# "Distant or close cousins: Connectedness between cryptocurrencies and traditional currencies volatilities"

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## *Abstract*

This paper examines the volatility interconnection between the main cryptocurrencies and traditional currencies during the period of February 2014-September 2018 using both a framework proposed by Diebold and Yilmaz (2014) and the modified approach of Antonakakis and Gabauer (2017). Our results suggest that a 34.43%, of the total variance of the forecast errors is explained by shocks across the eight examined cryptocurrencies and traditional currencies, indicating that the remainder 65.57% of the variation is due to idiosyncratic shocks. Furthermore, we find that volatility connectedness varies over time, with a surge during periods of increasing economic and financial instability. When we aggregate both markets by blocks, we find that the block of traditional currencies and the block of cryptocurrencies are mostly disconnected with periods of mild net volatility spill over between both blocks. Finally, our findings suggest that financial market variables are the main drivers of total connectedness within the traditional currencies, while the cryptocurrency-specific variables are identified as the key determinant for the total connectedness within the traditional currencies and a combination of business cycles and cryptocurrency-specific variables explain the directional volatility connectedness between both blocks.

*JEL classification:* C53, E44, F31, G15.

*Keywords:* Exchange rates, Cryptocurrencies, Connectedness, Time-varying parameters, Stepwise regressions.

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## *Acknowledgements*

We thank Gary Koop and Dimitris Korobilis for providing the TVP-VAR programs, CaixaBank Research and BBVA Research for kindly providing the economic surprise indices and BBVA Research for kindly providing us with the indicators of risk appetite and the financial tension indices.

## 1. Introduction

Over the past few years, cryptocurrencies have experienced increased growth as well as sharp rises and falls, attracting extensive attention from policymakers, researchers, and investors[1]. Like traditional currencies, cryptocurrencies are intended to function as a store of value, a medium of exchange and a unit of account. They differ from the latter in that they are not issued by central banks, and in that they can be transferred electronically between users without the involvement of intermediaries or the oversight of a central authority (Treasury Committee, 2018). Moreover, cryptocurrencies lack intrinsic value capable of generating revenue like regular products or services[2]. Whereas traditional currencies rely on political and legal mechanisms for value and legitimacy, cryptocurrencies rely only on the cryptographic integrity of the network itself.

In order to test a popular view that cryptocurrencies may serve as another medium of exchange, this paper examines whether there is consistent evidence of systematic traditional currency exposures in cryptocurrencies. In particular, by studying volatility connectedness between cryptocurrencies and traditional currencies, we explore how the extreme volatility and trends observed in many cryptocurrencies has been transmitted within them and across currencies, analyzing the degree to which cryptocurrencies provide diversification benefits.

To our best knowledge, this study contributes to the literature in four important aspects. First, we are the first to comprehensively analyze of volatility connectedness between four highly capitalized cryptocurrencies and four major exchange rates using a framework

[1] See BIS (2018) and Fernandez-Villaverde and Sanches (2018) for an introduction to cryptocurrencies and Corbet *et al.* (2019) for a systematic review of the empirical literature on cryptocurrencies.

[2] Schiller (2017) contents that trading cryptocurrencies cannot be seen as investing but instead as a form of speculation that is similar to gambling.

proposed by Diebold and Yilmaz (2014), providing insights on the comparison of the extent and the nature of interdependencies and spillovers between them. Second, we apply a generalization of the connectedness framework developed by Greenwood-Nimmo *et al.* (2015, 2016) to directly capture connectedness within both groups of currencies or blocks. Third, we implement the Time-Varying Parameter Vector Autoregressive (TVP-VAR, hereafter) connectedness approach developed by Antonakakis and Gabauer (2017) to evaluate both the net directional connectedness for each currency. Fourth, we analyze the potential determinants of the detected dynamic volatility connectedness making use of stepwise regressions.

Our results suggest that a 34.43%, of the total variance of the forecast errors is explained by shocks across the eight examined cryptocurrencies and traditional currencies, indicating that the remainder 65.57% of the variation is due to idiosyncratic shocks. Furthermore, we find that volatility connectedness varies over time, with a surge during periods of increasing economic and financial instability. When we aggregate each market by blocks, we find that the block of traditional currencies and the block of cryptocurrencies are mostly disconnected with periods of mild net volatility spillover between both blocks. Finally, our findings suggest that financial market variables are the main drivers of total connectedness within the traditional currencies, while the cryptocurrency-specific variables are identified as the key determinant for the total connectedness within the traditional currencies and a combination of business cycle and cryptocurrency-specific variables explain the directional volatility connectedness between both blocks.

The paper proceeds as follows. Section 2 provides a brief review of the relevant literature. Section 3 outlines the econometric framework to quantify both the total and directional volatility connectedness. Section 4 presents our data and a preliminary analysis. In

Section 5 we report the empirical results (both static and dynamic) obtained for our sample of four market volatility indices (a system-wide measure of connectedness), while Section 6 explores the determinants of the detected total and directional dynamic connectedness Finally, Section 7 summarizes the findings and offers some concluding remarks.

## 2. Related literature

Given the media attention, one strand of the literature has studied Bitcoin from a financial perspective. Another strand of literature examines the relationship of cryptocurrencies to other financial assets.

Regarding the first category, Cheah and Fry (2015) show that, as with many asset classes, Bitcoin exhibits speculative bubbles and that its fundamental price is zero. Dwyer (2015) shows that the average monthly volatility of Bitcoin is higher than that of gold or a set of foreign currencies. Dyhrberg (2016) shows that Bitcoin can act as a hedge against the US dollar and the UK stock market, sharing similar hedging capabilities to gold. Bouri *et al* (2017), employing Engle (2002)'s dynamic conditional correlation model, show limited evidence of the hedging and safe haven properties of Bitcoin, although it can still be an effective diversifier.

More recently, Platanakis and Urquhart (2018) examine the benefit of including this cryptocurrency in a traditional stock-bond portfolio, finding that across all different asset allocation strategies and risk aversions the benefits of Bitcoin are quite considerable. Furthermore, they also show that including Bitcoin in a stock, bond and commodity portfolio offers substantially higher risk-adjusted returns.

Using methods recently proposed by Phillips *et al.* (2011) and Phillips *et al.* (2015), Cheung *et al.* (2015) observe several short-lived bubbles and three huge bubbles in

Bitcoin prices during the period 2011-2013, Guegan and Frunza (2018) find episodes of bubbles in the Bitcoin/USD rates in 2013 and 2017, while Corbet *et al.* (2018a) detect bubble-like behavior in Bitcoin around the 2013/2014 turn of the year and in early 2017, and in the early 2016 and mid-2017 periods for Ethereum.

Finally, Baur e*t al.* (2018) analyze the statistical properties of Bitcoin and find that it is uncorrelated with traditional asset classes such as stocks, bonds and commodities both in normal times and in periods of financial turmoil.

As for the empirical studies carrying out a more comprehensive analysis by considering a wider group of cryptocurrencies, Bouri *et al* (2019), applying a rolling-window analysis, find significant time-varying herding behavior in the digital currency market, mostly driven by economic policy uncertainty.

Employing different long-memory methods, Caporale and Gil-Alana (2018) detect persistence in the case of the four main digital currencies (BitCoin, LiteCoin, Ripple, Dash) over the sample period 2013-2017, representing evidence of market inefficiency.

Bação *et al.* (2018) investigate the information transmission between Bitcoin, Litecoin, Ripple, Ethereum and Bitcoin Cash, using a VAR modelling approach and associated generalized impulse response functions. Their results suggest that most of the information transmission is contemporaneous, although some lagged feedback effects are found, mainly from other digital currencies to Bitcoin.

Walther and Klein (2018) apply the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-Mixed-data sampling (MIDAS) framework to forecast the daily, weekly, and monthly volatility of Bitcoin, Etherium, Litecoin, and Ripple as well as the digital currency index CRIX, finding that the most important exogenous drivers of volatility in cryptocurrency markets is the Global Real Economic Activity. Their results suggest that the volatility of digital currencies appears to be driven by the global business cycle rather than country-specific economic or financial variables.

Kurka (2019) examines connectedness between commodities, foreign exchange, stocks, financials and Bitcoin over the period June 2011 to December 2015. He documents a very low level of connectedness between Bitcoin as representative of cryptocurrencies and other traditional assets, the only exception being gold which receives a substantial amount of shocks from the Bitcoin market.

Baumöhl (2019) assess the interrelationship between six major currencies (Euro, Japanese Yen, British Pound, Swiss Franc, Canadian Dollar and Chinese Yuan) and six digital currencies (Bitcoin, Ether, Ripple, Litecoin, Stellar Lumens and NEM) using the quantile cross-spectral approach over the period of 1 September 2015 to 29 December 2017. His findings indicate that the intra-group dependencies are positive in the lower extreme quantiles, while inter-group dependencies are negative, suggesting that it is worth diversifying between these two currency groups.

Liu and Tsyvinski (2018) study the exposure of Bitcoin, Ripple and Ethereum returns to major currencies (Australian Dollar, Canadian Dollar, Euro, Singaporean Dollar, and UK Pound). The authors find that although these major currencies strongly commove, being the exposures of that digital currencies to these currencies small and not statistically significant. They conclude that there is no consistent evidence of systematic currency exposures in digital currencies.

Corbet *et al.* (2018b) analyze, in the time and frequency domains, the relationships between Bitcoin, Ripple and Litecoin and a variety of other financial assets (MSC GSCI Total Returns Index, the US$ Broad Exchange Rate, the SP500 Index and the COMEX closing gold price, VIX and the Markit ITTR110 index). Their results suggest that digital currencies are highly connected to each other and disconnected from mainstream assets, but the digital currency market contains its own idiosyncratic risks that are difficult to hedge against.

Yi *et al* (2018) study volatility connectedness between Bitcoin, Ripple, Litecoin, Peercoin, Namecoin, Feathercoin, Novacoin and Terracoin using daily data covering the period 4 August 2013 to 1 April 2018. They find that the total volatility connectedness between eight cryptocurrencies fluctuated periodically over the sample period and increased when the market is experiencing unstable economic conditions or unpredictable exogenous shocks. Yi *et al* (2018) further construct a volatility connectedness network linking 52 cryptocurrencies, finding that these 52 cryptocurrencies are tightly interconnected and "mega-cap" cryptocurrencies are more likely to propagate volatility shocks to others.

Ji *et al.* (2019) examine dynamic connectedness across six large cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Dash) from August 7, 2015 to February 22, 2018. Their results show that Litecoin and Bitcoin are at the centre of the connected network of returns, being Ripple and Ethereum the top recipients of negative-return shocks, whereas Ethereum and Dash exhibit very weak connectedness via positive returns. Regarding volatility spillovers, Ji *et al.* (2019) find that Bitcoin is the most influential, followed by Litecoin; Dash exhibits a very weak connectedness. Antonakakis *et al*. (2019) employ the TVP-FAVAR connectedness approach in order to investigate the transmission mechanism in the cryptocurrency market, concentrating on 9 cryptocurrencies. The authors find that the dynamic total connectedness across those cryptocurrencies exhibits large dynamic variability ranging between 25% and 75%, particularly, periods of high (low) market uncertainty correspond to strong (weak) connectedness.

Finally, Hong *et al.* (2018) analyze a dual currency regime with fiat currency and digital currency and investigate potential crowding-out effects of fiat currency or digital currency under the framework of the traditional monetary economic model. They find that crowding out only occurs under extreme assumptions: extremely high costs associated with the use of one currency and extremely low costs associated with the use of the other currency.

Our paper differs from the previous literature in several important aspects. First, we analyze of volatility connectedness between four highly capitalized cryptocurrencies and four major exchange rates applying the framework proposed by Diebold and Yilmaz (2014), together with the generalizations of the connectedness framework developed by Greenwood-Nimmo *et al.* (2015, 2016) to directly capture connectedness within both groups of currencies or blocks, and the TVP-VAR connectedness approach developed by Antonakakis and Gabauer (2017) to evaluate the dynamic total and directional connectedness for each currency. Finally, we analyze the potential determinants of the detected dynamic volatility connectedness making use of stepwise regressions.

## 3. Econometric methodology

The main tool for measuring the amount of connectedness is based on a decomposition of the forecast error variance. This section presents the econometric methodology used in the empirical analysis of the total and directional connectedness between cryptocurrencies and traditional currencies volatilities analyzed in the paper. We divide the presentation into three subsections. The first one briefly describes the methodological econometric framework of Diebold and Yilmaz (2014, 2015, 2016). In the second subsection, we present a generalization of the connectedness framework developed by Greenwood-Nimmo *et al.* (2015, 2016) to directly capture connectedness between subgroups of variables or blocks. Finally, subsection 3.3 outlines the dynamic connectedness procedure based on TVP-VAR provided by Antonakakis and Gabauer (2017).

*3.1 Diebold and Yilmaz's connectedness.*

Given a multivariate empirical time series, the forecast error variance decomposition is obtained from the following steps:

1. Fit a reduced-form vector autoregressive (VAR) model to the series,

$$Y_t = \beta Y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma) \tag{1}$$

where $Y_t$, represents an *Nx1* series vector at time *t*, $\beta$ is an $NxN_p$ dimensional coefficient matrix and $\varepsilon_t$ is an *Nx1* dimensional error-disturbance vector with an *NxN* variance-covariance matrix, $\Sigma$.

2. Using series data up to and including time *t*, establish an *H* period-ahead forecast (up to time *t* + *H*).

3. Decompose the error variance of the forecast for each component with respect to shocks from the same or other components at time *t*.

Diebold and Yilmaz (2014) propose several connectedness measures built from pieces of variance decompositions in which the forecast error variance of variable *i* is decomposed into parts attributed to the various variables in the system. Their approach has the considerable advantage that it fully accounts for contemporaneous effects and it also directly measures not only the direction but also the strength of linkages among the variables under study. This subsection provides a summary of their connectedness index methodology.

Let us denote by $d_{ij}^H$ the *ij*-th *H*-step variance decomposition component (i.e., the fraction of variable *i*'s *H*-step forecast error variance due to shocks in variable *j*). The connectedness measures are based on the “non-own”, or “cross”, variance decompositions, $d_{ij}^{H}$ , $i, j = 1,\ldots, N, i \neq j$.

Consider an $N$-dimensional covariance-stationary data-generating process (DGP) with orthogonal shocks: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \ldots$, $E(u_t, u_t') = I$. Note that $\Theta_0$ need not be diagonal. All aspects of connectedness are contained in this very general representation. Contemporaneous aspects of connectedness are summarized in $\Theta_0$ and dynamic aspects in $\{\Theta_1, \Theta_2, \ldots\}$. Transformation of $\{\Theta_1, \Theta_2, \ldots\}$ via variance decompositions is needed to reveal and compactly summarize connectedness. Diebold and Yilmaz (2014) propose a connectedness table such as Table 1 to understand the various connectedness measures and their relationships. Its main upper-left *NxN* block, which contains the variance decompositions, is called the “variance decomposition o connectedness matrix,” and is denoted by $D^H = [d_{ij}^H]$.

$$D^H = \begin{bmatrix} d_{11}^H d_{12}^H \ldots d_{1N}^H \\ d_{21}^H d_{22}^H \ldots d_{2N}^H \\ \\ d_{N1}^H d_{N2}^H \ldots d_{NN}^H \end{bmatrix} \qquad (2)$$

The connectedness table increases $D^H$ with a rightmost column containing row sums, a bottom row containing column sums, and a bottom-right element containing the grand average, in all cases for $i \neq j$.

