financial infrastructures with no intermediaries. That is the beginning of Decentralized Finance (DeFi), and several authors – see e.g., Harvey et al., 2021 – provide the advantages that DeFi may offer in contrast to the traditional financial system that can be displaced by this new bank concept in the future.

Nowadays, digital assets and platforms could represent a benefit for emerging and developed economies. For instance, digital

* Corresponding author.
E-mail addresses: inesjimenez@usal.es (I. Jiménez), a.mora262@uniandes.edu.co (A. Mora-Valencia), perote@usal.es (J. Perote).

https://doi.org/10.1016/j.ememar.2023.101054
Received 28 January 2022; Received in revised form 29 April 2023; Accepted 26 July 2023
Available online 29 July 2023

agriculture solutions have been provided useful in several African countries according to the UN Food and Agriculture Organization (FAO).[1] Moreover, Latin American countries – led by El Salvador – joint with several South Asian countries are experimenting with cryptocurrency platforms according to Chainalysis, a blockchain research company.[2] As a consequence, the benefits of the decentralized finance (DeFi) system are that users in emerging markets and developed economies are able to trade assets, saving deposits, and obtain loans.[3] Despite the above-mentioned advantages, the IMF warns that high volatility in cryptocurrency and digital asset prices may destabilize emerging market economies. Indeed, IMF's financial counselor, Tobias Adrian has recently argued[4] that "Officials believe sharp deleveraging episodes in cryptocurrencies are feeding into sell-offs in equity markets" and "The correlation between crypto and equity markets has been trending up strongly. Crypto is now very closely tied to what is happening in equities. We can't just dismiss it". For these reasons, a work that analyzes the interaction between digital assets and emerging markets (as well as developed markets), not only in volatility transmission but also high-order moment spillovers, may provide a deeper knowledge of its connection and alleviate concerns of investors, financial institutions, and regulators – especially in turbulent periods – allowing these participants to make better decisions in their respective areas.

In this regard, there are several salient studies concerning the modeling of conditional volatility either in a univariate setup (Corbet et al., 2018; Gkillas and Katsiampa, 2018; Stavroyiannis, 2018; Jiménez et al., 2022), or in a multivariate context (Aslanidis et al., 2019; Guesmi et al., 2019; Jiménez et al., 2020a). The volatility transmission with DCC-GARCH models has also been addressed (Fernández-Rodríguez and Sosvilla-Rivero, 2020; Gabauer, 2020), as well as the interdependence or volatility spillovers between cryptos (Jia et al., 2021; Qureshi et al., 2020), cryptos with different markets, including commodity markets, financial assets or even Forex markets (Bouri et al., 2018; Drozdz et al., 2019; Ji et al., 2019), between crypto exchanges from univariate and multivariate versions (Alexander et al., 2021). We should also not forget recent studies of Wang (2022) considering volatility spillovers with the new concept of NFTs and financial markets; the interconnectedness between the brand-new indices of the CBDC (Central Bank Digital Currency) Uncertainty Index and CBDC Attention Index linking digital currencies and financial variables with a DCC-GJR-GARCH model (Wang et al., 2022a); another Index of cryptocurrency environmental attention (ICEA) that may affect to uncertainty measures (Wang et al., 2022b) or the implications for the investor in a new cryptocurrency uncertainty index based on news coverage (Lucey et al., 2022), all of this underlines the importance of deep analysis the transmission related to the crypto industry.

Other related studies to conditional volatility in financial markets include higher-order moments such as conditional skewness and kurtosis and their spillovers (León et al., 2005; Del Brio et al., 2017; Hou et al., 2019; Ñíguez et al., 2019), comparatively, cryptocurrencies have few studies regarding higher order moments (Ahmed and Al Mafrachi, 2021; Jia et al., 2021).

In the latter framework, we exploit the flexibility of the semi-nonparametric with dynamic conditional correlation (SNP-DCC) model to investigate the performance of conditional volatility, skewness, and kurtosis and their spillover between the digital asset and emerging (developed) financial markets, which to the best of our knowledge has not been analyzed so far. A major advantage of this approach is its ability to parsimoniously approximate the multivariate distribution, admitting as many moments as necessary and accounting for the dynamic inter and intra relationships between the moment structures. Furthermore, the model is very tractable since a stepwise procedure for Maximum Likelihood (ML) estimation can be implemented to compute pairwise volatility, skewness, and kurtosis spillover effects (Del Brio et al., 2017).

For that purpose, we have considered daily returns on three indices that represent the market of the crypto industry and companies related to them, such as the Bloomberg Galaxy Crypto Index, Bloomberg Galaxy DeFi Index, and Bloomberg Future of Finance, and the three main emerging market indices: MSCI Emerging Markets Latin America Index, MSCI Emerging Markets Europe and MSCI Emerging Markets Asia Index.

To control for possible asynchrony biases a first-order moving average VMA(1) model is performed for daily returns. Additionally, to provide more robust results, larger time series of weekly data on three new digital indices are considered: CoinShare Blockchain Equity Index, Solactive FinTech Index, and Menai-MVIS Diversified Digital Assets Index. For these series (daily and weekly), volatility transmission was also controlled for general market uncertainty (proxied by the VIX index). Furthermore, to check potential differences between the spillovers of these indices and the emerging ones, we have also included developed markets considering the MSCI North America Index, MSCI Europe Index, and MSCI AC Asia Pacific Index in the analyses.

Concerning the analyzed data in our work, Umar and Gubareva (2020) employ a wavelet coherence measure and phase-difference based lead–lag relationship to examine the interdependence between the Bloomberg Galaxy Crypto Index and the Coronavirus Panic Index and identify high coherence and interdependence in mid of March 2020. As noted by Matkovskyy and Jalan (2019), the Bloomberg Galaxy Crypto Index plunged 10% caused to a decline in equity markets on October 11, 2018, and as a result a decline of 81% in 2018 (Anson, 2021). In addition, the authors analyze transmission between five equity markets (NASDAQ100, S&P500, Euronext100, FTSE100, and Nikkei225) and the Bitcoin markets by employing a regime-switching skew-normal model and find an increased transmission effect from financial markets to Bitcoin markets after the launch of Bitcoin futures. Though, works such as Bouri et al. (2017); Corbet et al. (2018); Giudici and Abu-Hashish (2019), did not find interdependence between Bitcoin and the financial

[1] How technology is driving change through the continent's food chain: Agriculture Businesses are using digital tools and best practices to transform the farming sector. By Golden Matonga. Financial Times; London (UK). 26 May 2022: 8.

[2] Bitcoin bond set for baptism of fire: Cryptocurrencies Analysts are skeptical about other countries following El Salvador's lead, by Patrick Mulholland. Financial Times. 21 Mar 2022: 8.

[3] Battle of the Blockchains, Anonymous. The Economist; London 442, N.9280, (Jan 22, 2022): 73–74.

[4] IMF warns gyrations in digital assets are 'destabilizing' emerging markets: Crypto by Flood, Chris. Financial Times; London (UK). 01 Feb 2022: 11.

market returns, other works support evidence of interdependence between equity and Crypto markets (Bouri et al., 2018; Umar et al., 2021).

An appealing result of Matkovskyy and Jalan (2019), is that the transmission effect is mainly due to co-skewness spillovers, which indicates an increasing integration between Bitcoin markets and financial markets. Therefore, it is relevant to a high-order interdependence analysis (beyond a volatility transmission) between the digital asset markets and traditional financial markets, and thus we include skewness and kurtosis spillovers in our study. Although there is still scarce literature on the relationship between emerging markets and the cryptocurrency industry, Bouraoui (2020) analyzes emerging countries (those with restricted access to bank systems) showing a significant impact on Bitcoin trading volume, at least in the short run.

As a result, our work indicates, in general, that emerging and developed markets are the main transmitters of volatility to the digital asset markets, but also that there are also skewness and kurtosis spillovers between them. Furthermore, the transmissions from crypto indices to those markets are mainly negative, which points to different sources of extreme events. This research may provide a useful understanding to investors (individual and institutional) since these interactions are extremely important for portfolio choice and risk management, helping them to make better investment decisions since many investment funds incorporate digital assets and blockchain technology, preventing from market instability generated by a potentially systemic digital industry.

In this framework, our main contributions are: (i) To perform a cross-market comparison between emerging (and developed) markets and breakthrough indices related to the new disruptive digital asset market; (ii) to apply a SNP-DCC approach to measuring high-order moments transmission between these two markets, (iii) to incorporate the effects of market uncertainty on the volatilities of the SNP-DCC model, and (iv) to fill the research gap in the digital asset market industry, not only cryptocurrencies, owing to the scarce presence of this topic.

The remainder of the paper is divided as follows: Section 2 describes the SNP-DCC approach featuring its ability to capture not only volatility but also skewness and kurtosis spillovers. Section 3 presents the empirical analyses and the results on moment spillovers between emerging and cryptocurrency markets and Section 4 discusses the main stylized facts and implications. Finally, Section 5 concludes.

2. The model

2.1. The SNP approach

The methodology for the analysis of high-order moment spillover effects lies in the multivariate semi-nonparametric (SNP) approach, which allows us to accurately estimate a full high-order moment model that incorporates conditional volatility, skewness, and kurtosis in a general and flexible framework.

The introduction of SNP modeling to the econometric techniques was at the end of the 70s and early 80s with the seminal works of Sargan (1976), Kendall and Stuart (1977), Freedman (1981) or Gallant and Nychka (1987) on the Edgeworth and Gram-Charlier (GC) expansions. Later on, many researchers reflected an interest in different fields such as physics, mathematics, or even bibliometrics (Blinnikov and Moessner, 1998; Hald, 2000; Cortés et al., 2016), without ignoring the economics and finance field (Mauleón and Perote, 2000; Jondeau and Rockinger, 2001). Since then, several studies have been published from a multivariate perspective (Mauleón, 2003, 2006; Perote, 2004; Del Brio et al., 2009, 2019, 2011), and financial risk quantification (Mauleón, 2010; Ñíguez and Perote, 2012; Del Brio et al., 2014, 2019, 2020; León and Moreno, 2017; Mora-Valencia, 2017; Zoia et al., 2018; Molina-Muñoz et al., 2020). Moreover, GC expansions have been considered to model electricity markets (Trespalacios et al., 2020, 2021) and even cryptocurrencies, not only in an univariate version but also in a multivariate setup (Jiménez et al., 2020a, 2020b, 2021, 2022).