[Insert Table 1 here]

The off-diagonal entries of $D^H$ are the parts of the $N$ forecast-error variance decompositions of relevance from a connectedness perspective. In particular, the *gross pairwise directional connectedness* from *j* to *i* is defined as follows:

$$C_{i\leftarrow j}^{H} = d_{ij}^{H}. \tag{3}$$

Since in general $C_{i\leftarrow j}^{H} \neq C_{j\leftarrow i}^{H}$, the *net pairwise directional connectedness* from *j* to *i*, can be defined as:

$$C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H}. \tag{4}$$

As for the off-diagonal row sums in Table 1, they give the share of the *H*-step forecast-error variance of variable $x_i$ coming from shocks arising in other variables (all others, as opposed to a single other). The off-diagonal column sums provide the share of the *H*-step forecast-error variance of variable $x_i$ going to shocks arising in other variables. Hence, the off-diagonal row and column sums, labelled "from" and "to" in the connectedness table, offer the total directional connectedness measures. In particular, *total directional connectedness from others to i* is defined as

$$C_{i\leftarrow\bullet}^{H} = \sum_{\substack{j=1\\ j\neq i}}^{N} d_{ij}^{H}, \tag{5}$$

and *total directional connectedness from j to others* is defined as

$$C_{\bullet\leftarrow j}^{H} = \sum_{\substack{i=1\\ j\neq i}}^{N} d_{ij}^{H}. \tag{6}$$

We can also define *net total directional connectedness* as

$$C_{i}^{H} = C_{\bullet\leftarrow i}^{H} - C_{i\leftarrow\bullet}^{H}. \tag{7}$$

Finally, the grand total of the off-diagonal entries in $D^H$ (equivalently, the sum of the "from" column or "to" row) measures *total connectedness*:

$$C^{H} = \frac{1}{N}\sum_{\substack{i,j=1\\ j\neq i}}^{N} d_{ij}^{H}. \tag{8}$$

For the case of non-orthogonal shocks, the variance decompositions are not as easily calculated as before, because the variance of a weighted sum is not an appropriate sum of variances. Otherwise, methodologies for providing orthogonal innovations like traditional Cholesky-factor identification may be sensitive to ordering. Therefore, following Diebold and Yilmaz (2014), a generalized variance decomposition (GVD), which is invariant to ordering, proposed by Koop *et al.* (1996) and Pesaran and Shin (1998) will be used. The $H$-step generalized variance decomposition matrix is defined as $D^{gH} = \left[ d_{ij}^{gH} \right]$, where

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left( e_i^{'} \Theta_h \Sigma e_j \right)^2}{\sum_{h=0}^{H-1} \left( e_i^{'} \Theta_h \Sigma \Theta_h^{'} e_i \right)} \tag{9}$$

In this case, $e_j$ is a vector with $j$th element unity and zeros elsewhere; $\Theta_h$ is the coefficient matrix in the infinite moving-average representation from VAR; $\Sigma$ is the covariance matrix of the shock vector in the non-orthogonalized-VAR, $\sigma_{jj}$ being its $j$th diagonal element. In this GVD framework, the lack of orthogonality means that the rows of $d_{ij}^{gH}$ do not have sum unity and, in order to obtain a generalized connectedness index $\tilde{D}^g = \left[ \tilde{d}_{ij}^g \right]$, the following normalization is necessary: $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^{N} d_{ij}^g}$, where by construction $\sum_{j=1}^{N} \tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^{N} \tilde{d}_{ij}^g = N$.

The matrix $\tilde{D}^g = \left[ \tilde{d}_{ij}^g \right]$ permits us to define similar concepts as defined before for the orthogonal case, that is, *total directional connectedness*, *net total directional connectedness*, and *total connectedness.*

It is worthily to note that the Diebold and Yilmaz's (2014) connectedness framework is closely linked with both modern network theory (see Glover and Richards-Shubik, 2014) and modern measures of systemic risk (see Ang and Longstaff, 2013 or Acemoglu *et al*., 2015). This framework has been used by Diebold and Yilmaz (2015) for defining, measuring, and monitoring connectedness in financial and related macroeconomic environments (cross-firm, cross-asset, cross-market, cross-country, etc.). The degree of connectedness, on the other hand, measures the contribution of individual units to systemic network events, in a fashion very similar to the conditional value at risk (CoVaR) of this unit (see, e.g., Adrian and Brunnermeier, 2016).

*3.2 A generalization of the Diebold and Yilmaz's connectedness*

Greenwood *et al*. (2015, 2016) provides a simple way to measures spillovers among groups of variables or blocks (i.e., traditional currencies and cryptocurrencies in our context). These authors develop a generalized framework that exploits block aggregation of the connectedness matrix. Block aggregation introduces a new stratum between the level of individual variables and the system-wide aggregate level, thereby enhancing the flexibility of the Diebold-Yilmaz framework. Due to the order-invariant of GVDs, the variables can be re-ordered as necessary to support any desired block structure. For instance, the traditional currencies (cryptocurrencies) own connectedness can be obtained as the sum of all the elements of the upper-left (lower-right) sub-matrix of elements for the traditional currencies divided by the total number of currencies in the block.

Suppose that there are three variables for market *i*-th $\{x_{it}, y_{it}, z_{it}\}$ in the order $Y_t = (x_{1t}, y_{1t}, z_{1t}, x_{2t}, y_{2t}, x_{2t}, \ldots, x_{Nt}, y_{Nt}, z_{Nt})'$ and that we wish to evaluate the connectedness among the *N* markets in the model in a combined manner that encompasses all three variables in each market. We can re-write the connectedness matrix $D^H$ in block form with *g*=*N* groups each composed of *m*=3 variables as follows:

$$D^{H} = \begin{bmatrix} B_{11}^{H} B_{12}^{H} \ldots B_{1N}^{H} \\ B_{21}^{H} B_{22}^{H} \ldots B_{2N}^{H} \\ \ldots \\ B_{N1}^{H} B_{N2}^{H} \ldots B_{NN}^{H} \end{bmatrix}, \tag{10}$$

Where $B_{ij}^{H} = \begin{bmatrix} d_{x_i x_j}^{H} d_{x_i y_j}^{H} d_{x_i z_j}^{H} \\ d_{y_i x_j}^{H} d_{y_i y_j}^{H} d_{y_i z_j}^{H} \\ d_{z_i x_j}^{H} d_{z_i y_j}^{H} d_{z_i z_j}^{H} \end{bmatrix}$ for $i, j = 1, \ldots, N$, and where the block $B_{ii}^{H}$ collects all the within-market effects for market *i* while $B_{ij}^{H}$ collects all spillover effects from market *j* to market *i*.

Total within market forecast error variance contribution for market *i* is given as:

$$W_{ii}^{H} = \frac{1}{m} e_{m}^{'} B_{ii}^{H} e_{m}, \tag{11}$$

and the total pairwise directional spillover from market *j* to market *i* ($i \neq j$) at horizon *H* is given as:

$$P_{ij}^{H} = \frac{1}{m} e_{m}^{'} B_{ij}^{H} e_{m}, \tag{12}$$

where *m* is the number of variables that each group is composed of (in this case, *m*=3) and $e_m$ is an *m*x1 vector of ones.

Hence, the aggregated connectedness matrix following Greenwood-Nimmo et al. (2015) can be written as:

$$D^{H} = \begin{bmatrix} W_{11}^{H} P_{12}^{H} \ldots P_{1N}^{H} \\ P_{21}^{H} W_{22}^{H} \ldots P_{2N}^{H} \\ \\ P_{N1}^{H} P_{N2}^{H} \ldots W_{NN}^{H} \end{bmatrix}. \tag{13}$$

Now, total within-market contribution, $W_{ii}^{H}$, can be decomposed into common-variable forecast error variance contribution within-market *i*, $O_{ii}^{H}$, and cross-variable effects, $C_{ii}^{H}$, which are given as follows:

$$O_{ii}^{H} = \frac{1}{m} trace(B_{ii}^{H}) \tag{14}$$

and

$$C_{ii}^{H} = W_{ii}^{H} - O_{ii}^{H}. \tag{15}$$

It should be emphasized here that $O_{ii}^{H}$ is the proportion of forecast error variance of $Y_{it}$ that is not attributable to spillovers among innovations within market *i* nor to the spillovers from market *j* with $i \neq j$. On the other hand, $C_{ii}^{H}$ is the proportion of forecast error variance of $Y_{it}$ attributable to spillovers among innovations within market *i*.

The total pairwise directional spillovers from market *j* to market *i* at horizon *H* are given by Equation (12), while total directional spillovers transmitted by market *i* from and to all other markets, in other words, the aggregate from and to connectedness of market *i* are expressed as:

$$P_{i\leftarrow\bullet}^{H} = \sum_{j=1, j\neq i}^{N} P_{ij}^{H} \tag{16}$$

and

$$P_{\bullet\leftarrow i}^{H} = \sum_{j=1, j\neq i}^{N} P_{ji}^{H}, \tag{17}$$

respectively. Where the net directional spillovers transmitted from market *i* to all other markets is

$$P^{H} = P_{\bullet\leftarrow i}^{H} - P_{i\leftarrow\bullet}^{H} \tag{18}$$

Finally, the aggregate between-market spillover measure and the aggregate within-market effect are:

$$S^H = \frac{1}{N}\sum_{i=1}^{N} P_{i\leftarrow\bullet}^H \tag{19}$$

and

$$H^H = 100 - S^H. \tag{20}$$

*3.3 Dynamic connectedness based on TVP-VAR*

Antonakakis and Gabauer (2017) extend and refine the current dynamic connectedness literature by applying TVP-VAR, as an alternative to the currently proposed rolling-window VAR. This approach improves the methodology provided by Diebold and Yilmaz (2014) substantially, because under their proposed methodology: (1) there is no need to arbitrarily set the rolling window-size, (2) it employs the entire sample to estimate the dynamic connectedness so there is no major loss of observations, and (3) it is not outlier sensitive. Another advantage of their proposed TVP-VAR-based measure of connectedness is that it adjusts immediately to events.[3]

The TVP-VAR methodology allows both the VAR parameters and the variances to vary via a stochastic volatility Kalman Filter estimation with forgetting factors introduced by

[3] Antonakakis *et al.* (2018) apply the TVP-VAR to study the transmission channel of uncertainty between developed economies, examining potential spill-over effects between the US, the EU, the UK, Japan and Canada, and finding a significant spill over of uncertainty from the EU to the US. Gabauer and Gupta (2018) study the internal and external categorical economic policy uncertainty (EPU) spillovers between the US and Japan using the TVP-VAR connectedness approach, finding that monetary policy uncertainty is the main driver, followed by uncertainties associated with fiscal, currency market and trade policies.

Koop and Korobilis (2014). As such, this approach can also be conducted to examine dynamic connectedness with limited time-series data.

The TVP-VAR model can be written as follows,

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t, \quad \varepsilon_t | F_{t-1} \sim N(0, \Sigma_t) \tag{21}$$

$$\beta_t = \beta_{t-1} + v_t, \quad v_t | F_{t-1} \sim N(0, R_t) \tag{22}$$

Where $\beta_t$ is an $NxN_p$ dimensional time-varying coefficient matrix and $\varepsilon_t$ is an $Nx1$ dimensional error-disturbance vector with an $NxN$ time-varying variance-covariance matrix, $\Sigma_t$, and $F_{t-1}$ is the given information through time *t-1*. The parameters $\beta_t$ follow a random walk and depend on their own lagged values $\beta_{t-1}$ and on an $NxN_p$ dimensional matrix with an $N_p xN_p$ variance-covariance matrix, $R_t$.[4]

The time-varying coefficients $\beta_t$ and $\Sigma_t$ can be used in the Diebold and Yilmaz's connectedness measure where the dynamic *H*-step generalized variance decomposition matrix is now

$$d_{ij,t}^{gH} = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} \left( e_i' \Theta_{h,t} \Sigma_t e_j \right)^2}{\sum_{h=0}^{H-1} \left( e_i' \Theta_{h,t} \Sigma_t \Theta_{h,t}' e_i \right)} \tag{23}$$

[4] Following Koop and Korobilis (2014), we use the same non-informative initial conditions in the Kalman filter, a decay factor of 0.96 and a forgetting factor of 0.99 (see online appendix in Koop and Korobilis, 2014, for the technical details). Without loss of generality, we normalize the series, $Y_t$, to get a faster convergence in the Kalman filter and smoother. This normalization does not have any effect on the connectedness matrix.

Which after normalization would be $\tilde{d}^{g}_{ij,t} = \frac{d^{gH}_{ij,t}}{\sum_{j=1}^{N} d^{gH}_{ij,t}}$. Similarly, the matrix $\tilde{D}^{g}_{t} = \left[\tilde{d}^{g}_{ij,t}\right]$ permits us to define the dynamic *total directional connectedness*, *net total directional connectedness*, and *total connectedness.*

## 4. Data and preliminary analysis

In our paper, both types of currencies are considered against the US dollar. The data on traditional currencies consists of daily exchange rate series for the euro (EUR), the Australian dollar (AUD), the Japanese yen (JPY) and the British pound (GBP) offered by the Federal Reserve Economic Data (FRED), a database maintained by the Research division of the Federal Reserve Bank of St. Louis.[5] Note that focusing on these four major exchange rates, we cover the currencies with the largest market turnover, e.g., these currencies covered the 165.3% of global foreign exchange market turnover between 2001 to 2016 [6].

Besides, we use daily data of highly capitalized cryptocurrencies (Bitcoin-XBT; Ripple-XRP; Litecoin-XLT; and Dash-XDS), that constitute 56.44% of the overall cryptocurrency market capitalization.[7]

[5] https://fred.stlouisfed.org/.

[6] Average of currency distribution of global foreign exchange market turnover over 2001, 2004, 2007, 2010, 2013 and 2016 (Bank for International Settlements, 2016). Because two currencies are involved in each transaction, the sum of the percentage shares of individual currencies totals 200% instead of 100%.

[7] On 31 December 2017, according to Coinmarketcap.com the market capitalization of XBT was USD 220,903,949,498 (38.59%), of XLT was USD 12,000,947,760 (2.10%), of XRP was USD 82,199,880,481 (14.38%) and of XDS was USD 7,850,364,658 (1.37%).

Our sample spans from 14 February 2014 until 28 September 2018 (i.e. a total of 1160 observations). The sample size has been conditioned by the availability of cryptocurrency data.

Following a common practice in applied financial market research[8], we make use of the GARCH model (Bollerslev, 1986; and Taylor, 1986) to estimate the variance of the series at a particular point in time (Enders, 2009). In particular, we find that a GARCH(1,1) successfully describes the time-varying conditional second-order moment (variance) of the series under study using past unpredictable changes in the returns of that series. To easy exposition and faster convergence in the Kalman filter, we normalize these GARCH volatilities.[9]

Figure 1a shows the daily evolution in the traditional currencies (Panel A) and cryptocurrencies (Panel B) exchange rates under study. As can be seen, the cryptocurrencies show a dramatic spike in late 2017 and January 2018, before falling precipitously through the rest of the sample. In contrast, the behaviour of the traditional currencies reveals relatively less substantial time variation.

[Insert Figure 1 here]

Plots of the daily normalized volatilities are given in Figure 1b. As can be seen, these series are characterized by volatility clustering and notable jumps at different time periods, being the volatility of the cryptocurrencies significantly and manifestly higher than that of the traditional currencies.

[8] GARCH models have a good record in providing accurate estimates for the volatility of returns from financial assets (see, e. g. Pagan, 1996, or Diebold and Lopez, 1996).
[9] EViews© 11 software has been used to obtain the GARCH volatility series. The GARCH estimations are available from the authors.

Panel A of Table 2 provides the descriptive statistics for all the series, along with the Jarque-Bera test for normality. As per construction, the mean and standard deviation of all the normalized volatility series are cero and one, respectively, and hence, we do not report them. The estimated skewness is negative for EUR, GBP, AUD, XBT and XDS (suggesting that the distribution has a long-left tail), while it is positive for JBY, XRP and XLT (indicating that the distribution has a long right tail). Kurtosis statistics are  high in all cases, suggesting that the distribution is peaked relative to the normal. This asymmetry and leptokurtic excess are in line with the Jarque-Bera test results, justifying the rejection of the hypothesis of normal distribution at the 1% significance level. We report the pairwise correlations in Panel B of Table 2. As can be seen, the only significant pairwise correlation between both types of currencies is the negative and significant value obtained for the JPY and the XDS. By contrast, we observe positive and highly significant correlation within blocks of currencies, although this is not very strong. These correlations could shed light about the connections within currencies blocks rather than between blocks, which we develop further below as one of the main goals of this paper.

[Insert Table 2 here]

## 5. Empirical results on connectedness and directional connectedness

In this section, we report the empirical results of the volatility connectedness and directional spill-overs. First, successively examine the full-sample connectedness of all currencies (subsection 5.1) and by blocks of currencies (subsection 5.2). In subsection 5.3, we study the dynamic connectedness analysis through TVP-VAR. Finally, in subsection 5.4 we focus on net and dynamic net pair-wise directional volatility connectedness.

### *5.1 Static (full-sample, unconditional) analysis for all currencies*

In Table 3, we report the full-sample connectedness table where the off-diagonal elements measure the connectedness between the normalized volatility series. As mentioned in Section 2, the *ij*th entry of the upper-left 8x8 market submatrix gives the estimated *ij*th pair-wise directional connectedness contribution to the forecast error variance of currency *i*'s volatility coming from innovations to currency *j*. Hence, the off-diagonal column sums (labelled TO) and row sums (labelled FROM) gives the total directional connectedness to all others from *i* and from all others to *i*, respectively. The bottom-most row (labelled NET) gives the difference in total directional connectedness (TO minus FROM). Finally, the bottom-right element (in boldface) is total connectedness, which is calculated as the sum of the non-diagonal elements of the connectedness matrix, divided by the number of currencies.[10]

[Insert Table 3 here]

As can be seen, the diagonal elements (own connectedness) are the largest individual elements in the table, ranging from 57.71% (EUR) to 72.97% (JPY), being these values of similar magnitude in traditional currencies (with an average value of 66.07%) than those in cryptocurrencies (with an average of 65.06%). Interestingly, the own connectedness is higher than any total directional connectedness FROM and TO others, reflecting that these volatilities are relatively independent of each other. Namely, news shocks that influence the volatility of a particular currency do not fully spread on the volatilities of the others. Accordingly, the total connectedness of the eight volatilities under study is 34.43% (indicating that as much as 65.57% of the variation is due to

[10] All results are based on vector autoregressions of order 2 and generalized variance decompositions of 10-day ahead volatility forecast errors. To check for the sensitivity of the results to the choice of the order of VAR, we also calculated the connectedness index for orders 2 through 4, as well as for forecast horizons varying from 4 days to 10 days. The main results of our paper are not affected by these choices. Detailed results are available from the authors upon request.

idiosyncratic shocks). These results are much lower than the value of 78.3% obtained by Diebold and Yilmaz (2014) for the total connectedness between US financial institutions and lower than the value of 97.2% found by Diebold and Yilmaz (2012) for international financial markets.

Regarding to the net (TO minus FROM) contribution, our results suggest that the GBP (-2.14%), AUD (-1.77%), JPY (-3.88%), XRP (-4.51%) and XDS (-1.97%) are net receivers of volatility, being EUR (6.74%), XBT (4.55%) and XLT (2.98%) net volatility triggers. Finally, the highest observed net pairwise connectedness is from XBT to XLT (22.59%), followed by that from XLT to XBT (22.12%).

*5.2 Static (full-sample, unconditional) analysis by blocks of currencies*

As a complement to the previously documented positive and highly significant pairwise correlation within blocks of currencies in Table 2, Table 4 reports the static connectedness table by blocks of currencies using the generalization suggested by Greenwood *et al*. (2015, 2016). As can be seen, the own connectedness of each block, traditional currencies and cryptocurrencies, represents almost 100% of the volatility with only a negligent 0.26% net connectedness from cryptocurrencies to traditional currencies. This result clearly reflects that both blocks are highly intra-connected but highly disconnected to each other, being the total connectedness across blocks of merely 0.73%. Namely, shocks that come from traditional currencies do not spill over cryptocurrencies, and *vice versa*[11]. This result is in line with the literature reviewed in Section 2 where cryptocurrencies have shown low correlation, and accordingly, good diversification benefits with traditional assets (see e.g., the survey of cryptocurrencies literature in Corbet *et al*., 2019). Finally,

[11] This result is in line with the findings in Pelster *et al.* (2019) that the overall behavior of investors who enter crypto markets is driven by excitement-seeking, by an intentional strategy to enter a new promising asset class and by diversification purposes. This type of trading behavior can cause speculative price bubbles, as documented by Gandal *et al.* (2018).

the estimated total connectedness within the traditional currencies ($C_{ii}^{H}$ in Equation (15) for traditional currencies) is 33.07% and within cryptocurrencies ($C_{jj}^{H}$ in Equation (15) for cryptocurrencies) is 34.34%.

[Insert Table 4 here]

*5.3 Dynamic connectedness analysis*

The previous subsection provides a snapshot of the "unconditional", or full-sample, aspects of the connectedness measure between the volatility of cryptocurrencies and traditional currencies. However, the dynamics of the connectedness measures remains covered. As previously stated, we carry out an analysis of dynamic connectedness based on TVP-VAR.

[Insert Figure 2]

In Figure 2, we report the evolution of the total connectedness between the volatility of the eight traditional currencies and cryptocurrencies under study (shaded grey area).[12] Figure 2 also highlights several cycles of connectedness where the total connectedness is around the full sample average (34.43%), suggesting that connectedness between cryptocurrencies and traditional currencies volatilities are time-dependent. The most significant spikes are observed (i) in April 2014, following Janet Yellen's announcement that the Fed would keep interest rates low even when the US economy recovers; (ii) from August 2014 coinciding with divergences in monetary policy expectations and increased downside risks until July 2015 when a period of relative calm started in financial markets after the EU bailout agreement with Greece and the stabilization of the Chinese stock

[12] To eliminate the effect of the non-informative initial conditions in the Kalman filter, we have skipped the first 10 days of the sample and plot the results from March 03, 2014 to September 28, 2018.

market following the crash in June 2015; (iii) after temporary decline oscillations in the evolution of the total connectedness from July 2015 to December 2016 in a context of reduction in short-term risks to global financial stability, a renewed impulse is observed until March 2017, coinciding with a period of increased volatility due to political uncertainty about US economic policy and formal announcing by the British government of its plans to leave the European Union; (iv) the connectedness indicator experienced a gradual rise in the third quarter of 2017, propelled by reduced expectations of monetary tightening in the United States and positive macroeconomic news; (v) and a final increase in connectedness is found from the beginning of 2018 until the end of the sample, reflecting the popularity of cryptocurrencies and increased volatility as participants remained very sensitive to any perceived changes in central banks' messages. Interestingly, there are also important reductions in connectedness during our sample in March 2014 (coinciding the possibility that the Fed could end its massive bond-buying program and could start raising interest rates); in June and July 2014 (corresponding with a stunning fall in oil prices and a shifting risks with respect to the economic recovery in advanced economies, respectively); from July 2015 (in a context of increasing concern about the growing vulnerabilities in emerging market economies and China's bursting equity bubble) until November 2016 the total connectedness experienced some ups and downs, possibly related to the results of the US presidential election; in the second quarter of 2017 the total connectedness indicator registered a fast decrease until reaching low values in April 2017 (in a context of positive tone in economic data) and at the end of 2017 coinciding with renewed declines in implied volatility for equities, bonds and exchange rates.

Figure 2 also displays the differentiated behaviour of the total connectedness by blocks of currencies (i.e., $C_{ii,t}^{H}$ for traditional currencies and $C_{jj,t}^{H}$ cryptocurrencies in Equation

(15)): between the volatilities of the four traditional currencies (blue line) and between those of the four cryptocurrencies (red line). As expected, the connectedness indexes by blocks of currencies show a similar time-varying pattern over the vertical lines that delimit the before episodes in the evolution of the total connectedness. However, we observe several idiosyncratic spikes in the evolution of the total connectedness by blocks of currencies, reaching figures of over 50% in several periods of our sample. At the beginning of our sample the total connectedness index of the traditional currencies' block was the full sample lowest value (7.93%) but it registered a turbulent rise (in a context of retrenchment in emerging market economies and strength in advance economies affecting portfolio compositions and asset values), with large fluctuations, until reaching its first spikes in October 2014 (48.93%) and June 2015 (57.32%). Note, the sudden increase and decrease in the total connectedness index of the cryptocurrencies' block from lows (20.53%) in March 2014 until its first spike (59.18%) that we observe in April 2014, as the conflict in eastern Ukraine escalated in a context of the considerable uncertainty triggered by the crisis and the fall in energy prices, to repeat once again the minimum levels during June 2014. An episode of ups and downs in the evolution of the total connectedness within the cryptocurrencies characterized the subsequent period from August 2014 to July 2015, reaching several strong spikes at the beginning (49.08%), in the middle (January 2015, 55.53%) and before the end (46.66%) in a context of unsettled political climate in many countries, slumping commodity prices, China's bursting equity bubble and pressure on exchange rates. Interestingly, there were rapid simultaneous reductions from the highs reached in both connectedness indices per blocks at the end of this period in July 2015 (coinciding with the collapse in oil prices and its impact on other assets). After a period of relative stability around its full sample average (33.07%) from July 2015 to November 2016, the total connectedness between the volatilities of the four traditional currencies experienced a fast increase that it peaked (57.77%) at the beginning of 2017 after the United Kingdom formally begun negotiations to leave the European Union. Furthermore, the total connectedness between the volatility of the four cryptocurrencies was gradually decreasing along this period (July 2015-November 2016) with values below the full sample average of this index (34.34%), reverting also this trend at the beginning of the year 2017. In the periods thereafter, both registered various interesting contemporaneous episodes of downs and ups. An episode of free falls is detected from March 2017 following the US Securities and Exchange Commission twice denied requests for Bitcoin exchange-traded funds, reaching the connectedness index of the cryptocurrencies' block its full sample lowest value at the end of April 2017 (6.80%) and the connectedness index of the traditional currencies' block at its lowest values since August 2014 (17.01%). This last index was followed by an episode of renewed impulse until September 2017 where the former climbed a new spike (57.63%) and the values of the last one above its full sample average coinciding with China's ban on initial coin offerings and with the upsurge of political risk led by mounting US-North Korea tensions and terrorist attacks in Spain, to repeat once again sudden falls of both of them during the next period October 2017-January 2018 within a general context of protracted US dollar weakness. Finally, an abrupt increase in both of total connectedness indexes per blocks is found in the final days of January 2018 coinciding with a massive sell-off of most cryptocurrencies in a context of continued loosening of credit conditions and undaunted risk-taking in most asset classes. One can note that the connectedness index of the volatilities of the cryptocurrencies' block was increasing gradually along 2018 until reaching the full sample highest values (around 68%) in middle June 2018 as statements from regulators starting to reflect a deeper acknowledgement of the technology underlying cryptocurrencies and their future potential, slowly reversing this trend from that point in time. Meanwhile, the total connectedness of the volatilities of the four traditional currencies' block experienced with moderate fluctuations on a downward trend until the end of the sample in September 2018, when cryptocurrencies collapsed 80% from their peak in January 2018 after report stating that Goldman Sachs was abandoning its plans to trade in cryptocurrencies.

*5.4 Net and dynamic net pair-wise directional volatility connectedness plots*

We now turn our focus to the net total and net pairwise directional connectedness measures of the system. As the dynamic total connectedness measure presented in subsection 5.2, our analysis also relies on the TVP-VAR connectedness approach. In contrast with Table 3 where we report the static net contribution, Figures 3a to 3h display the dynamic net directional volatility connectedness (shaded grey area). These figures show how the volatility indices have switched from generators to receivers of volatility, and *vice versa*, throughout the sample.

[Insert Figures 3a to 3h here]

By construction, the net directional connectedness from currency volatility $i$-th to others is equal to the sum of all the net pair-wise connectedness from currency volatility $i$-th to volatility $j$-th, for all $j$ with $i \neq j$. Having this relationship in mind, in Figures 3a to 3h, the dynamics of the net pairwise directional connectedness of the currency volatility $i$-th with respect to the other currency volatilities under study are added to the net directional connectedness (grey area) explained before, using a similar approach than that in subsection 3.2. This decomposition of the dynamics of net directional connectedness into their pairwise directional connectedness per blocks under study (blue and red lines for traditional currencies and cryptocurrencies, respectively) is appealing since it allows a deeper understanding how the transmission of volatility works for each currency under study.

As can be seen in Figure 3a, EUR is the net trigger of volatility in our sample. Indeed, 77.4% of the computed values in the net directional connectedness are positive, indicating that during most of the sample period EUR transmitted volatility, principally to the net pair-wise directional connectedness per blocks of the traditional currencies (blue line). Interesting, EUR is a net receiver of volatility from the net pair-wise directional connectedness of the cryptocurrencies' block (red line) in August 2014 (when market participants started to look for further monetary stimulus, shifting forward rates down following remarks by ECB President Mario Draghi). Disaggregated (unreported) results show that this is mostly due to net pair-wise directional connectedness from XLT and XDS to EUR. EUR is also a net receiver of volatility from the net pair-wise directional connectedness of the cryptocurrencies' block in late 2017 (in a context of dollar weakened as economic prospects brightened the euro area), also this is mainly from XDS, and XBT to EUR.

Regarding the GBP and AUD, they are net receivers of volatility from the net pair-wise directional connectedness per blocks of the traditional currencies during much of the sample (Figures 3b and 3c, respectably), being 79.3% and 75.8% of the computed values negatives. Nevertheless, it is worth noting a transmission of volatility received from the block of cryptocurrencies in August 2014 by both traditional currencies, it is strong in the case of GBP, being possibly partly driven by uncertainty related to the Scottish referendum. GBP was a net trigger of both net directional connectedness per blocks in the early spring and summer of 2016, reflecting the global financial turmoil after the UK voted to leave the European Union in June 2016.

As for JPY, Figure 3d shows a swing in the net directional connectedness where periods of net generation of volatility to all the net pair-wise directional connectedness per blocks are followed by periods where this is a net receiver of volatility to those. Interestingly, JPY is a net receiver of volatility from the net pair-wise directional connectedness of the cryptocurrencies in August 2014. The biggest net block-wise connectedness is from JPY to traditional currencies.

Turning to the case of the XBT, in Figure 3e we observe that it is a net generator of volatility in our sample. Indeed, 73.13% of the computed values in the net directional connectedness are positive, indicating that during most of the sample period XBT transmitted principally to the net pair-wise directional connectedness of the other cryptocurrencies. Interestingly, XBT is a net receiver of volatility from the net pair-wise directional connectedness of the traditional currencies at late 2016, and from the net pair-wise directional connectedness of the other cryptocurrencies at the beginning of 2018, coinciding with the great cryptocurrency crash of January 2018.

As regards XRP and XDS, they are mostly net receiver of volatility from the net pair-wise directional connectedness per blocks of the cryptocurrencies during much of the sample (Figures 3f and 3h), being 74.1% and 69.4% of the computed values negatives. Nevertheless, it is worth noting a strong transmission of volatility triggered from XDS to the block of traditional currencies in August 2014, as commented before.

Concerning XLT, Figure 3g shows a swing in the net directional connectedness where periods of a net generation of volatility are followed by periods where XLT is a net receiver of volatility. Interestingly, XLT is a net trigger of volatility to the net pair-wise directional connectedness of the traditional currencies' block in August 2014, which unreported results show this is mostly due to net pair-wise directional connectedness to EUR, GBP and JYP. Moreover, XLT is a net absorber of volatility from the net pair-wise directional connectedness of the traditional currencies' block from the second half of September 2016 to late December 2016.

Figure 4 plots the dynamic net connectedness from the block of traditional currencies to the block of cryptocurrencies (i.e., $P^H$ in Equation (18)). Although the static net connectedness from the block of traditional currencies to the block of cryptocurrencies shows that these two blocks are disconnected as Table 4 suggested, the dynamic net connectedness shows a different picture, ranging the net connectedness from close to -14% to 10%. The net connectedness from the block of traditional currencies to the block of cryptocurrencies can be divided into three periods:

i) from the beginning of the sample until mid-2014 where the block of cryptocurrencies is a generator of volatility toward the block of traditional currencies, in a context of widespread pessimism and negative investor sentiment in the cryptocurrency market and the absence of real positive development for investors to track and serve as a counterbalance to the bearish trend, after the collapse of Bitcoin's biggest exchange (Mt Gox).

ii) from late-2014 until early 2017 where the block of traditional currencies is a generator of volatility toward the block of cryptocurrencies in a context marked by the continued divergence in the monetary policy stance of the major economies, tensions about the implementation of the Greek adjustment programme, the UK Brexit vote and the surprise result of the US election; and

iii) from late-2017 until the end of the sample where again the block of cryptocurrencies is a generator of volatility toward the block of traditional currencies, a period characterized by a huge increase in trading activity and media coverage in cryptocurrencies, an explosive behaviour in cryptocurrency prices, and several events leading people to be suspicious of the security and anonymity of cryptocurrencies in the future (Hafner, 2019).