The SNP modeling is usually characterized by a probability distribution function (pdf) truncated at an arbitrary k, as follows

$$f_k(x_t) = \left[1 + \sum_{s=1}^{k} d_s H_s(x_t)\right]\phi(x_t) \tag{1}$$

where x_t is the (standardized) log returns for each index (in our case), $\phi(x_t)$ denotes the standard Gaussian pdf, d_s $\forall s = 2, \ldots, n$ correspond to the GC parameters and $H_s(x_t)$ is the Hermite polynomial (HP) of order s, which can be defined in terms of the s-*th* order derivative of $\phi(x_t)$:

$$\frac{d^s\phi(x_t)}{dx_t{}^s} = (-1)^s H_s(x_t)\phi(x_t) \tag{2}$$

Although there are some studies with SNP distributions truncated at higher terms of the expansion, it is not usually assumed an expansion beyond the third and fourth terms. Since d_3 and d_4 parameters are related to the skewness and excess of kurtosis, a convenient expression in terms of conditional skewness (s_t) and kurtosis (k_t) is displayed in Eq. (3) - see e.g. León et al., (2005) for further details. Note that, without loss of generality, it is assumed $d_1 = d_2 = 0$ so as the x_t has zero mean and unit variance.

$$f_4(x_t) = [1 + d_3H_3(x_t) + d_4H_4(x_t)]\phi(x_t) = [1 + s_tH_3(x_t) + k_tH_4(x_t)]\phi(x_t) = \psi(x_t)\phi(x_t) \tag{3}$$

where $H_3(x_t) = x_t^3 - 3x_t$ and $H_4(x_t) = x_t^4 - 6x_t^2 + 3$.

A well-known disadvantage of this specification is that, without further restrictions, it cannot be strictly considered as a pdf, since it is not guaranteed that $f_k(x_t) \geq 0$ on the full domain of the parametric space. Some authors tackled this shortcoming defining positive

SNP distributions (Gallant and Nychka, 1987; León et al., 2009), selecting the appropriate initial values (Mauleón and Perote, 2000) or implementing parametric constraints (Jondeau and Rockinger, 2001). In this study we propose a positive version based on Gallant and Nychka's (1987) transformation that implies a positive distribution in the whole domain, e.g. for the case in Eq. (3) we have

$$f_4^*(x_t) = \omega_t^{-1}\psi^2(x_t)\phi(x_t) \tag{4}$$

where $\omega_t = 1 + s_t^2 + k_t^2$. That is, by squaring the HP expansion, and scaling by the constant ω_t that makes the density integrating up to one. Although assuring positivity in the whole parametric space, this is at the expense of losing the linear relationship between non-central moments and parameters, although, according to Ñíguez et al. (2009), the conditional skewness and kurtosis accurately capture the dynamics of the higher moments.

2.2. The dynamic conditional correlation model

The dynamic nature of conditional variance and covariance matrix can be incorporated into the SNP approach by considering multivariate GARCH models, i.e. the so-called multivariate SNP-DCC model (Del Brio et al., 2011; Ñíguez and Perote, 2016). The full model for a vector $\boldsymbol{r}_t \in \mathbb{R}^n$ can be expressed as in Eqs. (5)–(10):

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{u}_t \tag{5}$$

$$\boldsymbol{u}_t|\Omega_{t-1} \approx SNP(0, \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t) \tag{6}$$

$$\boldsymbol{D}_t^2 = diag\{\alpha_i\} + diag\{\beta_i\}^{\circ}\boldsymbol{u}_{t-1}\boldsymbol{u}_{t-1}^{'} + diag\{\boldsymbol{\Gamma d}_{t-1}\} \tag{7}$$

$$\boldsymbol{x}_t = \boldsymbol{D}_t^{-1}\boldsymbol{u}_t \tag{8}$$

$$\boldsymbol{Q}_t = \overline{\boldsymbol{Q}} \circ (\boldsymbol{ii}^{'} - \boldsymbol{A} - \boldsymbol{B}) + \boldsymbol{A} \circ \boldsymbol{x}_{t-1}\boldsymbol{x}_{t-1}^{'} + \boldsymbol{B} \circ \boldsymbol{Q}_{t-1} \tag{9}$$

$$\boldsymbol{R}_t = \widetilde{\boldsymbol{Q}}_t^{-1/2}\boldsymbol{Q}_t\widetilde{\boldsymbol{Q}}_t^{-1/2} \tag{10}$$

where $\boldsymbol{u}_t \in \mathbb{R}^n$ is a random vector with conditional mean represented by the $n \times 1$ vector $\boldsymbol{\mu}_t$ and conditional variances gathered in either the $n \times 1$ vector $\boldsymbol{d}_t$ or the $n \times n$ diagonal matrix $\boldsymbol{D}_t^2$. These variances are GARCH(1,1) type with parameters included in the $n \times n$ diagonal matrices $diag\{\alpha_i\}$ and $diag\{\beta_i\}$ and the $n \times n$ matrix $\boldsymbol{\Gamma}$ with a general element $\{\delta_{ij}\}$ that incorporates the spillover effect from asset i to asset j (when $i \neq j$). The variance-covariance and correlation matrices are denoted by $\boldsymbol{Q}_t$ and $\boldsymbol{R}_t$, respectively - note that $\widetilde{\boldsymbol{Q}}_t = diag\{\boldsymbol{Q}_t\}$ and $diag\{\boldsymbol{\Gamma d}_{t-1}\}$ represent diagonal matrices with the same diagonal as $\boldsymbol{Q}_t$ and $\boldsymbol{\Gamma d}_{t-1}$, respectively. $\boldsymbol{A}$, $\boldsymbol{B}$ are $n \times n$ positive definite matrices with general elements $\{\alpha_i\}$ and $\{\beta_i\}$, respectively, and $\boldsymbol{ii}' - \boldsymbol{A} - \boldsymbol{B}$ is also positive definite; $\boldsymbol{i}$ is a vector of ones and $\circ$ is the Hadamard product of two identically sized matrices (computed by element-by-element multiplication).

The standardized random vector $\boldsymbol{x}_t$ is assumed to be multivariate SNP distributed, whose pdf conditioned on the information set Ω_{t-1} is displayed in Eq. (11) - see Del Brio et al. (2011) for further details.

$$F_4^*(\boldsymbol{x}_t|\Omega_{t-1}) = \frac{1}{n}(2\pi)^{-\frac{n}{2}}|\boldsymbol{R}_t|^{-\frac{1}{2}}exp\left\{-\frac{1}{2}\boldsymbol{x}_t^{'}\boldsymbol{R}_t^{-1}\boldsymbol{x}_t\right\}\left[\sum_{i=1}^{n}\omega_{it}^{-1}\psi_i^2(\boldsymbol{\varepsilon}_t)\right] \tag{11}$$

where ω_{it} and $\psi_i(\bullet)$ follow the same notation as in Eq. (4) and $\boldsymbol{\varepsilon}_t = \boldsymbol{R}_t^{-1/2}\boldsymbol{x}_t$ being the transformation that removes conditional correlation, i.e. for the bivariate case:

$$\varepsilon_{1t} = a_t x_{1t} + b_t x_{2t} \text{ and } \varepsilon_{2t} = b_t x_{1t} + a_t x_{2t} \tag{12}$$

where $a_t = \frac{1}{2}\left(\frac{1}{\sqrt{1+\rho_t}} + \frac{1}{\sqrt{1-\rho_t}}\right)$, $b_t = \frac{1}{2}\left(\frac{1}{\sqrt{1+\rho_t}} - \frac{1}{\sqrt{1-\rho_t}}\right)$ and ρ_t being the correlation between the two assets.

A salient feature of this SNP-DCC model is that, since log-likelihood function is separable, ML estimation procedure can be independently obtained in two stages:

1. Conditional mean and variance are independently estimated under Gaussian innovations (Quasi ML).
2. Conditional correlations, as well as conditional skewness and kurtosis, are jointly estimated for each pairwise variables under a bivariate standardized SNP density constrained to the conditional mean and variance first-stage estimates.

2.3. High order moments and spillovers

For the sake of clarity, this section describes the details on the conditional moments (variance, skewness, and kurtosis) and their spillover effects resulting from the implementation of the SNP-DCC model in a bivariate setup.

The specification of the three moments follows a GARCH(1,1)-type process. For the conditional volatility, σ_{it}^2, the model in Eq. (7)

can be rewritten as in Eq. (13),

$$\begin{bmatrix} \sigma_{it}^2 \\ \sigma_{jt}^2 \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} + \begin{bmatrix} \beta_i & 0 \\ 0 & \beta_j \end{bmatrix} \begin{bmatrix} u_{i,t-1}^2 \\ u_{j,t-1}^2 \end{bmatrix} + \begin{bmatrix} \delta_{ii} & \delta_{ij} \\ \delta_{ji} & \delta_{jj} \end{bmatrix} \begin{bmatrix} \sigma_{it-1}^2 \\ \sigma_{jt-1}^2 \end{bmatrix} \tag{13}$$

where, for the sake of simplicity, $\beta_{ij} = 0$ $(i \neq j)$; δ_{ij} refers to the volatility transmission from asset j to asset i $(i \neq j)$ and $\alpha_i \geq 0$, $\beta_i \geq 0$, $\delta_{ii} \geq 0$ and $\beta_i + \delta_{ii} < 1 \forall i = 1, 2$ - see Nakatani and Teräsvirta (2009) for further information.

Likewise, the conditional skewness and kurtosis can be parameterized as in Eq. (14) and (15) respectively:

$$\begin{bmatrix} s_{it} \\ s_{jt} \end{bmatrix} = \begin{bmatrix} \xi_i \\ \xi_j \end{bmatrix} + \begin{bmatrix} \gamma_i & 0 \\ 0 & \gamma_j \end{bmatrix} \begin{bmatrix} \eta_{i,t-1}^3 \\ \eta_{j,t-1}^3 \end{bmatrix} + \begin{bmatrix} \Theta_{ii} & \Theta_{ij} \\ \Theta_{ji} & \Theta_{jj} \end{bmatrix} \begin{bmatrix} s_{i,t-1} \\ s_{j,t-1} \end{bmatrix} \tag{14}$$

$$\begin{bmatrix} k_{it} \\ k_{jt} \end{bmatrix} = \begin{bmatrix} \varsigma_i \\ \varsigma_j \end{bmatrix} + \begin{bmatrix} \lambda_i & 0 \\ 0 & \lambda_j \end{bmatrix} \begin{bmatrix} \eta_{i,t-1}^4 \\ \eta_{j,t-1}^4 \end{bmatrix} + \begin{bmatrix} \vartheta_{ii} & \vartheta_{ij} \\ \vartheta_{ji} & \vartheta_{jj} \end{bmatrix} \begin{bmatrix} k_{i,t-1} \\ k_{j,t-1} \end{bmatrix} \tag{15}$$

where Θ_{ij} accounts for the skewness spillover and ϑ_{ij} for the kurtosis spillover from asset j to asset i $(i \neq j)$.

3. Empirical analysis

One important feature in our volatility transmission analysis is the fact that volatility spillovers might be induced by common effects on the volatilities of the series (e.g. volatility of major indices or general market uncertainty might be a significant driver for all the series).[5] To control for these potential effects, we modify our stage-wise estimation procedure, by including the CBOE VIX,[6] as an external regressor in the volatility equations. This index has been found to have a significant effect on GARCH-type models (Kambouroudis and McMillan, 2016), but, to the best of our knowledge, it has never been employed in a SNP-DCC framework (see also Bouraoui, 2020, for other alternative volatility drivers).

The estimation procedure for the SNP-DCC model controlling for VIX effects in volatility is included in the following three stages -see e.g. Pan et al. (2022) for a similar procedure implemented to the Gaussian DCC-GARCH and based on Engle and Sheppard (2001):

1. Standardized residuals for every Emerging and Developed market index are obtained by incorporating the VIX as an external regressor in a GARCH (1,1) model.
2. Conditional variance and volatility transmission are estimated for every pair of indices by employing Quasi ML and considering the standardized residuals obtained in the previous stage.
3. Conditional correlations, as well as conditional skewness and kurtosis, are jointly estimated for each pairwise of indices under the bivariate standardized SNP density.

Before applying the above-mentioned methodology, daily returns $\boldsymbol{r}_t$ were synchronized according to a first-order vector moving average VMA(1) model, as suggested by Burns et al. (1998) and usually employed in the literature (see e.g., BenSaida, 2019). The method builds up the synchronous returns on the basis of estimates of the VMA(1) model in Eq. (16), where ϵ_t stands for white noise and $\boldsymbol{M}$ is the weighting matrix:

$$\boldsymbol{r}_t = \epsilon_t + \boldsymbol{M}\epsilon_{t-1} \tag{16}$$

3.1. Daily frequency

3.1.1. Data

The focus of this article is on the analysis of the high-order conditional moments spillovers between emerging markets and the digital asset markets, which fills a relevant gap in the financial literature. Furthermore, in order to provide a more comprehensive analysis, developed markets have also been included. On the one hand, the three leading emerging markets selected are: MSCI Emerging Markets Latin America Index (Latin America), MSCI Emerging Markets Europe Index (Emerging Europe), and MSCI Emerging Markets Asia Index (Emerging Asia). In addition, to compare similar regions of the world, the developed markets' MSCI North America Index (North America), MSCI Europe Index (Europe), and MSCI Asia Pacific Index (Asia Pacific) indices are also analyzed.

On the other hand, the three brand new indices related to digital asset markets are the Bloomberg Galaxy Crypto Index (Crypto), Bloomberg Galaxy DeFi Index (DeFi), and Bloomberg Grayscale Future of Finance Index (Future of Finance). Setting out briefly, Crypto Index is compounded by 80% of Bitcoin and Ethereum, the most relevant cryptocurrencies by market capitalization; DeFi Index

[5] We are grateful to an anonymous reviewer for this insightful comment.

[6] Chicago Board Options Exchange Volatility Index is a widely used index to benchmark market uncertainty and expectations on the basis of the S&P500 index.

Table 1
Descriptive statistics for daily index returns.

	Min.	Max.	Mean	Median	Std. Dev.	Skewness	Ex. Kurt.
Digital Indices							
Crypto	−21.314	19.828	0.072	0.182	5.101	−0.513	4.854
DeFi	−26.684	26.629	−0.039	0.000	6.849	−0.197	4.537
Future of Finance	−17.128	15.804	−0.155	−0.256	4.438	0.114	4.197
Emerging Markets							
Latin America	−5.225	3.743	−0.007	0.111	1.403	−0.522	3.606
Emerging Europe	−79.705	15.008	−0.492	0.136	5.265	−10.692	151.470
Emerging Asia	−3.410	6.163	−0.066	−0.082	1.168	0.241	5.365
Developed Markets							
North America	−3.846	2.863	−0.001	0.054	1.060	−0.559	4.182
Europe	−5.331	6.265	−0.039	0.402	1.054	−0.270	8.437
Asia Pacific	−2.837	2.768	−0.063	−0.036	0.826	0.035	3.973

Returns ranged from January December 31st, 2020, to May 20th, 2022. For emerging markets and developed markets indices, returns are synchronized.

considers a basket of digital assets related to the use of smart contracts on blockchain except for Ethereum, and Future of Finance Index takes into account those companies which provide technology or are directly linked to the crypto market. The daily data collected for every index are downloaded from the Bloomberg platform and cover the period from December 31st, 2020, to May 20th, 2022, comprising 362 observations due to data availability[7] (see Appendix A for further details on the indices).

For such index i we compute the percent daily returns as

$$r_{it} = 100[ln(p_{it}) - ln(p_{it-1})] \tag{17}$$

where r_{it} refers to returns and p_{it} is the (daily) price of every one of the above-mentioned indices. Descriptive statistics, in Table 1, exhibit high volatility, mainly in digital asset markets, which means around five or six times higher than that of the emerging and developed markets, except for Emerging Europe, since this index has been hugely influenced by the tensions in Ukraine (note the salient minimum value of −79.705 in this index). The overall minimum daily returns for digital asset series are prominent (−21.314 for Crypto, −26.689 for DeFi, and − 17.128 for Future of Finance) in comparison to those of emerging markets (−5.225 for Latin America and − 3.410 for Emerging Asia) and for the developed markets (−3.846 for North America, −5.331 for Europe, and − 2.837 for Asia Pacific). These stylized features for digital indices may be explained by the nature of these unregulated and decentralized asset markets, where no institution can limit the price even in the most extreme market conditions. Furthermore, all series are highly leptokurtic and negatively skewed (positively, for the Future of Finance index, Emerging Asia, and Asia Pacific) due to the abundant presence of extreme values.

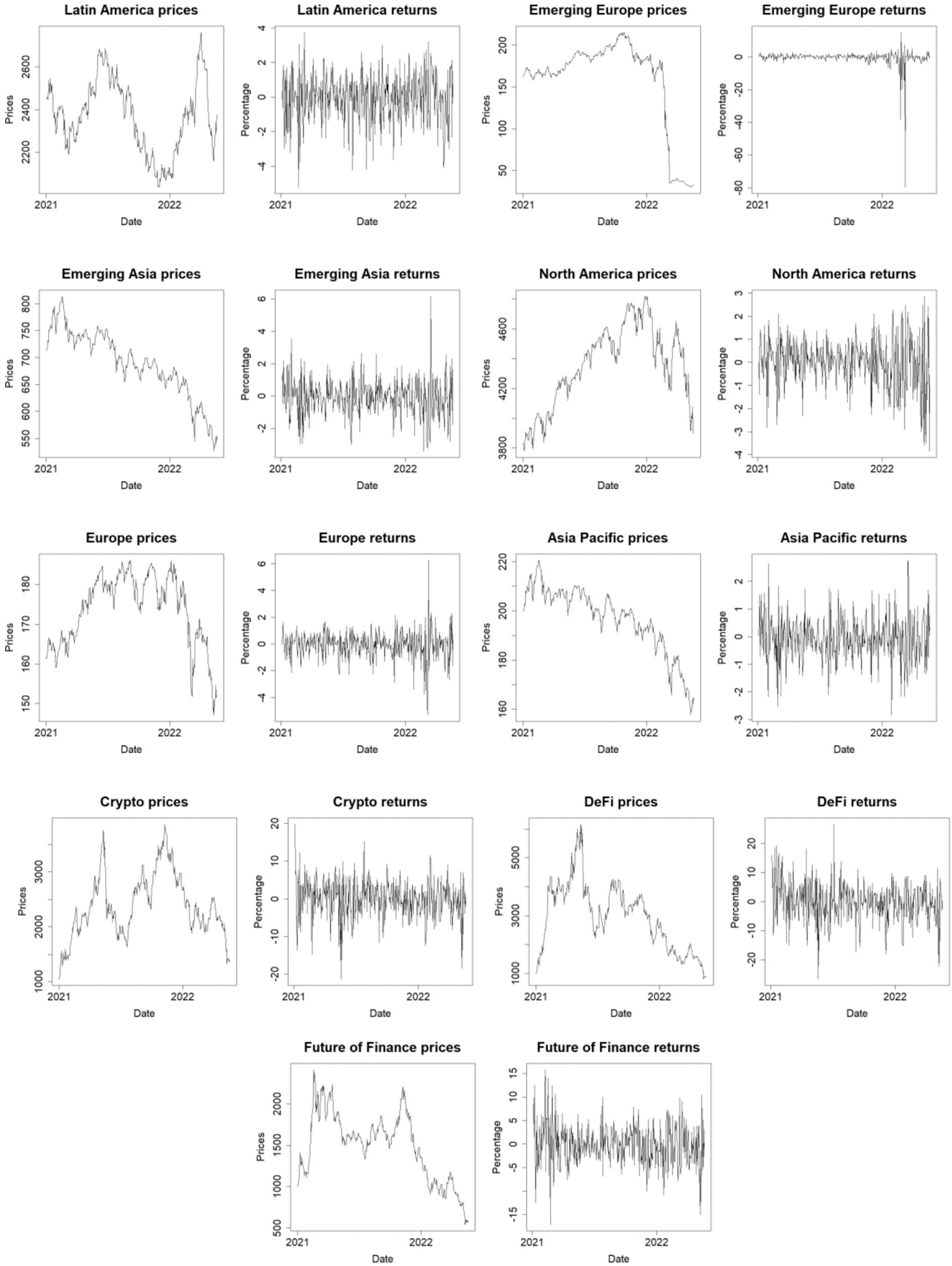
Fig. 1 shows the index series in levels and log-returns. At first sight, the evolution of prices differs from one index to another, except for the digital markets which exhibit similar patterns. Likewise, the returns related to those markets have sharpened ups and downs triggered by the extreme values. One explanation for the similar performance of these new indices could be the high correlations among the crypto assets of each index. It should be remarked the plunge of the emerging Europe index at the beginning of the Ukrainian conflict.

3.1.2. Estimation results

In this section, we present the main findings of our analysis. Table 2 shows the result of the parameter estimates for the spillover effects from the DCC-SNP model for volatility, skewness, and kurtosis. Those δ_{ij} parameters indicate the transmission from market j to market i. Since δ_{12} (δ_{21}) is positive and significant (insignificant), we find a remarkable result: the main transmitter of daily volatility are the emerging stock markets to all digital asset markets. This seems a reasonable finding since the crypto industry is smaller than the emerging stock markets, which are more influential. The sign of all these volatility transmissions is positive and thus an increase (decrease) in volatility in one market increases (decreases) the volatility in the other.

On the other hand, conditional skewness is related to the asymmetric response of the distribution to negative and positive shocks, but also captures how long the tail of the distribution is. According to the skewness spillover there is a negative transmission between the Future of Finance index to Latin America, as well as a positive one from the Crypto Index to Emerging Asia. Regarding conditional kurtosis, the SNP-DCC model reveals that the Crypto index transmits kurtosis to the Emerging Asia index. Furthermore, the sign of the transmission of both the skewness and kurtosis for Crypto-Emerging Asia are positive, revealing that the news that drives extreme movements in crypto assets might also be a source of instability in the stock emerging markets, probably due to the high adoption of cryptos in these countries. It must be remarked that south-east Asian countries are responsible for most of the web traffic on

[7] It must be noted that for some brand-new indices as Bloomberg Galaxy Crypto Index, Bloomberg Galaxy DeFi Index, and Bloomberg Grayscale Future of Finance Index larger series were not available.