[Insert Figure 4]

As a complementary analysis of Figure 4, Figure 5 plots the decomposition of the dynamic net connectedness into directional volatility connectedness from block of traditional currencies to the block of cryptocurrencies, and *vice versa*. As can be seen, we identify a negative trend in the directional volatility connectedness from the block of traditional currencies to the block of cryptocurrencies, indicating a gradual reduction in the exposures of traditional to digital currencies in line with Liu and Tsyvinski (2018).

In summary, Figures 3a to 3h illustrate how the dynamics of the net pair-wise connectedness between all the currency's volatilities are not constant but switch from net generator to net receiver of volatility to others. Likewise, Figure 4 shows the net connectedness from the block of traditional currencies to the block of cryptocurrencies also switches from net generator to net receiver of volatility. Therefore, the unconditional or full-sample connectedness measure is not able to uncover all the dynamics of the connectedness between the different currencies' volatilities per currency and per block of currencies. The dynamic net connectedness approach identifies substantially different interrelationship episodes, yielding more accurate and sensible indicators of the spread of market disturbances.

## 6. Determinants of the total and net dynamic connectedness

Hitherto, we have documented that there is a general disconnection between the block of traditional currencies and the block of cryptocurrencies. However, as Figures 4 and 5 show, there are periods where there are a sizable net and total directional volatility connectedness effect between both types of currencies. We have also offered evidence in favour of the existence of a considerable total connectedness within each block. In this section, we try to identify the potential determinants of these four dynamic behaviours: 1) total connectedness within the traditional currencies (i.e., $C^H_{ii,t}$ in Equation (15) for traditional currencies); 2) total connectedness within the cryptocurrencies (i.e., $C^H_{jj,t}$ in Equation (15) for cryptocurrencies); 3) the directional volatility connectedness from the block of cryptocurrencies to the block of traditional currencies (i.e., $P^H_{i\leftarrow j}$); and 4) the directional volatility connectedness from the block of traditional currencies to the block of cryptocurrencies (i.e., $P^{H}_{j \leftarrow i}$).

Although there is no consensus on the determinants of exchange rate volatility, many factors have been identified in the literature: the openness of an economy, the domestic and foreign money supplies, the exchange rate regime, interest rates, central bank independence, levels of output, income, inflation, and unpredictable circumstances (see, e. g., Morana, 2009). The degree of the impact of each of these factors varies and depends on a particular country's economic condition.

Regarding cryptocurrencies, their volatilities are also influenced by their differences in market capitalization, the transaction processing speed of their networks, the total number of coins that each cryptocurrency can produce, the different cryptographic algorithms which they employ, etc. (see, e. g., Gandal and Halaburda, 2014).

In this paper, we adopt an agnostic approach, using a general-to-specific modelling strategy, to empirically assess the relevance of the variables as potential drivers of the detected dynamic connectedness between cryptocurrencies and traditional currencies volatilities.

In particular, we analyze a set of 59 macroeconomic/business cycle, financial and cryptocurrencies-specific variables suggested both by the foreign exchange and cryptocurrency literature (see, e.g., Dornbusch *et al.*, 2000: Fratzscher, 2009; and Walther and Klein, 2018, among others).[13] Likewise, we also include the lagged dependent

[13] Given that most macroeconomic and financial data exhibit non-stationary, we tested for the order of integration of the variables under study using the Augmented Dickey-Fuller (ADF) tests. The results decisively reject the null hypothesis of a unit root at conventional significance levels for all the variables (indicating that they are stationary in levels), except for SP500, EFA ETF, BarGov, Gold, Brent, FSI, FCI, USFTI, DMFTI, KBE ETF, OFR FSI, Credit, Safe, Funding, EME, VBIT, CBIT, CLIT, VDAS, CDAS and CALL (suggesting that these variables can be treated as first-difference stationary). Furthermore, following Carrion-i-Silvestre *et al.*'s (2001) suggestion, we confirm these results using the Kwiatkowski *et al*. (1992) (KPSS) tests, where the null is a stationary process against the alternative of a unit root. Finally, these results (which are not shown here to save space but are available from the authors upon request) were confirmed

variable to control for the persistence in the total and directional connectedness series due to both the well-known clusters of volatilities and the TVP-VAR. Appendix A offers a summary of the explanatory variables used in the empirical analysis as well as the data sources. Our sample spans from 01 July 2015 until 28 September 2018 (i.e. a total of 797 observations). The sample size has been conditioned by the availability of cryptocurrencies-specific data. In order to select the main drivers of the detected dynamic connectedness, we use the stepwise regression, frequently employed in empirical research both to select useful subsets of variables and to evaluate the order of importance of variables (see, e. g., Huberty, 1994).

As mentioned before, we apply a general-to-specific modelling strategy to empirically evaluate the relevance of the potential drivers of the detected dynamic connectedness. The empirical analysis commences from this general specification and is then tested for mis-specifications; if none are apparent, it is simplified allowing us to select a parsimonious, consistent representation that significantly explain the dependent variable, being each simplification step checked by diagnostic testing.[14]

As a previous step, we confirm the total connectedness within the traditional currencies and the directional volatility connectedness from the block of cryptocurrencies to the block of traditional currencies are stationary in levels, so no transformation is required (see Appendix B). However, the total connectedness within cryptocurrencies is nonstationary and the directional volatility connectedness from the block of traditional currencies to the block of cryptocurrencies is trend-stationary, so both dependent variables require first differences and de-trending, respectively. All the dependent

using Phillips and Perron (1988) unit root tests controlling for serial correlation and heteroskedasticity in the errors.

[14]We used the stepwise regressions within the Statistical Machine Learning Toolbox in MATLAB© to complete our work (MATLAB and Statistical Machine Learning Toolbox, 2018).

variables are stationaries after the appropriated transformation if it is required and hence the stepwise regression can be performed using the former four dependent variables. Appendix C reports the optimal models selected by the stepwise procedure when the dependent variable is the total connectedness within the traditional currencies (Figure 2 blue line, and Panel I in Appendix C), the total connectedness within the crypto-currencies (Figure 2 red line, and Panel II in Appendix C), the directional volatility connectedness from the block of crypto-currencies to the block of traditional currencies (Figure 5 red line, and Panel III in Appendix C) and the directional volatility connectedness from the block of traditional currencies to the block of crypto-currencies (Figure 5 blue line, and Panel IV in Appendix C).

Table 5 summaries the results of the stepwise regressions, examining the predictive power of the estimated model and assessing the relative contributions of the optimal explanatory variables per category is reported using a simple definition of standardized coefficients (Bring, 1994).[15] Columns 1 and 2 represent the actual and predicted values of the dependent variables averaged over the period of the analysis, while the remainder columns show the contribution of the explanatory variables.

[Insert Table 5]

The contribution of the lagged dependent variables is generally large, reflecting the high persistence in the dynamic total and directional connectedness series. Panel I reports the aggregate contribution of the explanatory variables for the total connectedness within the traditional currencies. We can observe how, in relative terms, the financial variables

[12] See Appendix D for further details on the standardization of regression coefficients and the calculation of the relative contributions of the optimal explanatory variables in stepwise regression.

contribute the most in the explanation of the total connectedness within the traditional currencies model with a 10.90% of the total volatility; this is followed by business cycle variables with a merely 1.84%. However, the total connectedness within the traditional currencies is completely unaffected by the cryptocurrency-specific variables. Individually, the Funding component of the Office of Financial Research's Financial Stress Index (Funding- a measure related to how easily financial institutions can fund their activities) contributes the most with a 2.61%, followed closely by Gold implied volatility (GVZ) with a 2.59%.

Panel II shows a different picture where the cryptocurrency-specific variables overwhelmingly contribute the most to the total connectedness within the cryptocurrencies with 74.80%. Among those variables, the market capitalization of Dash and Ripple have the largest individual contributions, followed by the volume of all the cryptocurrencies (VALL). These findings confirm our previous results of the disconnection between both traditional and cryptocurrencies.

Panels III and IV report the contributions to the directional volatility connectedness between blocks. In relative terms, the business cycle variables contribute the most to the spillover from the cryptocurrencies to traditional currencies (16.56%) followed by the cryptocurrency-specific variables (11.93%). This may reflect the fact that the level and fluctuations of global real economic activity is a key determinant of asset prices in general and exchange rate in particular[16] and that, as documented findings in Conrad *et al.* (2018)

[16] Theory predicts that cyclical movements in the real exchange rate over the business cycle depend on the relative importance of different shocks that drive the cycle (see, e. g., Clarinda and Gali, 1994). Furthermore, Duarte *et al.* (2007) relate the volatility of exchange rates to their co-movement with macroeconomic aggregates and business cycles.

for Bitcoin and with Walther and Klein (2018) four highly capitalized cryptocurrencies (Bitcoin, Etherium, Litecoin, and Ripple), that macroeconomic business cycle indicators contain important information for cryptocurrency volatility. Instead, the cryptocurrency-specific variables (9.46%) have a slightly larger contribution than business cycles variables (6.89%) to the spillover from the traditional currencies to cryptocurrencies. Interestingly, the business cycles variables that have a marginal effect in both total connectedness within the traditional currencies and the total connectedness within cryptocurrencies have a non-negligent contribution to the spillover between both blocks. In both Panels III and IV, the individual explanatory variables with the largest contribution are the market capitalization of Ripple (CRIP) and the sum of the trade volume of all the cryptocurrencies (VALL). Last but not least, the first two columns of Table 5 verify that the optimal stepwise models have good predicted power with predicted means close to the actual ones.

## 7. Concluding remarks

The exponential growth of BitCoin and other cryptocurrencies is a phenomenon that has attracted considerable attention in recent years as a new alternative investment. Our study applies both the connectedness framework proposed by Diebold and Yilmaz (2014) and the modified approach of Antonakakis and Gabauer (2017) to investigate the transmission mechanism between cryptocurrencies and traditional currencies volatilities. To that end, we use data on four highly capitalized cryptocurrencies and four major exchange rates during the period February 2014-September 2018.

The main findings of our research can be summarized as follows. In the first step, we found a system-wide value of 34.43% for the total connectedness between the eight cryptocurrencies and traditional currencies under study for the full sample period, indicating that the remainder 65.57% of the variation is due to idiosyncratic shocks. This level is much lower than that obtained by Diebold and Yilmaz (2012) for international financial markets. In the second step, our results indicate that both blocks of currencies are highly intra-connected but highly disconnected to each other. In a third step, we assess the dynamic propagation of volatilities between the examined currencies using a time-varying parameter vector autoregression (TVP-VAR)-based connectedness procedure, finding that volatility connectedness varies over time, with a surge during periods of increasing economic and financial instability. Finally, when analysing the determinants of the detected total and directional dynamic connectedness, our findings suggest that financial market variables are the main drivers of total connectedness within the traditional currencies, while the cryptocurrency-specific variables are identified as the key determinant for the total connectedness within the traditional currencies and a combination of business cycles and cryptocurrency-specific variables explain the directional volatility connectedness between both blocks.

Overall, our study has important implications for market participants in cryptocurrencies and traditional currencies markets, as well as within these markets. Sound knowledge of connectedness among different assets and markets is useful for investors to determine hedging positions for risk minimisation through optimal portfolio construction. In addition, the results also give guidance to international portfolio risk managers, who seek greater diversification of portfolios.

**Acknowledgements**

We thank Gary Koop and Dimitris Korobilis for providing the TVP-VAR programs, CaixaBank Research and BBVA Research for kindly providing the economic surprise indices and BBVA Research for kindly providing us with the indicators of risk appetite and the financial tension indices.

**Funding**

This paper is based on work supported by the Spanish Ministry of Economy and Competitiveness [grant ECO2016-76203-C2-2-P] and Cabildo Insular de Gran Canaria [grant CABILDO2018-03].

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## Appendix 1: Definition of the explanatory variables and data sources

Appendix A.1: Definition of the macroeconomic/business cycle explanatory variables in the stepwise regression and data sources

| Name | Variable | Source |
|---|---|---|
| DEF | Difference between interest rates on BBB-rated corporate bonds and 10-year Treasury bonds | Federal Reserve Bank of St. Louis |
| TED | Difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill | Federal Reserve Bank of St. Louis |
| T10Y3M | Difference between 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity | Federal Reserve Bank of St. Louis |
| EPU | Economic Policy Uncertainty Index for United States | Federal Reserve Bank of St. Louis |
| CISS | Composite Indicator of Systemic Stress (linear interpolation from weekly data) | European Central Bank |
| Oildem | Cumulative Demand Shocks in Oil Price (linear interpolation from weekly data) | Federal Reserve Bank of New York |
| Oilsup | Cumulative Supply Shocks in Oil Price (linear interpolation from weekly data) | Federal Reserve Bank of New York |
| Oilres | Cumulative Residual Shocks in Oil Price (linear interpolation from weekly data) | Federal Reserve Bank of New York |
| BCI | Aruoba-Diebold-Scotti Business Conditions Index | Federal Reserve Bank of Philadelphia |
| USESI | USA Economic Surprise Index | Caixabank Research using data from Citigroup and Bloomberg |
| EZESI | Eurozone Economic Surprise Index | Caixabank Research using data from Citigroup and Bloomberg |
| EMESI | Emerging Market Economic Surprise Index | Caixabank Research using data from Citigroup and Bloomberg |

Appendix A.2: Definition of the financial explanatory variables in the stepwise regression and data sources

| Name | Variable | Source |
|---|---|---|
| SP500 | Standard & Poor's 500 Index | Federal Reserve Bank of St. Louis |
| EFA ETF | The iShares MSCI EAFE ETF tracks a market-cap-weighted index of developed-market securities based in Europe, Australia and the Far East. It excludes the US and Canada, and small-caps | Thomson Reuters Datastream |
| BarGov | Barclays U.S. Government (USD) | Thomson Reuters Datastream |
| Gold | Gold spot Fixing Price 3:00 P.M., London time, in London Bullion Market, based in U.S. Dollars | Federal Reserve Bank of St. Louis |
| Brent | Brent Crude oil spot prices | Federal Reserve Bank of St. Louis |
| VIX | The CBOE Volatility Index | Thomson Reuters Datastream |
| VXEFA | CBOE EFA ETF Volatility Index | Thomson Reuters Datastream |
| GVZ | CBOE Gold Volatility Index | Thomson Reuters Datastream |
| EVZ | CBOE Eurocurrency Volatility Index | Thomson Reuters Datastream |
| OVX | CBOE Crude Oil Volatility Index | Thomson Reuters Datastream |
| TYVIX | CBOE/CBOT 10-year U.S. Treasury Note Volatility Index | Thomson Reuters Datastream |
| Risk | Indicator of risk appetite (linear interpolation from weekly data) | BBVA Research from EPFR Fund Flows |
| Bull | Percentage of optimistic investors | AAII Investor Sentiment Survey |
| Bear | Percentage of pessimistic investors | AAII Investor Sentiment Survey |
| Neutral | Percentage of neutral investors | AAII Investor Sentiment Survey |
| FSI | St. Louis Fed Financial Stress Index (linear interpolation from weekly data) | Federal Reserve Bank of St. Louis |
| FCI | Chicago Fed National Financial Conditions Index (linear interpolation from weekly data) | Federal Reserve Bank of St. Louis |
| USFTI | Financial Tension Index USA (linear interpolation from weekly data) | BBVA research |

*Cont. Appendix A.2: Definition of the financial explanatory variables in the stepwise regression and data sources*

| Name | Variable | Source |
|---|---|---|
| DMFTI | Financial Tension Index, Developed markets without the effect of US (linear interpolation from weekly data) | BBVA research |
| PDD | Portfolio distance-to-default, reflecting the market's perception of the systematic insolvency risk of the banking system as a whole | Federal Reserve Bank of Cleveland |
| ADD | Average distance-to-default, reflecting the market's perception of the average risk of insolvency among major US banks | Federal Reserve Bank of Cleveland |
| Spread | Difference between PDD and ADD | Federal Reserve Bank of Cleveland |
| KBE | KBE ETF index, tracking an equal-weighted index of US banking stocks | Federal Reserve Bank of Cleveland |
| OFR FSI | Financial Stress Index | Office of Financial Research |
| Credit | Credit component of OFR FSI | Office of Financial Research |
| EquVal | Equity valuation component of OFR FSI | Office of Financial Research |
| Safe | Safe assets component of OFR FSI | Office of Financial Research |
| Funding | Funding component of OFR FSI | Office of Financial Research |
| VOL | Volatility component of OFR FSI | Office of Financial Research |
| US | United States component of OFR FSI | Office of Financial Research |
| OAE | Other advanced economies component of OFR FSI | Office of Financial Research |
| EME | Emerging markets component of OFR FSI | Office of Financial Research |

Appendix A.3: Definition of the cryptocurrency-specific explanatory variables in the stepwise regression and data sources

| **Name** | **Variable** | **Source** |
|---|---|---|
| WBIT | Wikipedia search for keyword "Bitcoin" | https://tools.wmflabs.org/pageviews |
| WLIT | Wikipedia search for keyword "Litecoin" | https://tools.wmflabs.org/pageviews |
| WDAS | Wikipedia search for keyword "Dash (cryptocurrency)" | https://tools.wmflabs.org/pageviews |
| WRIP | Wikipedia search for keyword "Ripple (payment protocol)" | https://tools.wmflabs.org/pageviews |
| WSUM | Sum of Wikipedia searches "Bitcoin", "Litecoin", "Dash (cryptocurrency)" and "Ripple (payment protocol)" | https://tools.wmflabs.org/pageviews |
| VBIT | Trade volume for Bitcoin | https://coinmarketcap.com/ |
| CBIT | Market capitalization for Bitcoin | https://coinmarketcap.com/ |
| VLIT | Trade volume for Litecoin | https://coinmarketcap.com/ |
| CLIT | Market capitalization for Litecoin | https://coinmarketcap.com/ |
| VDAS | Trade volume for Dash | https://coinmarketcap.com/ |
| CDAS | Market capitalization for Dash | https://coinmarketcap.com/ |
| VRIP | Trade volume for Ripple | https://coinmarketcap.com/ |
| CRIP | Market capitalization for Ripple | https://coinmarketcap.com/ |
| VALL | Sum of trade volume for Bitcoin, Litecoin, Dash and Ripple | https://coinmarketcap.com/ |
| CALL | Sum of market capitalization for Bitcoin, Litecoin, Dash and Ripple | https://coinmarketcap.com/ |

## Appendix B. Statistical properties of connectedness indices

| | | | |
|---|---|---|---|
| **Panel I: Total connectedness index within traditional currencies** | | | |
| Mean | 36.5693 | Standard Deviation | 8.1676 |
| Minimum | 17.0052 | Maximum | 57.7772 |
| ADF test in levels (1) | -4.4311$^{a}$ (<0.0010) | | |
| KPSS test in levels (2) | 0.4630 (>0.1000) | | |
| DW test | 2.0391 (0.6578) | | |
| Engle' arch test (5 lags) | 0.9645 (0.9752) | Engle'arch test (20 lags) | 3.4481 (1.0000) |
| **Panel II: Total connectedness index within cryptocurrencies** | | | |
| Mean | 34.1805 | Standard Deviation | 16.8184 |
| Minimum | 6.8028 | Maximum | 69.7333 |
| ADF test in levels (1) | -2.2874 (0.4504) | ADF test in differences (1) | -6.4628$^{a}$ (<0.0010) |
| KPSS test in levels (2) | 0.5081$^{a}$ (<0.0100) | KPSS test in differences (2) | 0.1264 (>0.1000) |
| DW test | 2.0035 (0.9346) | | |
| Engle' arch test (5 lags) | 0.1656 (0.9994) | Engle' arch test (20 lags) | 2.5813 (1.0000) |
| **Panel III: Directional volatility conn. from cryptocurrencies (block) to traditional currencies (block)** | | | |
| Mean | 5.4232 | Standard Deviation | 2.0508 |
| Minimum | 1.4706 | Maximum | 12.5992 |
| ADF test in levels (1) | -4.0038$^{a}$ (0.0019) | | |
| KPSS test in levels (2) | 0.2953 (>0.1000) | | |
| DW test | 2.0331 (0.6629) | | |
| Engle' arch test (5 lags) | 4.5633 (0.4714) | Engle' arch test (20 lags) | 11.9630 (0.9173) |
| **Panel IV: Directional volatility conn. from traditional currencies (block) to cryptocurrencies (block)** | | | |
| Mean | 5.2904 | Standard Deviation | 2.4389 |
| Minimum | 0.8372 | Maximum | 11.2316 |
| ADF test in levels (1) | -3.6739$^{b}$ (0.0248) | ADF test (1) | -3.6824$^{a}$ (<0.0010) |
| KPSS test in levels (2) | 0.1409$^{c}$ (0.0594) | KPSS test (2) | 0.1409 (>0.1000) |
| DW test | 2.1109 (0.1248) | | |
| Engle' arch test (5 lags) | 7.5586 (0.1823) | Engle' arch test (20 lags) | 12.7778 (0.8867) |

Notes:

$^{a, b, c}$ indicates significance at the 1%, 5% and 10% level, respectively.

(1) Schwert (1989) suggest that a maximum lag $\left\lfloor 12(T/100)^{\frac{1}{4}} \right\rfloor$, where T is the sample size,

(2) Kwiatkowski *et al*. (1994) suggest that a number of lags on the order of $\sqrt{T}$, where T is the sample size.

## Appendix C. Stepwise regression results

**Panel I: Total connectedness within traditional currencies as dependent variable**

| | | | |
|---|---|---|---|
| **Lagged dep.** | Total connectedness within traditional currencies | 0.9543[a] | (0.0000) |
| **EPU** | Economic Policy Uncertainty Index for United States | 0.0038[b] | (0.0298) |
| **Gold** | Gold spot Fixing Price 3:00 P.M., London time, based in U.S. Dollars | 17.8486[b] | (0.0432) |
| **VXEFA** | CBOE EFA ETF Volatility Index | -0.0637[a] | (0.0071) |
| **GVZ** | CBOE Gold Volatility Index | 0.1045[a] | (0.0011) |
| **Bull** | Percentage of optimistic investors | 0.0231[a] | (0.0046) |
| **Funding** | Funding component of OFR FSI | 11.1373[a] | (0.0021) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $R_{adj}^2$ | 0.9336 | h-DW test | -0.5667 (0.5710) | BG test | 11.859 (0.9208) | Engle test | 3.1513 (1.0000) |

**Panel II: Total connectedness within cryptocurrencies as dependent variable**

| | | | |
|---|---|---|---|
| **Lagged dep.** | Total connectedness within cryptocurrencies | 0.0847[a] | (0.0106) |
| **Oilres** | Cumulative Residual Shocks in Oil Price | -9.0506[b] | (0.0297) |
| **OFR FSI** | Financial Stress Index | 0.7820[a] | (0.0080) |
| **WBIT** | Wikipedia search for keyword "Bitcoin" | -0.000[a] | (0.0016) |
| **WDAS** | Wikipedia search for keyword "Dash" | 0.0009[b] | (0.0218) |
| **WSUM** | Sum of Wikipedia searches "Bitcoin", "Litecoin", "Dash" and "Ripple" | 0.0001[a] | (0.0071) |
| **CDAS** | Market capitalization for Dash | -1.5851e-09[a] | (0.0000) |
| **CRIP** | Market capitalization for Ripple | -1.3979e-10[a] | (0.0000) |
| **VALL** | Sum of trade volume for Bitcoin, Litecoin, Dash and Ripple | 1.7008e-10[a] | (0.0006) |
| **CALL** | Sum of market capitalization for Bitcoin, Litecoin, Dash and Ripple | -2.0623e-10[a] | (0.0900) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $R_{adj}^2$ | 0.1605 | h-DW test | 0.2474 (0.8046) | BG test | 37.4761 (0.0103) | Engle test | 23.4540 (0.2671) |

**Panel III: Directional volatility conn. from cryptocurrencies to traditional currencies as dependent variable**

| | | | |
|---|---|---|---|
| **Lagged dep.** | Directional conn. from cryptocurr. (block) to traditional curr. (block) | 0.8665[a] | (0.0000) |
| **TED** | Difference between 3-Month LIBOR ($) and 3-Month Treasury Bill | -0.6974[b] | (0.0220) |
| **T10Y3M** | Difference between 10-Year Treasury Minus 3-Month Treasury | -0.1649[b] | (0.0391) |
| **Oilres** | Cumulative Residual Shocks in Oil Price | -7.4770[a] | (0.0002) |
| **USESI** | USA Economic Surprise Index | 0.0035[a] | (0.0015) |
| **EMESI** | Emerging Market Economic Surprise Index | -0.0040[c] | (0.0557) |
| **Risk** | Indicator of risk appetite | -0.1330[a] | (0.0096) |
| **DMFTI** | Financial Tension Index, Developed markets without the effect of US | 1.5340[a] | (0.0017) |
| **OFR FSI** | Financial Stress Index | 0.3443[b] | (0.0145) |
| **CRIP** | Market capitalization for Ripple | -5.1664e-11[a] | (0.0000) |
| **VALL** | Sum of trade volume for Bitcoin, Litecoin, Dash and Ripple | 9.9368e-11[a] | (0.0000) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $R_{adj}^2$ | 0.8414 | h-DW test | -0.3155 (0.7524) | BG test | 11.550 (0.9307) | Engle test | 10.5503 (0.9672) |

**Panel IV: Directional volatility conn. from traditional currencies to cryptocurrencies as dependent variable**

| | | | |
|---|---|---|---|
| **Lagged dep.** | Directional conn. from traditional curr. (block) to cryptocurr. (block) | 0.9066[a] | (0.0000) |
| **EPU** | Economic Policy Uncertainty Index for United States | 0.0016[a] | (0.0093) |
| **Oilres** | Cumulative Residual Shocks in Oil Price | -4.6652[a] | (0.0093) |
| **OFR FSI** | Financial Stress Index | 0.2461[c] | (0.0604) |
| **Funding** | Funding component of OFR FSI | 2.5907[b] | (0.0485) |
| **CRIP** | Market capitalization for Ripple | -3.8080e-11[a] | (0.0003) |
| **VALL** | Sum of trade volume for Bitcoin, Litecoin, Dash and Ripple | 6.2705e-11[a] | (0.0005) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $R_{adj}^2$ | 0.8243 | h-DW test | -1.3758 (0.1689) | BG test | 16.7039 (0.6721) | Engle test | 17.4038 (0.6266) |

**Notes:**

[a, b, c] indicates significance at the 1%, 5% and 10% level, respectively.

All the models include an unreported constant.

## Appendix D. Procedure to standardize regression coefficients and to calculate relative contributions

Bring (1994) suggested an approach to calculate the standardized coefficient, multiplying the ordinary coefficient $\hat{\beta}_i$ by the partial or conditional standard deviation,

$$\hat{\beta}_i^* = \hat{\beta}_i \cdot s_i^*$$

where the partial or conditional standard deviation $s_i^*$ can be estimated by regressing $x_i$ on the other independent variables. This estimated can obtain by using the variance inflation, VIF. When $y$ is regressed on $x_1, x_2, \ldots, x_k$ each independent variable is associated with a VIF:

$$VIF = \frac{1}{1 - R_{k-1}^2}$$

where $R_{k-1}^2$ is the coefficient of determination when $x_i$ is regressed on the $k-1$ other independent variables. Then the partial standard deviation is

$$s_i^* = \frac{s_i}{\sqrt{VIF_i}} \sqrt{\frac{n-1}{n-k}}$$

The individual relative contributions of the optimal explanatory variables in a stepwise regression after normalization would be

$$rc\_x_i = \frac{\left|\hat{\beta}_i^*\right|}{\sum_{i=1}^{k}\left|\hat{\beta}_i^*\right|} \times 100, \quad i = 1,2,\ldots,k\,.$$

**Table 1: Schematic connectedness table**

| | $x_1$ | $x_2$ | … | $x_N$ | **Connectedness from others** |
|---|---|---|---|---|---|
| $x_1$ | $d_{11}^H$ | $d_{12}^H$ | $\cdots$ | $d_{1N}^H$ | $\sum_{j=1}^{N} d_{1j}^H, j \neq 1$ |
| $x_2$ | $d_{21}^H$ | $d_{22}^H$ | $\cdots$ | $d_{2N}^H$ | $\sum_{j=1}^{N} d_{2j}^H, j \neq 2$ |
| . | . | . | . | | |
| . | . | . | . | | |
| . | . | . | . | | |
| $x_N$ | $d_{N1}^H$ | $d_{N2}^H$ | $\cdots$ | $d_{NN}^H$ | $\sum_{j=1}^{N} d_{Nj}^H, j \neq N$ |
| **Connectedness to others** | $\sum_{i=1}^{N} d_{i1}^H$ $i \neq 1$ | $\sum_{i=1}^{N} d_{i2}^H$ $i \neq 2$ | $\cdots$ | $\sum_{i=1}^{N} d_{iN}^H$ $i \neq N$ | **Total connectedness =** $\frac{1}{N}\sum_{\substack{i,j=1 \\ i \neq j}}^{N} d_{ij}^H$ |

**Table 2: Descriptive statistics and contemporaneous Pearson correlations of daily normalized volatilities**

| | EUR | GBP | AUD | JPY | XBT | XRP | XLT | XDS |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Descriptive statistics** | | | | | | | | |
| **Min** | -5.563092 | -8.265512 | -4.446462 | -5.23395 | -6.991469 | -6.098891 | -5.142891 | -7.378419 |
| **Median** | -0.049344 | -0.012208 | 0 | -0.045822 | 0.061895 | -0.070824 | 0 | -0.04295 |
| **Max** | 4.871424 | 4.148731 | 3.279684 | 5.795282 | 5.698112 | 8.698162 | 11.23695 | 5.602051 |
| **Skewness** | -0.221685 | -0.552769 | -0.146898 | 0.134574 | -0.399539 | 0.875759 | 1.54224 | -0.03962 |
| **Kurtosis** | 5.148096 | 7.86181 | 3.80522 | 5.561507 | 9.446596 | 13.15702 | 22.11406 | 8.275951 |
| **Observations** | 1159 | 1159 | 1159 | 1159 | 1159 | 1159 | 1159 | 1159 |
| **Jarque-Bera** | 232.326[a] | 1200.503[a] | 35.47968[a] | 320.3553[a] | 2037.769[a] | 5130.16[a] | 18102.68[a] | 1344.533[a] |
| ***p-value*** | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| | | | | | | | | |
| | **EUR** | **GBP** | **AUD** | **JPY** | **XBT** | **XRP** | **XLT** | **XDS** |
| **Panel B: Matrix correlations** | | | | | | | | |
| **EUR** | 1.0000 | | | | | | | |
| **GBP** | 0.5309[a] | 1.0000 | | | | | | |
| **AUD** | 0.4485[a] | 0.3990[a] | 1.0000 | | | | | |
| **JPY** | 0.4680 [a] | 0.2298[a] | 0.3081[a] | 1.0000 | | | | |
| **XBT** | 0.0102 | -0.0176 | -0.0067 | -0.0028 | 1.0000 | | | |
| **XRP** | 0.0032 | 0.0034 | -0.0258 | 0.0149 | 0.1543[a] | 1.0000 | | |
| **XLT** | -0.0147 | -0.0320 | -0.0050 | -0.0053 | 0.5959[a] | 0.1342[a] | 1.0000 | |
| **XDS** | 0.0064 | -0.0220 | -0.0052 | -0.0816[a] | 0.4052[a] | 0.0983[a] | 0.3441[a] | 1.0000 |

Notes:

Daily data from February 14, 2014 to September 28, 2018.