(caption on next page)

Fig. 1. Daily prices and returns.
Fig. 1 Prices and returns for Future of Finance, Crypto and DeFi indices. Prices and synchronized returns for Latin America, Emerging Europe, Emerging Asia, North America, Europe and Asia Pacific indices from December 31st, 2020, to May 20th, 2022.

Table 2
High-order spillover effects between emerging markets and digital indices.

Transmission effect	δ_{12}	δ_{21}	θ_{12}	θ_{21}	ϑ_{12}	ϑ_{21}
Crypto ↔ Latin America	0.917	0.001	−0.038	−0.001	−0.001	−0.001
	(0.000)	(0.981)	(0.350)	(0.428)	(0.633)	(0.813)
Crypto ↔ Emerging Europe	0.496	0.004	0.064	0.002	0.072	−0.003
	(0.000)	(0.847)	(0.983)	(0.200)	(0.916)	(0.147)
Crypto ↔ Emerging Asia	1.073	0.019	0.000	0.373	0.001	0.071
	(0.000)	(0.790)	(0.968)	**(0.026)**	(0.858)	**(0.071)**
DeFi ↔ Latin America	0.663	0.003	−0.105	−0.001	−0.001	−0.002
	(0.000)	(0.948)	(0.457)	(0.361)	(0.704)	(0.276)
DeFi ↔ Emerging Europe	2.973	0.000	0.028	−0.002	−0.187	−0.002
	(0.000)	(0.999)	(0.595)	(0.639)	(0.116)	(0.427)
DeFi ↔ Emerging Asia	2.337	0.007	−0.201	0.006	−0.027	−0.018
	(0.000)	(0.917)	(0.454)	(0.653)	(0.102)	(0.622)
Future of Finance ↔ Latin America	0.364	0.014	0.004	−0.042	−0.017	−0.004
	(0.000)	(0.779)	(0.795)	**(0.008)**	(0.272)	(0.776)
Future of Finance ↔ Emerging Europe	0.289	0.008	−0.045	0.007	−0.165	0.000
	(0.000)	(0.692)	(0.776)	(0.408)	(0.926)	(0.490)
Future of Finance ↔ Emerging Asia	1.978	0.014	−3.993	0.001	−0.836	−0.504
	(0.000)	(0.828)	(0.433)	(0.941)	(0.549)	(0.472)

Emerging markets indices: Latin America, Emerging Europe, and Emerging Asia. Digital indices: Future of Finance, Crypto, and DeFi. Data from December 31st, 2020 to May 20th, 2022. *P*-values in parenthesis. Significant parameters at 10% confidence are highlighted in boldface. δ_{ij}: volatility transmission from index *j* to index *i*; θ_{ij}: skewness transmission from index *j* to index *i*; ϑ_{ij}: kurtosis transmission from index *j* to index *i*.

cryptocurrency platforms - a report by KPMG jointly with HSBC Bank[8] reveals that more than a quarter of startups in these countries are related to the crypto industry. Erik Feyen et al. (2021) explains the high propensity of adoption of cryptos in these countries owing to the “unbanked” or inefficient payment system, which is also reported by the IMF.[9] Although there might also be other special features (e.g., demography, expected growth, or digitalization) that make these countries focal points for the expansion of this industry, what is observed is that this fact impacts worldwide financial markets. This skewness and kurtosis transmission from Emerging Asia to other areas of the World is found by Del Brio et al. (2017) with equity markets.

Table 3 represents the summary of Table 2 highlighting the sign of the significant interactions.

Table 3
Summary results on moment transmission between emerging markets and digital indices.

Digital index or Emerging market transmission (→direction)	Volatility	Skewness	Kurtosis
Crypto → Latin America	—	—	—
Crypto → Emerging Europe	—	—	—
Crypto → Emerging Asia	—	**Positive**	**Positive**
DeFi → Latin America	—	—	—
DeFi → Emerging Europe	—	—	—
DeFi → Emerging Asia	—	—	—
Future of Finance → Latin America	—	**Negative**	—
Future of Finance → Emerging Europe	—	—	—
Future of Finance → Emerging Asia	—	—	—
Latin America → Future of Finance	**Positive**	—	—
Latin America → Crypto	**Positive**	—	—
Latin America → DeFi	**Positive**	—	—
Emerging Europe → Future of Finance	**Positive**	—	—
Emerging Europe → Crypto	**Positive**	—	—
Emerging Europe → DeFi	**Positive**	—	—
Emerging Asia → Future of Finance	**Positive**	—	—
Emerging Asia → Crypto	**Positive**	—	—
Emerging Asia → DeFi	**Positive**	—	—

The first column summarizes the main effects. Symbol → signals the direction of the transmission.

[8] Emerging giants in Asia pacific. https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2022/07/emerging-giants-in-asia-pacific.pdf

[9] Chapter 2, “In the Global financial stability report: COVID-19, crypto, and climate: navigating challenging transitions” Written by Parma Bains, Mohamed Diaby, Dimitris Drakopoulos (co-lead), Julia Faltermeier, Federico Grinberg, Evan Papageorgiou (co-lead), Dmitri Petrov, Patrick Schneider, and Nobu Sugimoto, under the supervision of Tobias Adrian, Fabio Natalucci, Dong He, and Aditya Narain (2021).

Table 4
High-order spillover effects between developed markets and digital indices.

Transmission effect	δ_{12}	δ_{21}	θ_{12}	θ_{21}	ϑ_{12}	ϑ_{21}
Crypto ↔ North America	10.233	0.000	0.006	−1.611	−0.011	−0.046
	(0.000)	(0.999)	**(0.000)**	**(0.000)**	(0.248)	(0.619)
Crypto ↔ Europe	1.020	0.004	−0.025	0.223	−0.003	−0.393
	(0.000)	(0.931)	(0.342)	(0.392)	(0.378)	(0.178)
Crypto ↔ Asia Pacific	1.016	0.007	−0.002	−0.073	−0.044	−0.005
	(0.000)	(0.932)	(0.736)	**(0.031)**	(0.848)	(0.328)
DeFi ↔ North America	12.090	0.003	4.529	−0.237	−0.058	−1.052
	(0.000)	(0.934)	(0.301)	(0.634)	(0.488)	(0.549)
DeFi ↔ Europe	3.794	0.000	−0.060	−0.006	0.000	−0.002
	(0.000)	(0.999)	(0.382)	(0.440)	(0.836)	(0.501)
DeFi ↔ Asia Pacific	23.922	0.008	−0.008	0.003	−0.006	0.001
	(0.000)	(0.898)	(0.527)	(0.904)	(0.190)	(0.662)
Future of Finance ↔ North America	3.710	0.008	0.000	0.081	−0.057	−0.016
	(0.000)	(0.898)	(0.968)	**(0.000)**	(0.512)	**(0.095)**
Future of Finance ↔ Europe	0.334	0.000	−0.085	−0.354	0.653	−1.304
	(0.000)	(0.997)	(0.831)	(0.595)	(0.723)	(0.331)
Future of Finance ↔ Asia Pacific	0.483	0.013	−1.834	0.002	−0.102	−1.283
	(0.000)	(0.866)	(0.218)	(0.528)	(0.750)	(0.388)

Developed markets indices: North America, Europe, and Asia Pacific. Digital indices: Future of Finance, Crypto, and DeFi. Data from December 31st, 2020 to May 20th, 2022. P-values in parenthesis. Significant parameters at 10% confidence are highlighted in boldface. δ_{ij}: volatility transmission from index j to index i; θ_{ij}: skewness transmission from index j to index i; ϑ_{ij}: kurtosis transmission from index j to index i.

Table 4 gathers the parameter estimates for high-order transmission between developed markets and digital indices. Volatility transmission from all the developed markets indices to the digital ones is positive and significant, similar to the results shown in Table 2. According to skewness and kurtosis, we find the following significant effects: (i) There is a bidirectional transmission of skewness from the pair of Crypto-North America. Whilst an increase in North American equity skewness also increases the Crypto index skewness (positive sign), the higher skewness in the Crypto index, probably driven by idiosyncratic shocks, does not generate skewness in North American stocks (negative sign). (ii) The negative skewness spillover is also found from the Crypto index to Asia Pacific, which is remarkable, given that the Crypto index transmits positive skewness to Emerging Asia, and reflects a different implantation and concern about the crypto industry in both areas. (iii) Future of Finance transmits positive skewness and negative kurtosis to the North American index. The interpretation of both mixed effects is unclear, given that the Future of Finance (North America) index exhibits positive (negative) skewness (Table 1). Therefore, a positive skewness spillover means that when the Future of Finance index becomes more negatively skewed then the North America index becomes less positively skewed (i.e., more Gaussian). This is compatible with a negative transmission of kurtosis, revealing that high turbulences in digital markets may be associated with low volatility in stock markets. Table 5 summarizes the signs of the significant interactions.

Table 5
Summary results on moment transmission between developed markets and digital indices.

Digital index or Developed market transmission (→direction)	Volatility	Skewness	Kurtosis
Crypto → North America	—	**Negative**	—
Crypto → Europe	—	—	—
Crypto → Asia Pacific	—	**Negative**	—
DeFi → North America	—	—	—
DeFi → Europe	—	—	—
DeFi → Asia Pacific	—	—	—
Future of Finance → North America	—	**Positive**	**Negative**
Future of Finance → Europe	—	—	—
Future of Finance → Asia Pacific	—	—	—
North America → Crypto	**Positive**	**Positive**	—
North America → DeFi	**Positive**	—	—
North America → Future of Finance	**Positive**	—	—
Europe → Crypto	**Positive**	—	—
Europe → DeFi	**Positive**	—	—
Europe → Future of Finance	**Positive**	—	—
Asia Pacific → Crypto	**Positive**	—	—
Asia Pacific → DeFi	**Positive**	—	—
Asia Pacific → Future of Finance	**Positive**	—	—

The first column summarizes the main effects. Symbol → signals the direction of the transmission.

Table 6
Descriptive Statistics for weekly index returns.

	Min.	Max.	Mean	Median	Std. Dev.	Skewness	Ex. Kurt.
Digital Indices							
Blockchain	−17.754	14.103	0.241	0.349	4.041	−0.069	5.407
Solfint	−21.056	15.194	0.124	0.376	3.891	−0.418	8.490
Diversified	−63.333	56.370	0.687	1.530	13.476	−0.504	6.566
Emerging Markets Indices							
Latin America	−23.269	14.678	−0.090	0.211	4.037	−0.963	9.516
Emerging Europe	−84.896	11.456	−0.655	0.279	7.247	−7.536	81.075
Emerging Asia	−10.598	6.784	−0.001	0.281	2.657	−0.576	4.211
Developed Markets Indices							
North America	−16.334	11.574	0.171	0.460	2.741	−1.156	11.417
Europe	−22.540	9.937	−0.006	0.206	2.963	−1.939	17.926
Asia Pacifico	−13.595	8.970	0.003	0.336	2.381	−0.830	8.114

Returns ranged from October 6th, 2017, to May 20th, 2022.

3.2. *Weekly frequency*

3.2.1. *Data*

In order to provide more robust results with respect to the data frequency, in this section high-order conditional spillovers between emerging and digital asset markets are computed on a weekly data basis. For comparison purposes, we also include the developed market indices in the analyses. To this end, we have selected nine indices: The six abovementioned from emerging markets indices (Latin America, Emerging Europe, and Emerging Asia), and developed market indices such as MSCI North America Index (North America) MSCI Europe Index (Europe), and MSCI Asia Pacific Index (Asia Pacific) in order to compare similar regions of the world; and three new digital indices such as CoinShare Blockchain Equity Index (Blockchain), Solactive FinTech Index (SolFint) and Menai-MVIS Diversified Digital Assets Index (Diversified). Those are composed of similar portfolios to the previously selected indices (Future of Finance, Crypto, and DeFi), but allow larger weekly data series. The first digital index, Blockchain, considers those companies that participate in the blockchain or cryptocurrency industry and is similar to the DeFi index; Solfint Index is focused on companies that provide innovative software solutions within the financial services (Fintech), analogously to Future of Finance; and Diversified Index is based on crypto-assets, where Bitcoin and Ethereum account for more than 60% of the index, similarly to Crypto index. Further details on every index are provided in Appendix A.

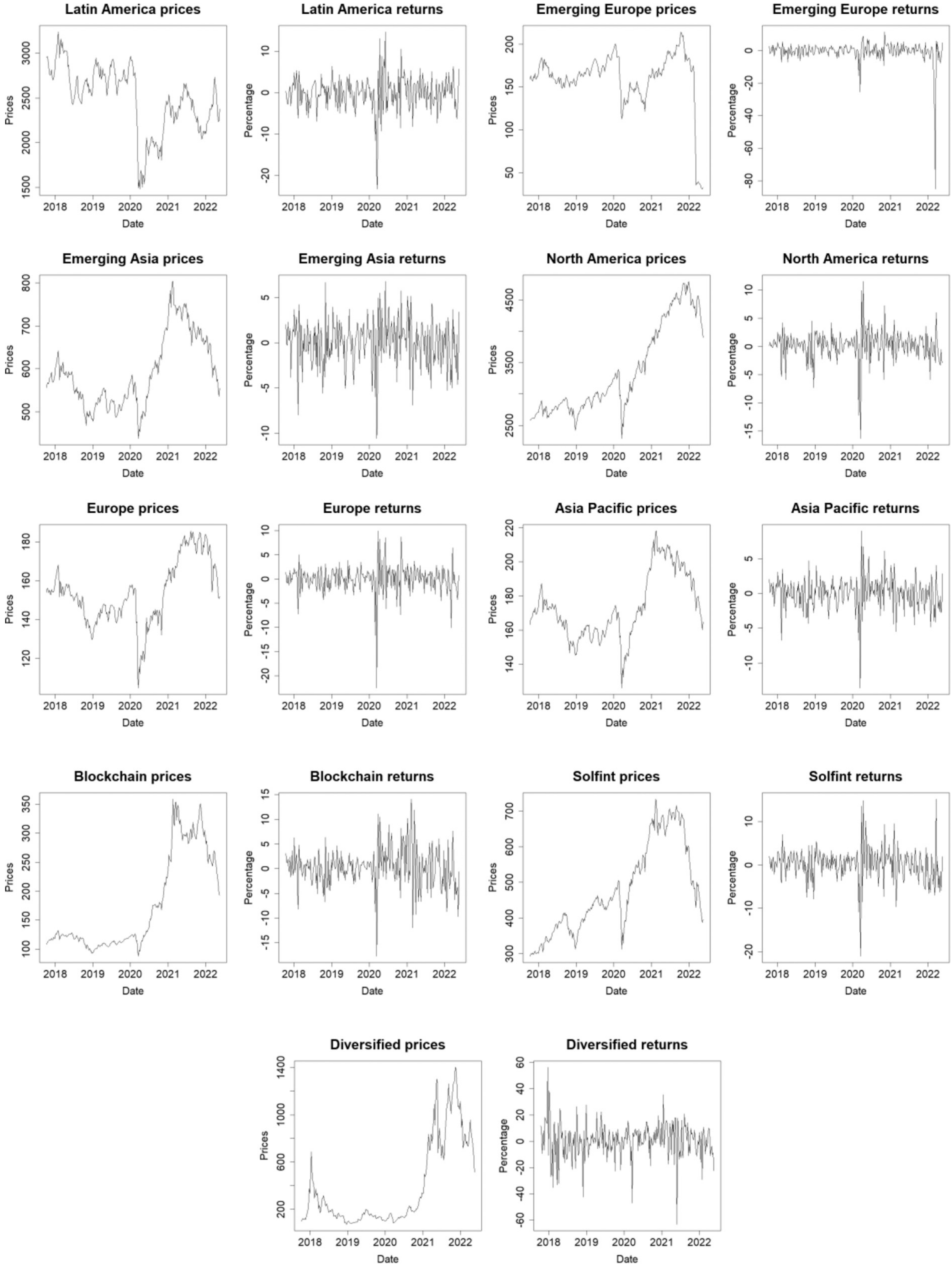
The weekly data spans from October 6th, 2017, to May 20th, 2022 (242 observations), and the descriptive statistics are displayed in Table 6, where the weekly returns are computed as in Eq. (17). As can be observed, large extreme events are featured by all indices, remarkably for the Diversified Index ranging from −63.333 to 56.370 and Emerging Europe from −84.896 to 11.456. As a consequence, the high volatility of Digital Indices and Emerging Markets is noticeable, the most prominent cases are those of the Diversified Index (13.347) and Emerging Europe (7.247). Like in the case of daily data, it is also noteworthy the contribution of the last trading values to the significant volatility, which experienced a sharp drop from the end of February (see Fig. 2), as a consequence of the beginning of the Ukrainian conflict and the exposition of emerging European countries to this event. A salient negative skewness (−7.536 for Emerging Europe) and excess kurtosis with values from 5.407 (for Blockchain) to 81.075 (for Emerging Europe), are also exhibited for all the series.

Fig. 2 depicts the nine indices in levels and log-returns where all of them experienced a remarkable drop in 2020 coinciding with the beginning of the lockdown due to the COVID-19 pandemic. Apart from that, every group of indices has a similar performance except for the Emerging Markets group.

3.2.2. *Estimation results*

Tables 7 and 9 show the transmission between emerging markets indices and developed market indices, with the digital indices. The selected parameters are: δ_{ij}, for conditional volatility; θ_{ij}, for conditional skewness; and ϑ_{ij}, for conditional kurtosis which captures the transmission from index j to index i.

As in the previous 3.1.2 Section, the strong influence of the more established markets (emerging and developed) is clear in volatility transmission, being the principal transmitter to the digital ones, with only one insignificant exception (see Table 7). The relatively small size and less mature crypto industry might explain such performance. Moreover, as observed in Tables 8 and 10, the sign of the interaction is always positive revealing a direct transmission of volatility.



(caption on next page)

Fig. 2. Weekly prices and returns.
Fig. 2 Prices and returns for Emerging markets indices: Latin America, Emerging Europe, and Emerging Asia; Developed markets indices: North America, Europe, and Asia Pacifico; Digital indices: Blockchain Global Index, Solactive Fintech Index, and Diversified Digital Assets Index. From October 6th, 2017, to May 20th, 2022.

Table 7
High-order spillover effects between emerging markets indices and digital indices.

Transmission effect	δ_{12}	δ_{21}	θ_{12}	θ_{21}	ϑ_{12}	ϑ_{21}
Blockchain ↔ Latin America	0.001	0.004	0.002	−0.001	−0.014	0.024
	(0.989)	(0.921)	(0.511)	(0.618)	(0.873)	**(0.001)**
Blockchain ↔ Emerging Europe	0.419	0.000	0.002	0.001	0.000	−0.005
	(0.000)	(0.999)	(0.751)	(0.943)	(0.860)	**(0.046)**
Blockchain ↔ Emerging Asia	0.326	0.000	−0.001	−0.049	−0.367	0.002
	(0.000)	(0.999)	**(0.006)**	**(0.036)**	**(0.061)**	(0.794)
Solfint ↔ Latin America	0.414	0.008	−0.001	0.024	−0.048	0.006
	(0.000)	(0.879)	(0.443)	(0.217)	(0.189)	(0.649)
Solfint ↔ Emerging Europe	0.548	0.012	0.000	−0.027	0.014	0.045
	(0.000)	(0.671)	(0.872)	**(0.072)**	(0.263)	**(0.047)**
Solfint ↔ Emerging Asia	0.177	0.000	−0.904	0.000	−0.074	−0.003
	(0.000)	(0.999)	**(0.018)**	(0.708)	(0.186)	(0.982)
Diversified ↔ Latin America	1.498	0.001	0.456	−0.001	0.239	0.000
	(0.000)	(0.997)	(0.239)	(0.586)	(0.856)	(0.649)
Diversified ↔ Emerging Europe	75.505	0.004	0.003	−0.002	0.000	0.000
	(0.000)	(0.895)	(0.738)	(0.398)	(0.886)	(0.757)
Diversified ↔ Emerging Asia	5.622	0.000	0.123	−0.016	0.347	−0.039
	(0.000)	(0.984)	**(0.001)**	(0.319)	(0.345)	(0.327)

Emerging markets: Latin America, Emerging Europe, and Emerging Asia. Digital Markets: Blockchain, Solfint and Diversified. Weekly data from October 6th, 2017, to May 20th, 2022. P-values in parenthesis. Significant parameters at 10% confidence are highlighted in boldface. δ_{ij}: volatility transmission from index j to index i; θ_{ij}: skewness transmission from index j to index i; ϑ_{ij}: kurtosis transmission from index j to index i.

Table 8
Summary results on moment transmission between emerging markets and digital indices.