[a, b, c] indicates significance at the 1%, 5% and 10% level, respectively

**Table 3: Full-sample connectedness**

| | EUR | GBP | AUD | JPY | XBT | XRP | XLT | XDS | Directional *FROM* Others |
|---|---|---|---|---|---|---|---|---|---|
| **EUR** | 57.7058 | 16.7002 | 12.2844 | 12.3470 | 0.0490 | 0.1745 | 0.0535 | 0.6858 | 42.2942 |
| **GBP** | 19.0523 | 65.9000 | 10.5386 | 3.2539 | 0.4227 | 0.1700 | 0.3210 | 0.3413 | 34.1000 |
| **AUD** | 14.3228 | 11.1161 | 67.7276 | 6.4921 | 0.0297 | 0.0410 | 0.0152 | 0.2556 | 32.2724 |
| **JPY** | 15.2860 | 3.6545 | 7.2166 | 72.9712 | 0.0365 | 0.0635 | 0.0117 | 0.7601 | 27.0288 |
| **XBT** | 0.0061 | 0.0433 | 0.1508 | 0.0169 | 58.7197 | 7.5710 | 22.1151 | 11.3771 | 41.2803 |
| **XRP** | 0.2530 | 0.1983 | 0.0803 | 0.4650 | 9.1989 | 72.6631 | 10.6362 | 6.5051 | 27.3369 |
| **XLT** | 0.0876 | 0.1206 | 0.1807 | 0.0648 | 22.5928 | 8.4122 | 59.6596 | 8.8817 | 40.3404 |
| **XDS** | 0.0310 | 0.1262 | 0.0512 | 0.5043 | 13.5031 | 6.3939 | 10.1682 | 69.2223 | 30.7777 |
| **Directional *TO* Others** | 49.0388 | 31.9592 | 30.5026 | 23.1440 | 45.8327 | 22.8260 | 43.3208 | 28.8066 | **34.4288** |
| **Net Contribution (To – From) Others** | 6.7446 | -2.1408 | -1.7698 | -3.8848 | 4.5524 | -4.5108 | 2.9804 | -1.9711 | - |

**Table 4: Full-sample connectedness by blocks of currencies**

| | Traditional currencies | Cryptocurrencies |
|---|---|---|
| **Traditional currencies** | 99.14 | 0.86 |
| *Total connectedness within Trad. currencies* | *33.07* | - |
| **Cryptocurrencies** | 0.60 | 99.40 |
| *Total connectedness within Cryptocurrencies* | - | *34.34* |
| **Net Contribution (To – From) Others** | -0.26 | 0.26 |
| ***Total connectedness across blocks*** | | *0.73* |

**Table 5: Predicted power and relative contributions of explanatory variables**

**Panel I: Total connectedness within traditional currencies as dependent variable**

| | | Individual contribution (%) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Actual | Predicted | **Lagged dep** | **EPU** | **Gold** | **VXEFA** | **GVZ** | **Bull** | **Funding** |
| 36.5693 | 36.5692 | 87.2657 | 1.8359 | 1.7151 | 2.2379 | 2.5913 | 1.7436 | 2.6104 |
| | | | Aggregate contribution (%) | | | | | |
| | | | **Business cycles variables** | | **Financial market variables** | | **Cryptocurrency-specific variables** | |
| | | | 1.8359 | | 10.8984 | | 0 | |

**Panel II: Total connectedness within cryptocurrencies as dependent variable**

| | | Individual contribution (%) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Actual | Predicted | **Lagged dep** | **Oilres** | **OFR FSI** | **WBIT** | **WDAS** | **WSUM** | **CDAS** | **CRIP** | **VALL** | **CALL** |
| 34.1805 | 34.1350 | 8.7333 | 7.4041 | 9.0680 | 10.8210 | 7.8361 | 9.9203 | 15.1372 | 14.2951 | 11.7163 | 5.7586 |
| | | | Aggregate contribution (%) | | | | | | | | |
| | | | **Business cycles variables** | | | **Financial market variables** | | | **Cryptocurrency-specific variables** | | |
| | | | 7.4041 | | | 9.0680 | | | 74.7964 | | |

**Panel III: Directional volatility connectedness from cryptocurrencies (block) to traditional currencies (block) as dependent variable**

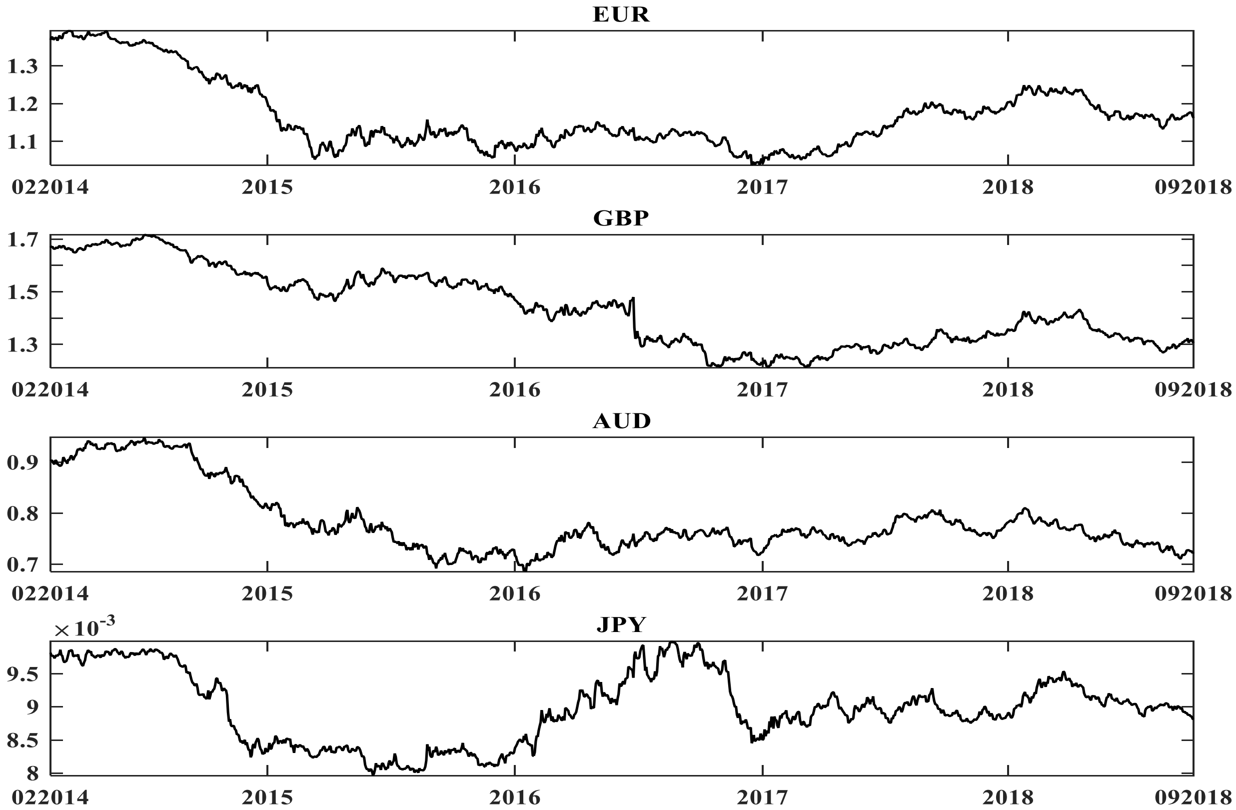
| | | Individual contribution (%) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Actual | Predicted | **Lagged dep** | **TED** | **T10Y3M** | **Oilres** | **USESI** | **EMESI** | **Risk** | **DMFTI** | **OFR FSI** | **CRIP** | **VALL** |
| 5.4232 | 5.4232 | 61.1862 | 2.8890 | 2.6015 | 4.6488 | 4.0068 | 2.4123 | 3.2695 | 3.9724 | 3.0845 | 5.6342 | 6.2949 |
| | | | Aggregate contribution (%) | | | | | | | | | |
| | | | **Business cycles variables** | | | | **Financial market variables** | | | **Cryptocurrency-specific variables** | | |
| | | | 16.5583 | | | | 10.3264 | | | 11.9290 | | |

**Panel IV: Directional volatility connectedness from traditional currencies (block) to cryptocurrencies (block) as dependent variable**

| | | Individual contribution (%) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Actual | Predicted | **Lagged dep** | **EPU** | **Oilres** | **OFR FSI** | **Funding** | **CRIP** | **VALL** |
| 5.2904 | 5.2904 | 78.5580 | 3.4429 | 3.4433 | 2.4825 | 2.6081 | 4.8527 | 4.6125 |
| | | | Aggregate contribution (%) | | | | | |
| | | | **Business cycles variables** | | **Financial market variables** | | **Cryptocurrency-specific variables** | |
| | | | 6.8862 | | 5.0906 | | 9.4652 | |

**Figure 1a: Daily exchange rates**

**Panel A: Traditional currencies**



*Cont. Figure 1a: Daily exchange rates*

**Panel B: Cryptocurrencies**

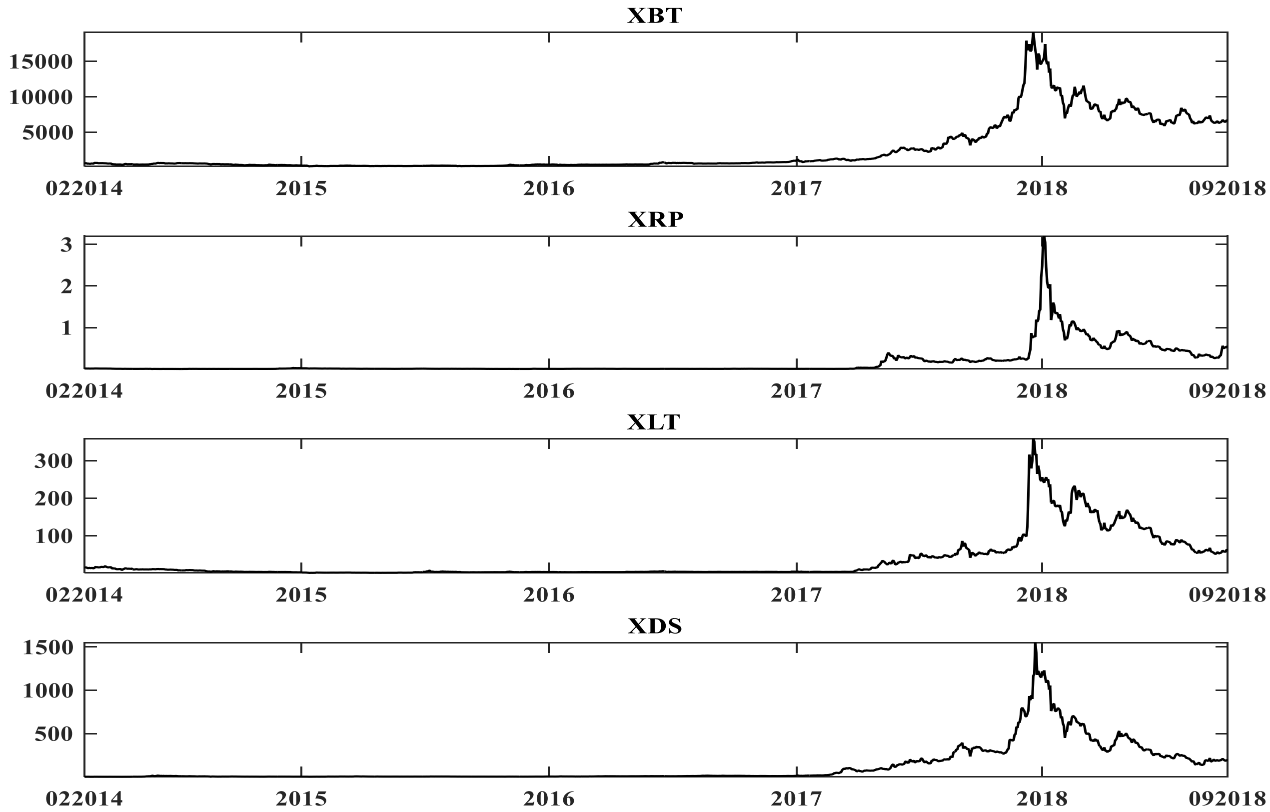
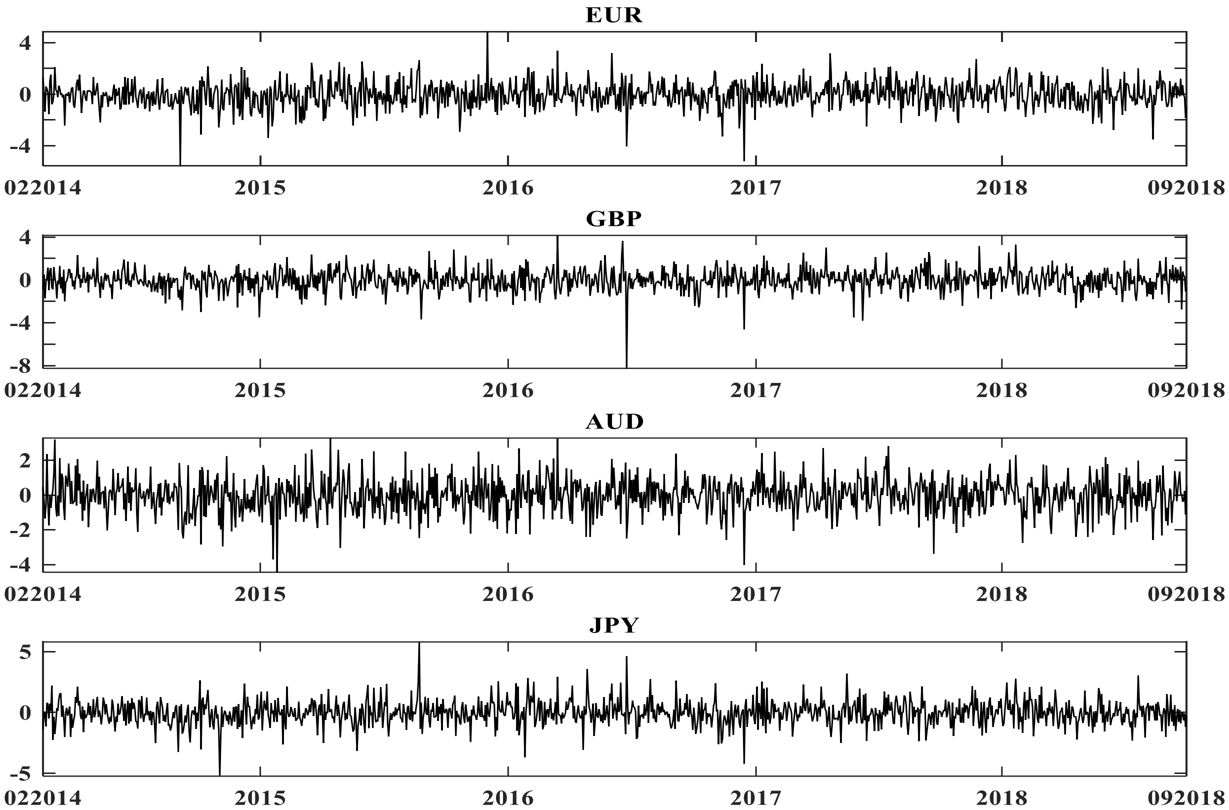


**Figure 1b: Daily normalized volatilities**

**Panel A: Traditional currencies**



*Cont. Figure 1b: Daily normalized volatilities*

**Panel B: Cryptocurrencies**

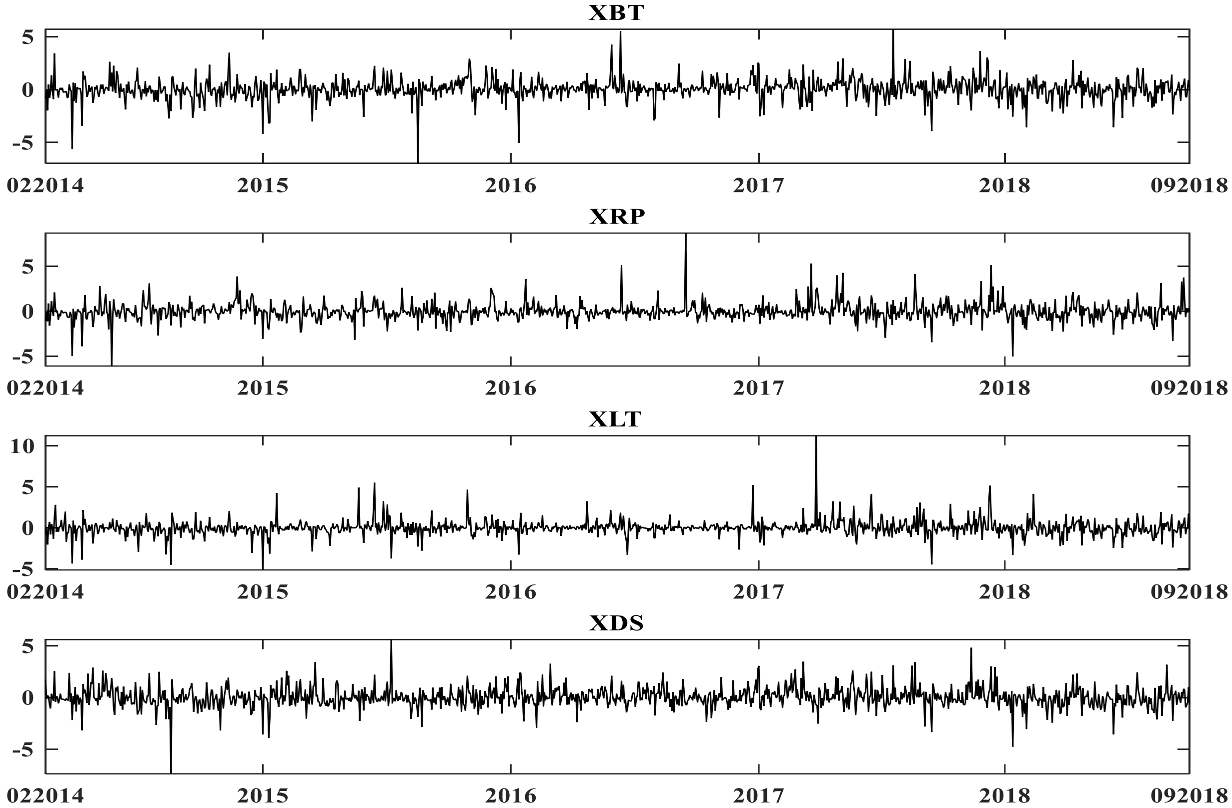
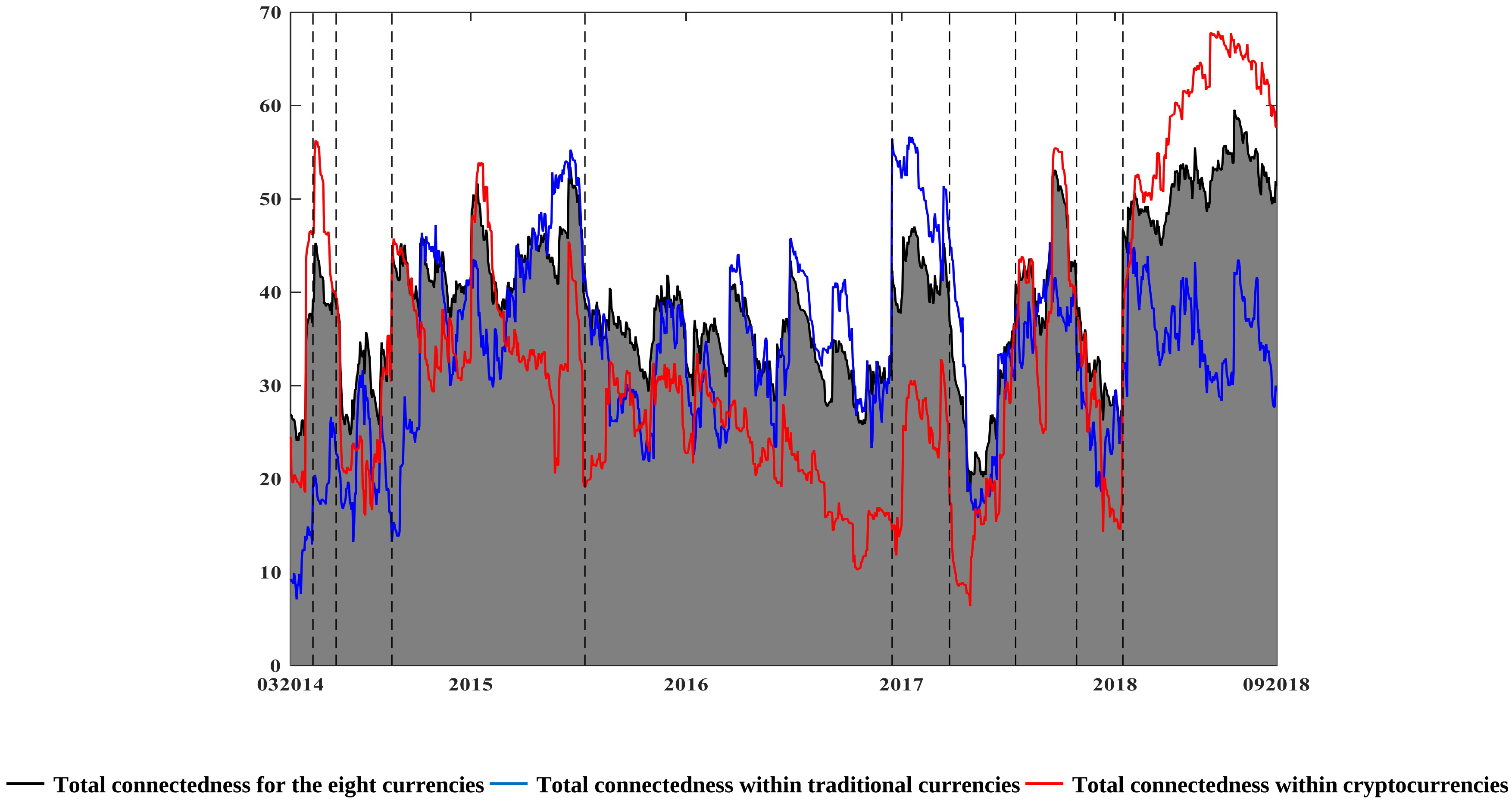
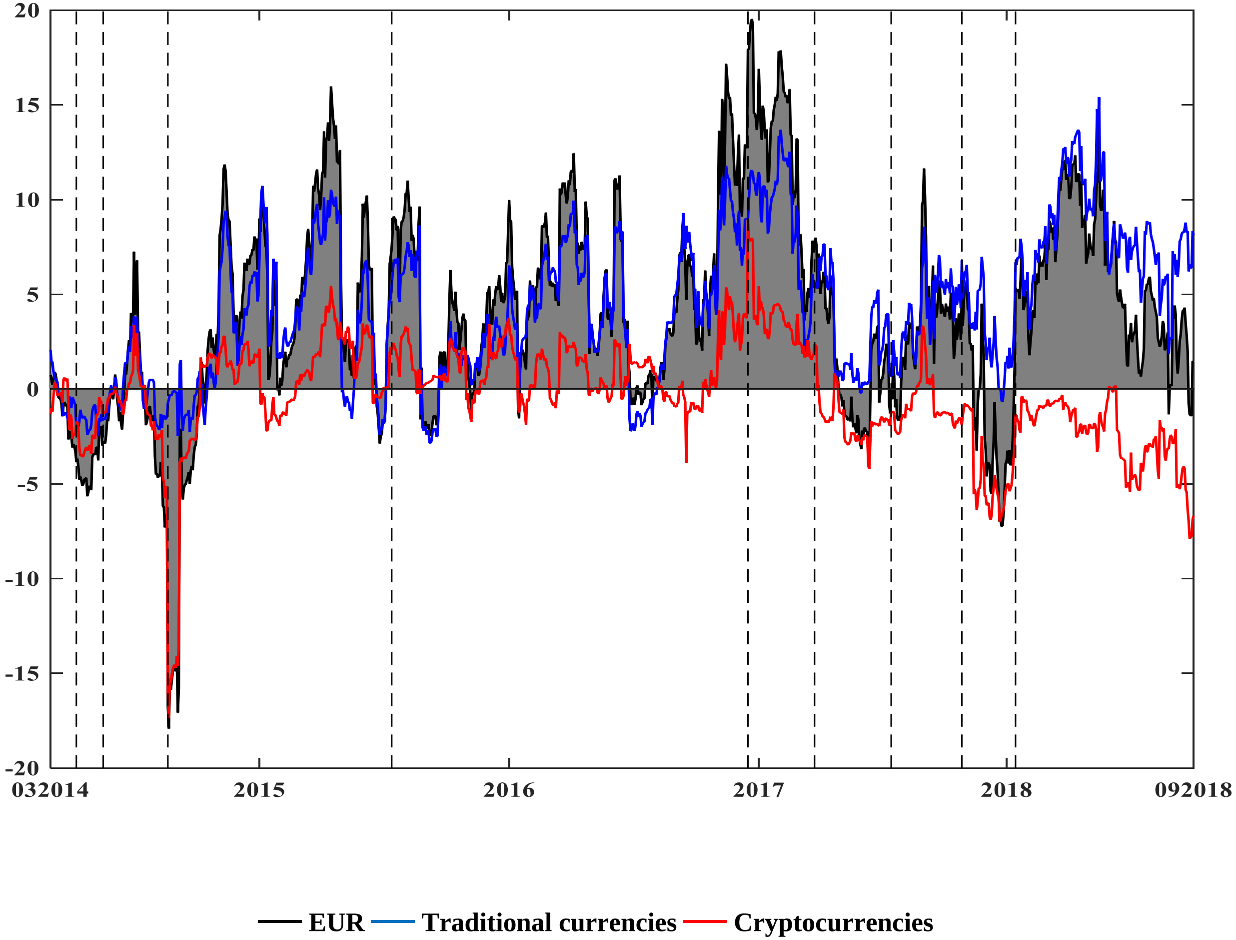


**Figure 2: Dynamic total connectedness for the eight currencies and by blocks of currencies**



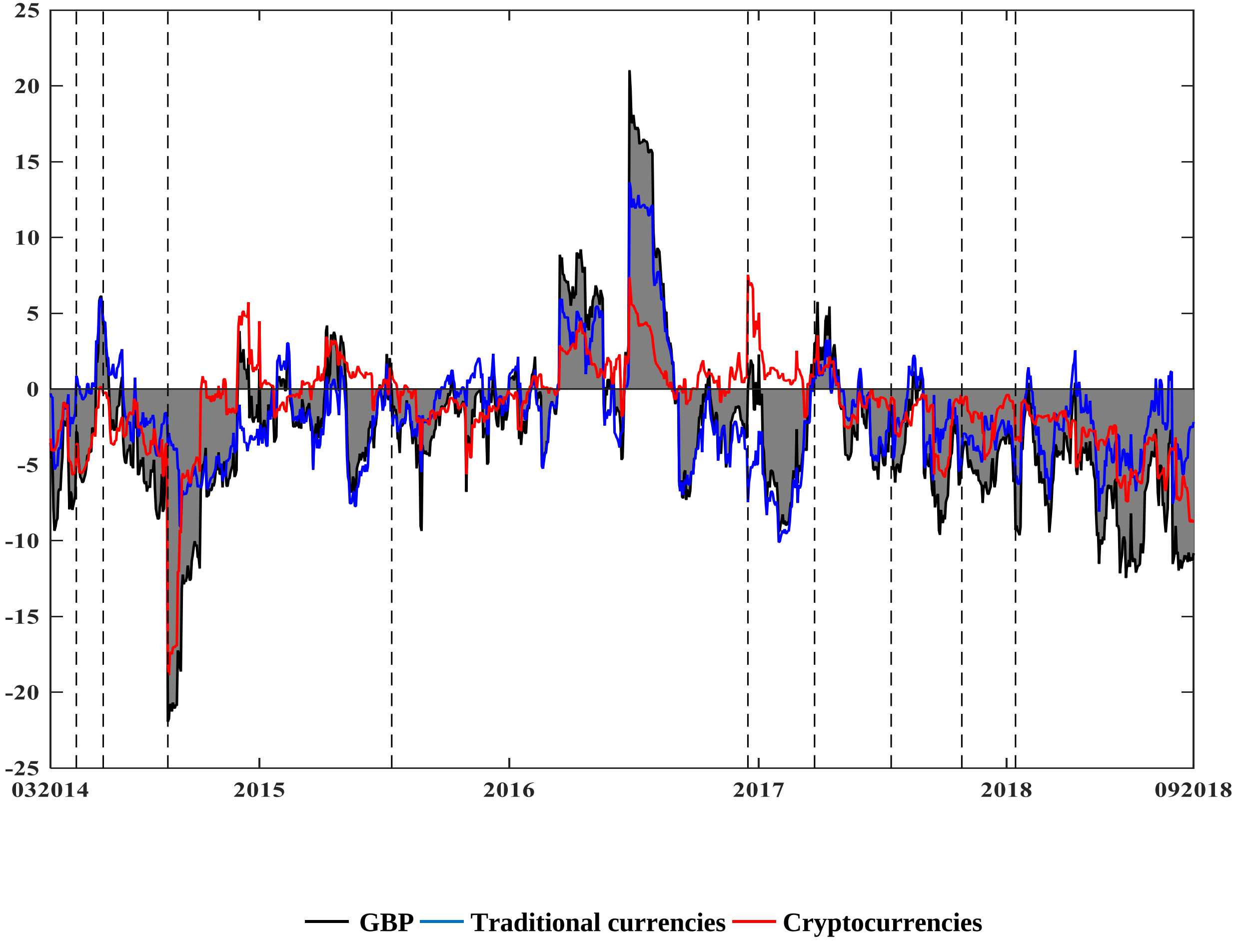

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3a: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for EUR**



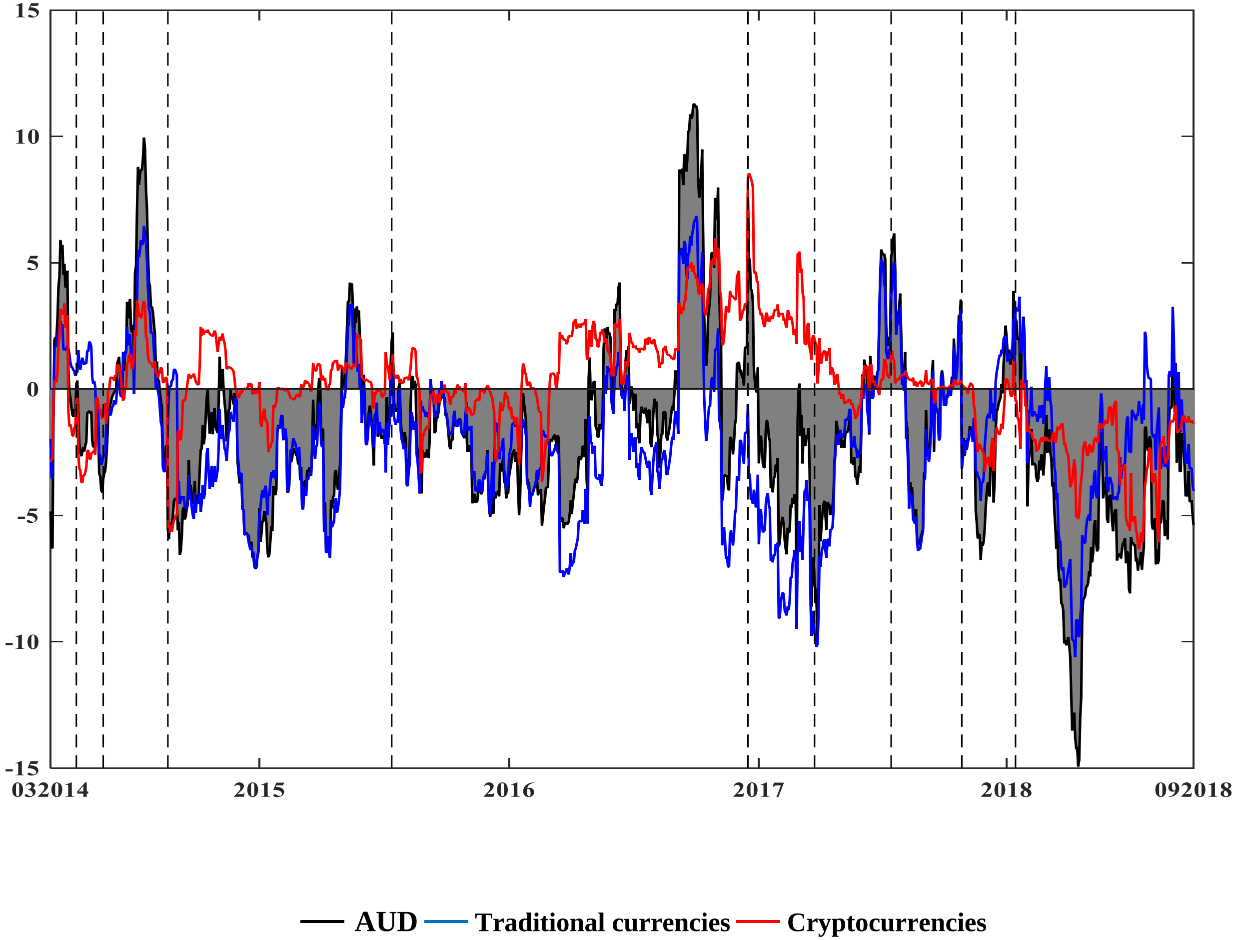

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3b: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for GBP**