Digital index or Emerging market transmission (→direction)	Volatility	Skewness	Kurtosis
Blockchain → Latin America	—	—	**Positive**
Blockchain → Emerging Europe	—	—	**Negative**
Blockchain → Emerging Asia	—	**Negative**	—
Solfint → Latin America	—	—	—
Solfint → Emerging Europe	—	**Negative**	**Positive**
Solfint → Emerging Asia	—	—	—
Diversified → Latin America	—	—	—
Diversified → Emerging Europe	—	—	—
Diversified → Emerging Asia	—	—	—
Latin America → Blockchain	—	—	—
Latin America → Solfint	**Positive**	—	—
Latin America → Diversified	**Positive**	—	—
Emerging Europe → Blockchain	**Positive**	—	—
Emerging → Solfint	**Positive**	—	—
Emerging Europe → Diversified	**Positive**	—	—
Emerging Asia → Blockchain	**Positive**	**Negative**	**Negative**
Emerging Asia → Solfint	**Positive**	**Negative**	—
Emerging Asia → Diversified	**Positive**	**Positive**	—

The first column summarizes the main effects, symbol → signals the direction of the transmission.

Regarding, high-order conditional moment's (i.e. skewness and kurtosis) transmission there is heterogeneity between Emerging markets and Developed markets. Firstly, looking at the significant skewness spillovers, Tables 7 and 8 show a negative bidirectional transmission of skewness for the pair Emerging Asia-Blockchain. It is noticeable, that on a daily basis, the similar index for the latter (DeFi) has no significant high-order spillover (only for volatility). Therefore, either the DeFi index is not the best proxy for the Blockchain index, or the effects are better captured on a weekly basis. The pairs Solfint-Emerging Europe and Emerging Asia-Solfint exhibit negative skewness transmission. Finally, a positive skewness transmission from Emerging Asia to the Diversified index is found, likely because Emerging Asia is one of the areas of the world where the crypto industry is more deep-rooted. Secondly, focusing on conditional kurtosis spillovers, the negative impact of extreme events from Emerging Asia to the Blockchain index is noticeable (maybe some financial shocks are interpreted as good news for blockchain technology implantation). Finally, Emerging Europe and Latin

Table 9
High-order spillover effects between developed markets indices and digital indices.

Transmission effect	δ_{12}	δ_{21}	θ_{12}	θ_{21}	ϑ_{12}	ϑ_{21}
Blockchain ↔North America	0.109	0.000	−0.263	−0.001	−0.539	−0.004
	(0.000)	(0.999)	**(0.041)**	(0.469)	**(0.079)**	(0.679)
Blockchain ↔ Europe	0.249	−0.000	−0.000	−0.018	−0.000	−0.002
	(0.000)	(0.999)	(0.980)	(0.387)	(0.861)	**(0.099)**
Blockchain ↔ Asia Pacific	0.185	0.000	0.007	−0.021	−0.001	0.001
	(0.000)	(0.999)	(0.349)	**(0.007)**	(0.609)	(0.935)
Solfint ↔ North America	0.108	0.000	1.031	−0.001	0.007	0.000
	(0.000)	(0.999)	(0.510)	(0.443)	(0.998)	(0.460)
Solfint ↔ Europe	0.570	0.000	−0.032	−0.025	0.000	−0.002
	(0.000)	(0.999)	(0.362)	**(0.025)**	(0.896)	(0.191)
Solfint ↔ Asia Pacific	0.359	0.000	−0.000	0.608	0.000	−0.318
	(0.000)	(0.999)	(0.903)	(0.327)	(0.992)	(0.456)
Diversified ↔ North America	1.790	0.000	0.005	0.000	0.000	−0.002
	(0.000)	(0.999)	(0.319)	(0.811)	(0.277)	(0.395)
Diversified ↔ Europe	1.940	0.004	0.002	0.017	0.000	0.013
	(0.000)	(0.908)	(0.421)	(0.154)	(0.935)	(0.110)
Diversified ↔ Asia Pacific	0.009	0.004	−0.000	−0.011	−0.257	0.006
	(0.013)	(0.923)	(0.169)	(0.177)	(0.840)	(0.700)

Developed markets: North America, Europe and Asia Pacific. Digital Markets: Blockchain, Solfint and Diversified. Weekly data from October 6th, 2017 to May 20th, 2022. P-values in parenthesis. Significant parameters at 10% confidence are highlighted in boldface. δ_{ij}: volatility transmission from index *j* to index *i*; θ_{ij}: skewness transmission from index *j* to index *i*; ϑ_{ij}: kurtosis transmission from index *j* to index *i*.

Table 10
Summary results on moment transmission between developed markets and digital indices.

Digital index or Developed market transmission (→direction)	Volatility	Skewness	Kurtosis
Blockchain → North America	—	—	—
Blockchain → Europe	—	—	**Negative**
Blockchain → Asia Pacific	—	**Negative**	—
Solfint → North America	—	—	—
Solfint → Europe	—	**Negative**	—
Solfint → Asia Pacific	—	—	—
Diversified → North America	—	—	—
Diversified → Europe	—	—	—
Diversified → Asia Pacific	—	—	—
North America → Blockchain	**Positive**	**Negative**	**Negative**
North America → Solfint	**Positive**	—	—
North America → Diversified	**Positive**	—	—
Europe → Blockchain	**Positive**	—	—
Europe → Solfint	**Positive**	—	—
Europe → Diversified	**Positive**	—	—
Asia Pacific → Blockchain	**Positive**	—	—
Asia Pacific → Solfint	**Positive**	—	—
Asia Pacific → Diversified	**Positive**	—	—

The first column summarizes the main effects, symbol → signals the direction of the transmission.

America equity markets seem to be impacted by extreme movements in Blockchain and Solfint indices, maybe due to the fact that companies that adopt blockchain technologies have a deep impact in Emerging Europe and Latin America. A summary of the transmission sign is gathered in Table 8.

Table 9 gathers the spillover effects between Developed markets indices and Digital indices. At first sight, it seems that the interaction between them is less marked than the Emerging indices. This is partly because of the relatively less adoption of crypto assets compared to emerging countries. Nevertheless, there is a positive transmission of volatility from North America, Europe, and Asia Pacific to all the Digital indices, which reinforces the influence of consolidated markets on the new ones. Even more, North American stock markets seem also to transmit negative skewness and kurtosis to the Blockchain index. Negative transmission for skewness exists between Blockchain Index and Asia Pacific, and Solfint to Europe. Finally, Blockchain transmits a negative conditional kurtosis to Europe. Similar to Emerging markets, developed markets barely have interactions with Diversified (similar to the Crypto Index composed of Bitcoin and Ethereum) with the exception of volatility and the positive transmission of skewness from Emerging Asia to Diversified (Tables 7 and 8). The sings of all of these interactions are summarized in Table 10.

4. Discussion

The interpretation of the signs of the impact of skewness and kurtosis from one market to the other is not obvious for different reasons. On the one hand, positive (negative) skewness implies a left-modal (right-modal) distribution but also a thicker right-side (left-side) tail. On the other hand, leptokurtosis means heavy tails, but also a concentration of the probability at the mean/mode. Therefore, a negative effect of both skewness and kurtosis interaction parameters implies that when a market becomes more skewed/ leptokurtic (maybe due to the presence of an adverse shock) the other becomes less skewed/leptokurtic (i.e., is more normal-shaped). This would mean that what drives strong movements in both markets is not the same kind of news. On the contrary, a positive high-order moment interaction coefficient means that extreme events affect both markets in the same direction (i.e., increasing the skewness/leptokurtosis of the distribution). Therefore, these positive spillovers are especially relevant for portfolio choice and risk management. Furthermore, a simultaneous effect in skewness and kurtosis with different signs (e.g., the case of the Future of Finance index to the North America index) has not a direct interpretation, since both effects have an impact on the distribution tails that might compensate but supports the existence of density spillovers.

A salient result is that volatility transmission from financial indices to digital indices has always a positive effect since uncertainty sources are induced by 'common factors' (and also exist size and maturity effects), but volatility transmission from digital indices depends on idiosyncratic issues that do not seem to induce higher volatility to stock market indices.

Importantly, our model lets us consider the transmission effects of extreme market movements explicitly and the results show that some markets are in fact reactive to these events. Particularly, digital assets extreme movements significantly affect some stock market indices, sometimes inducing instability, but sometimes 'normalizing' its density. For example, news such as China's decision to ban all virtual trading and speculation or Binance's order to halt crypto operations in Malaysia and Singapore might trigger strong movements in both the Crypto markets and the Asian Emerging stock markets where the exchange platforms were located, but also may contribute to 'normalize' other neighbor developed countries positioned against the crypto industry - e.g. skewness transmission from Crypto to Emerging Asia (Asia Pacific) is positive (negative). Anyhow, it should also be noteworthy that our model does not allow us to infer causality but correlation movements.

Having all of this in mind, it is clear that our study raises the interrelations between digital and stock market indices by explicitly considering the effects of extreme movements (non-normal features) and exploring these connections in emerging and developed countries, as well as the potential impact of the frequency of the observations. This is important since the crypto industry (e.g., exchange platforms location or 'friendly' regulation) is mainly based on emerging markets and cryptocurrencies exhibit high volatility at high frequencies.

Overall, our results give support to the following assessments: First, there exists volatility transmission from stock to digital indices, but not in the reverse direction; Second, high-order moment links between digital and stock markets exist, but only in some particular cases; Third, most of the observed high-order moment effects from digital to stock indices are negative, i.e. do not contribute to generating non-normal returns (only affect to volatility), this is particularly observed in developed markets; Fourth, in some cases digital asset may contribute to high instability in stock markets (e.g. in Emerging Asia and Latin America); Fifth, the inter-market links are not only observed at daily basis but also a weekly basis.

All these assessments point to the existence of potential spillovers between digital and stock markets that should affect not only investors' choices but also policymakers' decisions on the coordination of proper regulation of the crypto industry that organizes its physical location and implantation. Definitely, a global worldwide industry with local rules does not contribute to protecting investors and financial markets from systemic risk.

5. Conclusions

Due to the interconnectedness of the economic world, more research and analysis are needed to analyze the relationship between markets, particularly taking into account the new digital side of the alternative asset industry. For that reason, this paper presents an analysis of the moments' transmission between emerging markets and digital asset markets. As far as we know, this is the first study providing a cross-market comparison between well-known emerging market indices (Latin America, Emerging Asia, and Emerging Europe) and, as a novelty, three brand-new digital asset market indices, Crypto, DeFi, and Future of Finance, which cover a great number of cryptocurrencies and companies related to them.

Thanks to the flexible stepwise SNP-DCC methodology, we achieve consistent results related to the volatility spillovers and high-order moments such as conditional skewness and kurtosis. The results show evidence of volatility transmission between markets where Future of Finance, Crypto, and DeFi receive volatility from all emerging markets. The relationship is positive and thus there is a transmission effect between these markets in the sense that an increase (decrease) of volatility in emerging markets implies an increase (decrease) in digital markets.

Regarding the 'common' volatility, some studies decouple markets with Bitcoin (Drozdz et al., 2019) or assure that information spillovers change over time being one of the net transmitters of Bitcoin (Ji et al., 2019) in comparison to energy and commodity markets. Our results are in line with Matkovskyy and Jalan (2019), where the evidence of the transmission may indicate an increasing integration between digital asset markets and emerging financial markets, in our case.

In contrast to the volatility spillover, the joint estimate of skewness and kurtosis for spillovers is scarce in the crypto industry. Furthermore, higher-order moments transmission is more heterogeneous in terms of interpreting the results, especially for the sign and depending on the type of market. In this regard, Emerging Asia has specific features that differ from other countries since it is an expansion area of the crypto industry where the transmission of the high-order moments is positive from the Crypto index for daily data and from the Emerging Asia index to Diversified for weekly data. The opposite sign is for the pairs Crypto-Asia for Developed markets due to the fact that developed countries in this area have a different perspective from cryptos. The Future of Finance index, which is related to companies that develop infrastructure to use blockchain technology, has a different performance. It transmits skewness to the Latin America index. However, the sign of the latter high-order transmission is negative, which points to an opposite sign transfer of extreme co-movements. This is a particularly interesting result since direct transmission of volatility (mainly from emerging stock markets to cryptocurrency markets) is compatible with an indirect relationship of high-order moment transmission (skewness) between these markets since the drivers of extreme movements of crypto assets might be different from those of stock markets. As a consequence, the regulation of crypto assets, either in a positive or negative direction, might contribute to stabilizing emerging stock markets from potential extreme events.

In addition, to compare similar regions of the world, the developed markets' MSCI North America Index (North America), MSCI Europe Index (Europe), and MSCI Asia Pacific Index (Asia Pacific) indices are also analyzed. The results are quite similar to the emerging markets where those developed indices are the principal transmitters of volatility (positive) to the digital ones. In the case of high-order moments, the Crypto index transmits negative skewness to North America and Asia Pacific, and North America to the Crypto index a positive one. Finally, (positive) skewness and (negative) kurtosis go from the Future of Finance to North America.

For the special case of the daily data, the VMA(1) model has been used in order to control asynchrony, as well as potential common factors influencing volatilities, which are also accomplished in our research. Particularly, considering both daily and weekly frequencies, the VIX index is introduced as an external regressor in conditional variances. As an alternative robustness check of our results, we examine the spillovers between emerging, developed markets and digital markets considering three alternative digital indices such as Blockchain, Solfint, and Diversified, for weekly data. The latter are composed of similar portfolios to the previous daily digital indices but with longer series. Overall, meaningful results have arisen relating to high-order moments spillovers. Firstly, volatility spillovers follow the same patterns as daily results, i.e. transmission is positive and the main receivers are the digital markets. Secondly, the skewness and kurtosis spillovers are mainly negative and more limited to several markets.

Finally, as further research, it could also be worthwhile to examine intraday interdependence between markets in order to provide a deeper analysis. In this sense, it would be also interesting to analyze the impact of crypto exchange platforms in high-order moment transmission as in (Alexander et al., 2021), who find Binance as the main source for volatility transmission.

Data availability

Data will be made available on request.

Acknowledgements

Authors grateful acknowledge the organizers and participants of the CRC 2021, the funding from the Bank of Santander [Post-DoctoralResearch Scholarship], FAPA-Uniandes [PR.3.2016.2807] and the University of Salamanca [2022 Research Program I.A.].

Appendix A. Data description

Index	Description
LatinAmerica	The MSCI Emerging Markets (EM) Latin America Index captures large and mid cap representation across 5 Emerging Markets (EM) countries (Brazil, Chile, Colombia, Mexico, and Peru) in Latin America. With 93 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country
Emerging Europe	Europe The MSCI Emerging Markets Europe Index captures large and mid cap representation across 6 Emerging Markets (EM) countries (the Czech Republic, Greece, Hungary, Poland, Russia and Turkey.) in Europe. With 64 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country
Emerging Asia	The MSCI Emerging Markets (EM) Asia Index captures large and mid-cap representation across 8 Emerging Markets countries (China, India, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand). With 1159 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country
Crypto	The Bloomberg Galaxy Crypto Index (BGCI) is a benchmark designed to measure the performance of the largest cryptocurrencies traded in USD (Bitcoin,Ethereum, Litecoin, Bitcoin Cash and EOS). Cryptocurrency weightings are based on market capitalization (calculated as product of circulating supply and price), subject to weighting restrictions applied monthly such that no cryptocurrency constitutes more than 40% of the Index or constitutes less than 1%.
DeFi	The Bloomberg Galaxy DeFi Index is a modified market cap-weighted benchmark tracking the largest decentralized finance (DeFi) protocols and apps that use smart contracts on blockchains to offer financial services such as lending, market-making, and insurance, without a central financial intermediary (Uniswap, Aave, MakerDao, Compound, Yearn.finance, SushiSwap, Ox, Synthetix and Universal Markets assets). Cryptocurrency weightings are based on market capitalization (calculated as product of circulating supply and price), subject to weighting restrictions applied monthly such that no cryptocurrency constitutes more than 40% of the Index or constitutes less than 1%.
Future of Finance	The Bloomberg Grayscale Future of Finance Index is constructed to track the performance companies that have exposure to the digital asset and blockchain ecosystem. It includes companies that are involved in the mining of digital assets, developing of infrastructure to create applications utilizing blockchain technology, supplying the infrastructure necessary for mining or development of applications, or enabling the buying, selling, and transacting of digital assets. The index securities are modified market capitalization weighted. The initial weight of each issuer is determined by dividing the free float market capitalization of each issuer by the sum of the free float market capitalizations of all the issuers in the index. Using a two-step capping

(*continued on next page*)

(*continued*)

Index	Description
	process, the initial weights are distributed such that the top 5 issuers by free float market capitalization are subject to an 8% cap. Issuers after the top 5 by free float market capitalization are subject to a 4% cap.
North America	The MSCI North America Index is designed to measure the performance of the large and mid-cap segments of the US and Canada markets. With 714 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in the US and Canada.
Europe	The MSCI Europe Index captures large and mid-cap representation across 15 Developed Markets (DM) countries in Europe*. With 429 constituents, the index covers approximately 85% of the free float-adjusted market capitalization across the European Developed Markets equity universe. DM countries in Europe include: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK.
Asia Pacific	The MSCI AC Asia Pacific Index captures large and mid-cap representation across 5 Developed Markets countries* and 8 Emerging Markets countries* in the Asia Pacific region. With 1544 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country. Developed Markets countries in the index include: Australia, Hong Kong, Japan, New Zealand and Singapore. Emerging Markets countries include: China, India, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand.
Blockchain	The Index aims to offer exposure to listed companies that participate or have the potential to participate in the blockchain or cryptocurrency ecosystem. The Index is calculated and distributed by Solactive and is rebalanced quarterly.
Solfint	The Solactive FinTech Index tracks the performance of companies that utilize/provide transformational and innovative software solutions within the financial services industry. The index is calculated as a net total return index in US Dollar and adjusted quarterly.
Diversified	The index is passive, capitalization weighted, capped - providing a diversified, long-term and non-speculative investment approach based on a list of crypto assets derived from the three different use cases of digital assets.

Source: Blomberg, coinShares, msci.com, mvis-indices.com, solactive.com. Extracted from the factsheet of every index.

References

Ahmed, W.M.A., Al Mafrachi, M., 2021. Do higher-order realized moments matter for cryptocurrency returns? Int. Rev. Econ. Financ. 72, 483–499. https://doi.org/10.1016/j.iref.2020.12.009.

Alexander, C., Heck, D., Kaeck, A., 2021. The Role of Binance in Bitcoin Volatility Transmission. SSRN Electron. J. https://doi.org/10.2139/ssrn.3877949.

Anson, M., 2021. Initial exchange offerings: The next evolution in cryptocurrencies. J. Altern. Invest. 23, 110–121. https://doi.org/10.3905/JAI.2021.1.127.

Aslanidis, N., Bariviera, A.F., Martínez-Ibañez, O., 2019. An analysis of cryptocurrencies conditional cross correlations. Financ. Res. Lett. 31, 130–137. https://doi.org/10.1016/j.frl.2019.04.019.

BenSaida, A., 2019. Good and bad volatility spillovers: An asymmetric connectedness. J. Fin. Markets 43, 78–95. https://doi.org/10.1016/j.finmar.2018.12.005.

Blinnikov, S., Moessner, R., 1998. Expansions for nearly Gaussian distributions. Astron. Astrophys. Suppl. Ser. 130, 193–205. https://doi.org/10.1051/aas:1998221.

Bouraoui, T., 2020. The drivers of Bitcoin trading volume in selected emerging countries. Q. Rev. Econ. Fin. 76, 218–229. https://doi.org/10.1016/j.qref.2019.07.003.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Financ. Res. Lett. 20, 192–198. https://doi.org/10.1016/j.frl.2016.09.025.

Bouri, E., Das, M., Gupta, R., Roubaud, D., 2018. Spillovers between Bitcoin and other assets during bear and bull markets. Appl. Econ. 50, 5935–5949. https://doi.org/10.1080/00036846.2018.1488075.

Burns, P., Engle, R.F., Mezrich, J.J., 1998. Correlations and Volatilities of Asynchronous Data. J. Derivatives 5, 7–18. https://doi.org/10.3905/jod.1998.408000.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econ. Lett. 165, 28–34. https://doi.org/10.1016/j.econlet.2018.01.004.

Cortés, L.M., Mora-Valencia, A., Perote, J., 2016. The productivity of top researchers: a semi-nonparametric approach. Scientometrics 109, 891–915. https://doi.org/10.1007/s11192-016-2072-5.

Del Brio, E.B., Ñíguez, T.-M., Perote, J., 2009. Gram–Charlier densities: a multivariate approach. Q. Fin. 9, 855–868. https://doi.org/10.1080/14697680902773611.

Del Brio, E.B., Ñíguez, T.M., Perote, J., 2011. Multivariate semi-nonparametric distributions with dynamic conditional correlations. Int. J. Forecast. 27, 347–364. https://doi.org/10.1016/j.ijforecast.2010.02.005.

Del Brio, E.B., Mora-Valencia, A., Perote, J., 2014. VaR performance during the subprime and sovereign debt crises: An application to emerging markets. Emerg. Mark. Rev. 20, 23–41. https://doi.org/10.1016/j.ememar.2014.05.001.

Del Brio, E.B., Mora-Valencia, A., Perote, J., 2017. The kidnapping of Europe: High-order moments' transmission between developed and emerging markets. Emerg. Mark. Rev. 31, 96–115. https://doi.org/10.1016/j.ememar.2017.03.002.

Del Brio, E.B., Mora-Valencia, A., Perote, J., 2019. Expected shortfall assessment in commodity (L)ETF portfolios with semi-nonparametric specifications. Eur. J. Financ. 25, 1746–1764. https://doi.org/10.1080/1351847X.2018.1559213.

Del Brio, E.B., Mora-Valencia, A., Perote, J., 2020. Risk quantification for commodity ETFs: Backtesting value-at-risk and expected shortfall. Int. Rev. Financ. Anal. 70 https://doi.org/10.1016/j.irfa.2017.11.007.

Drozdz, S., Minati, L., Oświęcimka, P., Stanuszek, M., Watorek, M., 2019. Signatures of the crypto-currency market decoupling from the Forex. Future Internet 11. https://doi.org/10.3390/fi11070154.

Engle, R., Sheppard, K., 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate. GARCH Cambridge, MA. https://doi.org/10.3386/w8554.

Fernández-Rodríguez, F., Sosvilla-Rivero, S., 2020. Volatility transmission between stock and foreign exchange markets: a connectedness analysis. Appl. Econ. 52, 2096–2108. https://doi.org/10.1080/00036846.2019.1683143.

Freedman, R., 1981. On gram-charlier approximations. IEEE Trans. Commun. 29, 122–125. https://doi.org/10.1109/TCOM.1981.1094977.

Gabauer, D., 2020. Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. J. Forecast. 39, 788–796. https://doi.org/10.1002/for.2648.

Gallant, A.R., Nychka, D.W., 1987. Semi-nonparametric maximum likelihood estimation. Econometrica 55, 363. https://doi.org/10.2307/1913241.

Giudici, P., Abu-Hashish, I., 2019. What determines bitcoin exchange prices? A network VAR approach. Financ. Res. Lett. 28, 309–318. https://doi.org/10.1016/j.frl.2018.05.013.

Gkillas, K., Katsiampa, P., 2018. An application of extreme value theory to cryptocurrencies. Econ. Lett. 164, 109–111. https://doi.org/10.1016/j.econlet.2018.01.020.

Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2019. Portfolio diversification with virtual currency: Evidence from bitcoin. Int. Rev. Financ. Anal. 63, 431–437. https://doi.org/10.1016/j.irfa.2018.03.004.

Hald, A., 2000. The early history of the cumulants and the Gram-Charlier series. Int. Stat. Rev. 68, 137–153. https://doi.org/10.1111/j.1751-5823.2000.tb00318.x.

Harvey, C., Ramachandran, A., Santoro, J., 2021. DeFi and the Future of Finance. John Wiley & Sons, Inc., Hoboken, New Jersey.

Hou, Y., Li, S., Wen, F., 2019. Time-varying volatility spillover between Chinese fuel oil and stock index futures markets based on a DCC-GARCH model with a semi-nonparametric approach. Energy Econ. 83, 119–143. https://doi.org/10.1016/j.eneco.2019.06.020.
Ji, Q., Bouri, E., Roubaud, D., Kristoufek, L., 2019. Information interdependence among energy, cryptocurrency and major commodity markets. Energy Econ. 81, 1042–1055. https://doi.org/10.1016/j.eneco.2019.06.005.
Jia, Y., Liu, Y., Yan, S., 2021. Higher moments, extreme returns, and cross–section of cryptocurrency returns. Financ. Res. Lett. 39, 101536 https://doi.org/10.1016/j.frl.2020.101536.
Jiménez, I., Mora-Valencia, A., Ñíguez, T.-M., Perote, J., 2020a. Portfolio risk assessment under dynamic (equi)correlation and semi-nonparametric estimation: an application to cryptocurrencies. Mathematics 8, 2110. https://doi.org/10.3390/math8122110.
Jiménez, I., Mora-Valencia, A., Perote, J., 2020b. Risk quantification and validation for Bitcoin. Oper. Res. Lett. 48, 534–541. https://doi.org/10.1016/j.orl.2020.06.004.
Jiménez, I., Mora-Valencia, A., Perote, J., 2021. Dynamic selection of Gram–Charlier expansions with risk targets: an application to cryptocurrencies. Risk Manag. https://doi.org/10.1057/s41283-021-00084-5.
Jiménez, I., Mora-Valencia, A., Perote, J., 2022. Semi-nonparametric risk assessment with cryptocurrencies. Res. Int. Bus. Financ. 59 https://doi.org/10.1016/j.ribaf.2021.101567.
Jondeau, E., Rockinger, M., 2001. Gram–Charlier densities. J. Econ. Dyn. Control. 25, 1457–1483. https://doi.org/10.1016/S0165-1889(99)00082-2.
Kambouroudis, D.S., McMillan, D.G., 2016. Does VIX or volume improve GARCH volatility forecasts? Appl. Econ. 48, 1210–1228. https://doi.org/10.1080/00036846.2015.1096004.
Kendall, M., Stuart, A., 1977. The Advanced Theory of Statistics, , (4th Ed.).vol. I. Griffin & Co., London.
León, A., Moreno, M., 2017. One-sided performance measures under Gram-Charlier distributions. J. Bank. Financ. 74, 38–50. https://doi.org/10.1016/j.jbankfin.2016.10.005.
León, Á., Rubio, G., Serna, G., 2005. Autoregresive conditional volatility, skewness and kurtosis. Q. Rev. Econ. Fin. 45, 599–618. https://doi.org/10.1016/j.qref.2004.12.020.
León, Á., Mencía, J., Sentana, E., 2009. Parametric properties of semi-nonparametric distributions, with applications to option valuation. J. Bus. Econ. Stat. 27, 176–192. https://doi.org/10.1198/jbes.2009.0013.
Lucey, B.M., Vigne, S.A., Yarovaya, L., Wang, Y., 2022. The cryptocurrency uncertainty index. Financ. Res. Lett. 45, 102147 https://doi.org/10.1016/j.frl.2021.102147.
Matkovskyy, R., Jalan, A., 2019. From financial markets to Bitcoin markets: A fresh look at the contagion effect. Financ. Res. Lett. 31, 93–97. https://doi.org/10.1016/j.frl.2019.04.007.
Mauleón, I., 2003. Financial densities in emerging markets: an application of the multivariate ES density. Emerging Markets Rev. Emerg. Markets Rev. 4, 197–223. https://doi.org/10.1016/S1566-0141(03)00027-X.
Mauleón, I., 2006. Modelling multivariate moments in European Stock Markets. Eur. J. Fin. Eur. J. Fin. 12, 241–263. https://doi.org/10.1080/13518470500249233.
Mauleón, I., 2010. Assessing the value of Hermite densities for predictive distributions. J. Forecast. 29, 689–714. https://doi.org/10.1002/for.1160.
Mauleón, I., Perote, J., 2000. Testing densities with financial data: An empirical comparison of the Edgeworth-Sargan density to the student's t. Eur. J. Financ. 225–239.
Molina-Muñoz, E., Mora-Valencia, A., Perote, J., 2020. Backtesting expected shortfall for world stock index ETFs with extreme value theory and Gram–Charlier mixtures. Int. J. Financ. Econ. 1–27 https://doi.org/10.1002/ijfe.2009.
Mora-Valencia, A., 2017. A note on the standard measurement approach versus the loss distribution approach-advanced measurement approach: The dawning of a new regulation. J. Operational Risk 12, 51–69.
Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf [WWW Document].
Nakatani, T., Teräsvirta, T., 2009. Testing for volatility interactions in the Constant Conditional Correlation GARCH model. Econ. J. 12, 147–163. https://doi.org/10.1111/j.1368-423X.2008.00261.x.
Ñíguez, T.M., Perote, J., 2012. Forecasting heavy-tailed densities with Positive Edgeworth and Gram-Charlier expansions. Oxf. Bull. Econ. Stat. 74, 600–627. https://doi.org/10.1111/j.1468-0084.2011.00663.x.
Ñíguez, T.-M., Perote, J., 2016. Multivariate moments expansion density: Application of the dynamic equicorrelation model. J. Bank. Financ. 72, S216–S232. https://doi.org/10.1016/j.jbankfin.2015.12.012.
Ñíguez, T., Perote, J., Rubia, A., 2009. Are the high-order moments of the assets returns distribution forecastable? J. Curr. Issues Fin. Bus. Econ. 2, 383–401.
Ñíguez, T.-M., Paya, I., Peel, D., Perote, J., 2019. Flexible distribution functions, higher-order preferences and optimal portfolio allocation. Q. Fin. 19, 669–703.
Pan, Q., Mei, X., Gao, T., 2022. Modeling dynamic conditional correlations with leverage effects and volatility spillover effects: Evidence from the Chinese and US stock markets affected by the recent trade friction. N. Am. J. Econ. Financ. 59, 101591 https://doi.org/10.1016/j.najef.2021.101591.
Perote, J., 2004. The multivariate Edgeworth-Sargan density. Span. Econ. Rev. 6, 77–96. https://doi.org/10.1007/s10108-003-0075-x.
Qureshi, S., Aftab, M., Bouri, E., Saeed, T., 2020. Dynamic interdependence of cryptocurrency markets: An analysis across time and frequency. Phys. Statistical Mech. Appl. 559, 125077 https://doi.org/10.1016/j.physa.2020.125077.
Sargan, J.D., 1976. Econometric estimators and the Edgeworth approximation. Econometrica 421–448.
Stavroyiannis, S., 2018. Volatility modeling and risk assessment of the major digital currencies. SSRN Electron. J. https://doi.org/10.2139/ssrn.3092173.
Trespalacios, A., Cortés, L.M., Perote, J., 2020. Uncertainty in electricity markets from a semi-nonparametric approach. Energy Policy 137. https://doi.org/10.1016/j.enpol.2019.111091.
Trespalacios, A., Cortés, L.M., Perote, J., 2021. Modeling electricity price and quantity uncertainty: an application for hedging with forward contracts. Energies. https://doi.org/10.3390/en14113345.
Umar, Z., Gubareva, M., 2020. A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. J. Behav. Exp. Financ. 28, 100404 https://doi.org/10.1016/j.jbef.2020.100404.
Umar, M., Rizvi, S.K.A., Naqvi, B., 2021. Dance with the devil? The nexus of fourth industrial revolution, technological financial products and volatility spillovers in global financial system. Technol. Forecast. Soc. Change 163, 120450. https://doi.org/10.1016/j.techfore.2020.120450.
Wang, Y., 2022. Volatility spillovers across NFTs news attention and financial markets. Int. Rev. Financ. Anal. 83, 102313 https://doi.org/10.1016/j.irfa.2022.102313.
Wang, Y., Lucey, B.M., Vigne, S.A., Yarovaya, L., 2022a. The effects of central bank digital currencies news on financial markets. Technol. Forecast. Soc. Chang. 180, 121715 https://doi.org/10.1016/j.techfore.2022.121715.
Wang, Y., Lucey, B., Vigne, S.A., Yarovaya, L., 2022b. An index of cryptocurrency environmental attention (ICEA). China Fin. Rev. Int. https://doi.org/10.1108/CFRI-09-2021-0191.
Zoia, M.G., Biffi, P., Nicolussi, F., 2018. Value at risk and expected shortfall based on Gram-Charlier like expansions. J. Bank. Financ. 93, 92–104. https://doi.org/10.1016/j.jbankfin.2018.06.001.