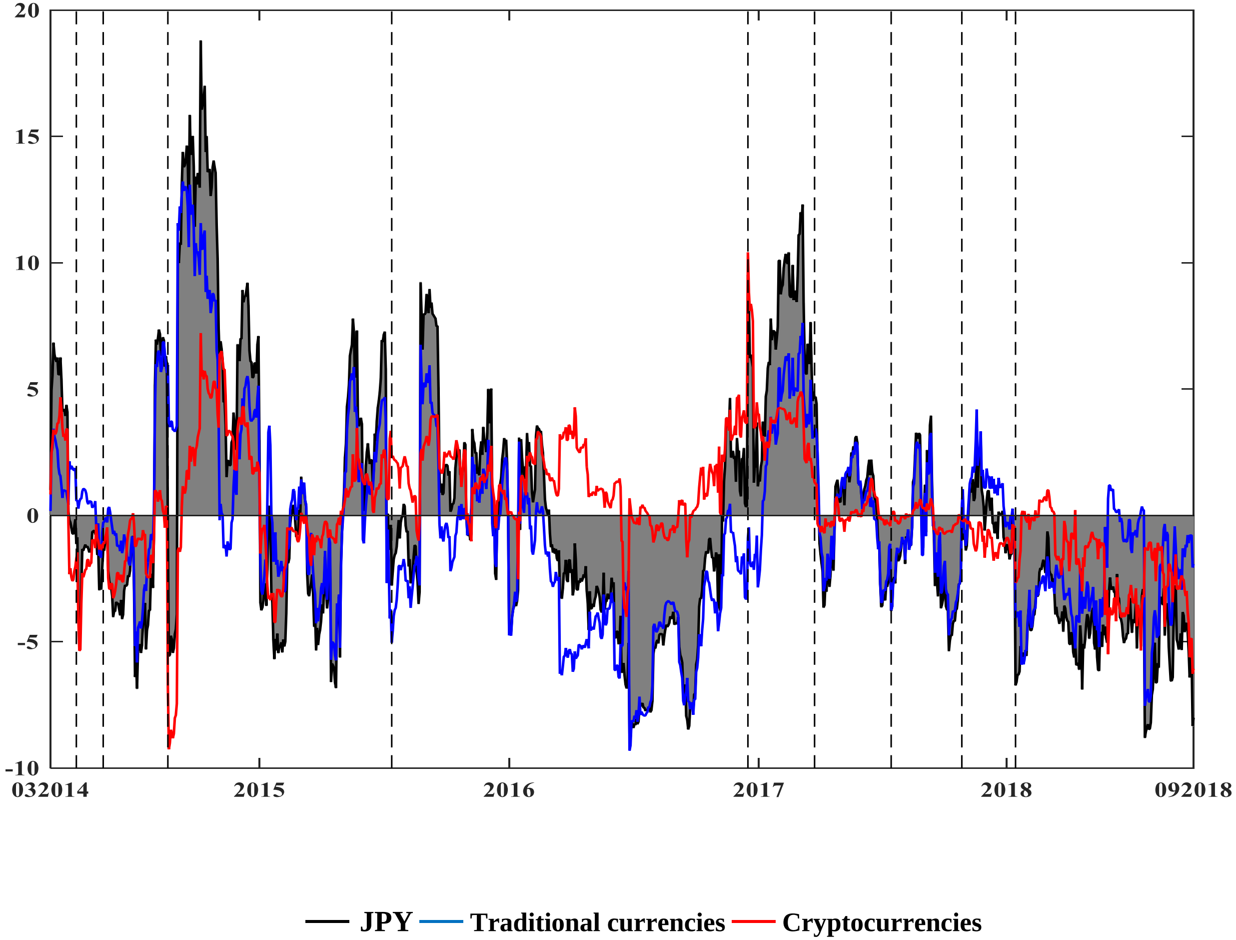

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3c: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for AUD**



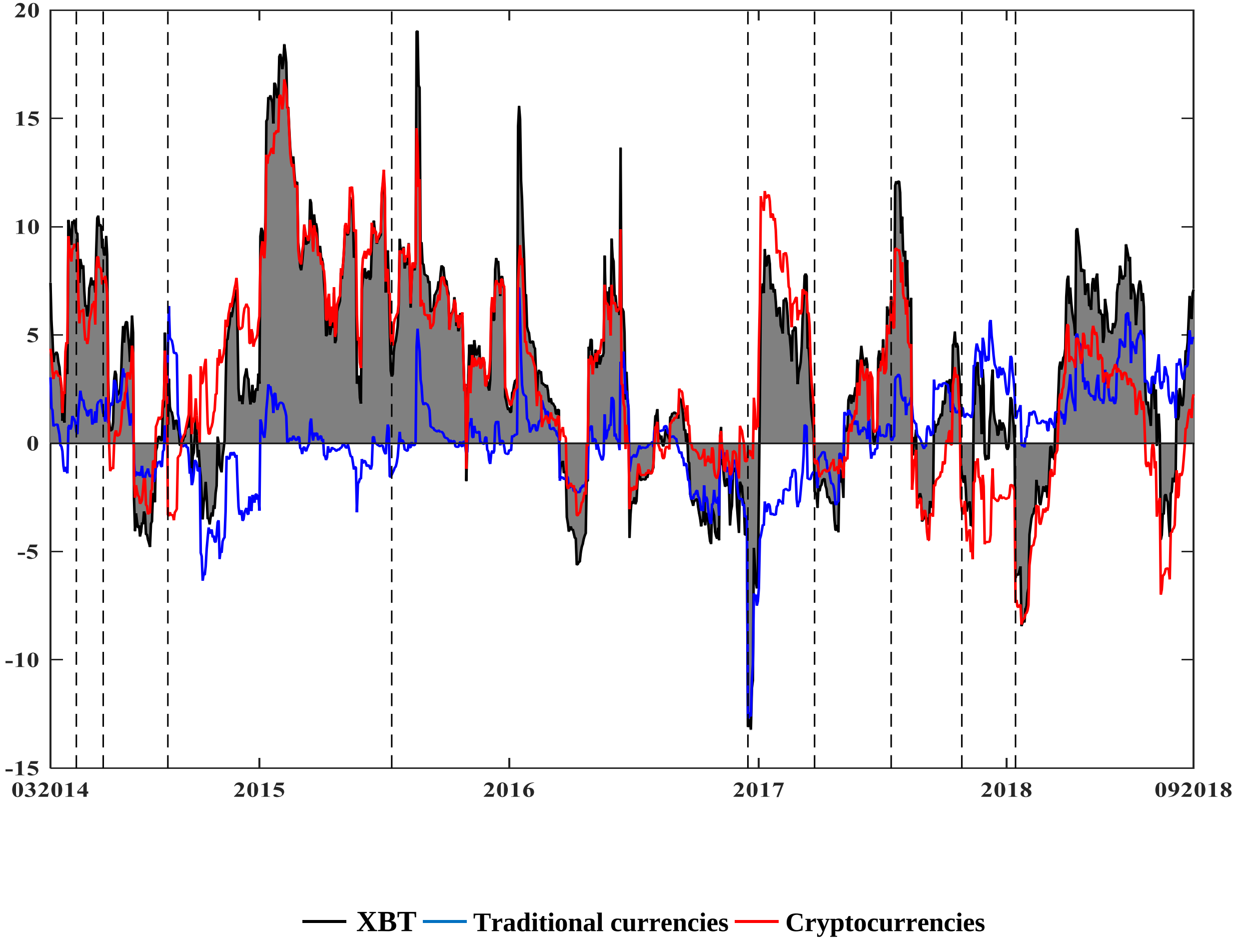

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3d: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for JPY**



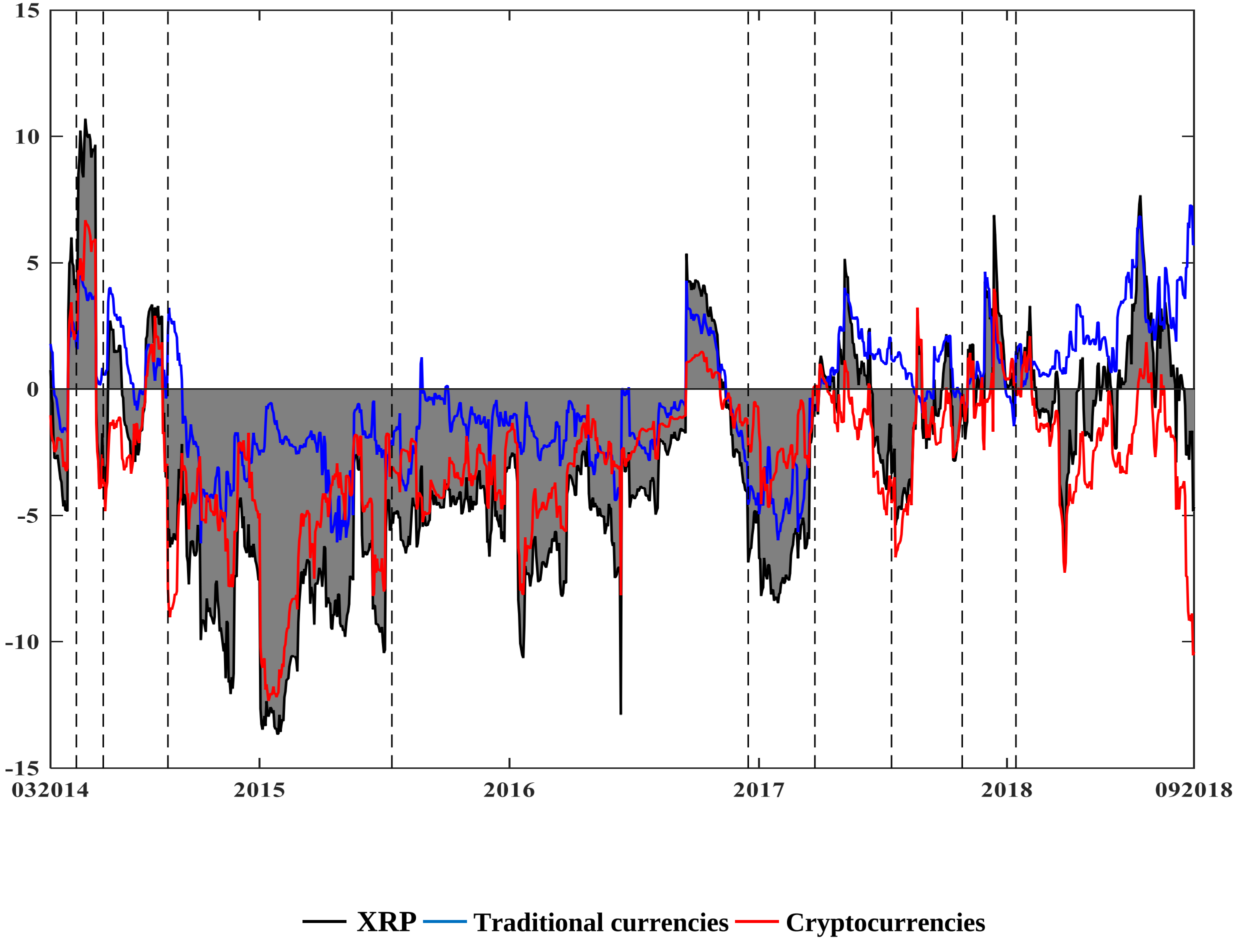

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3e: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for XBT**



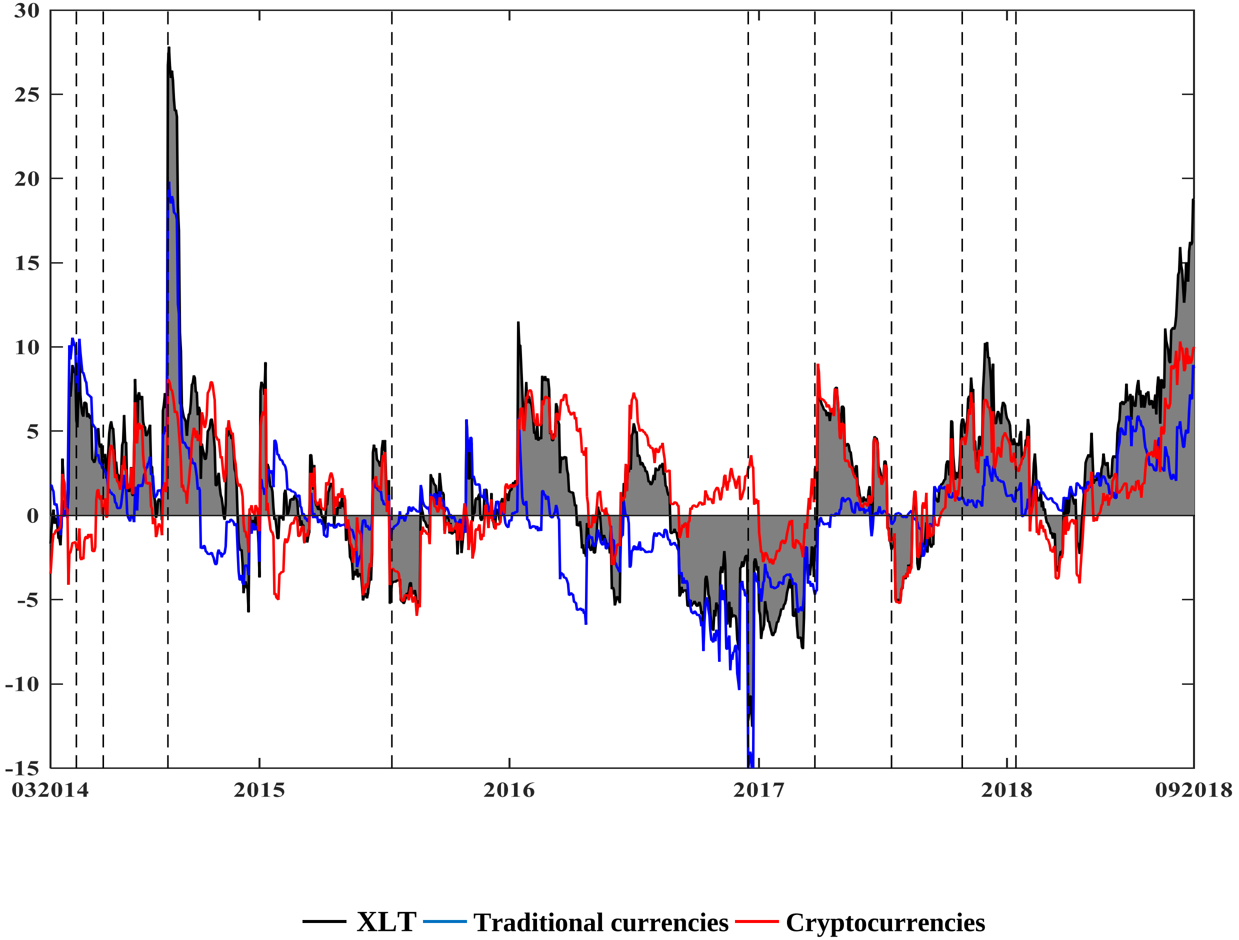

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3f: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for XRP**



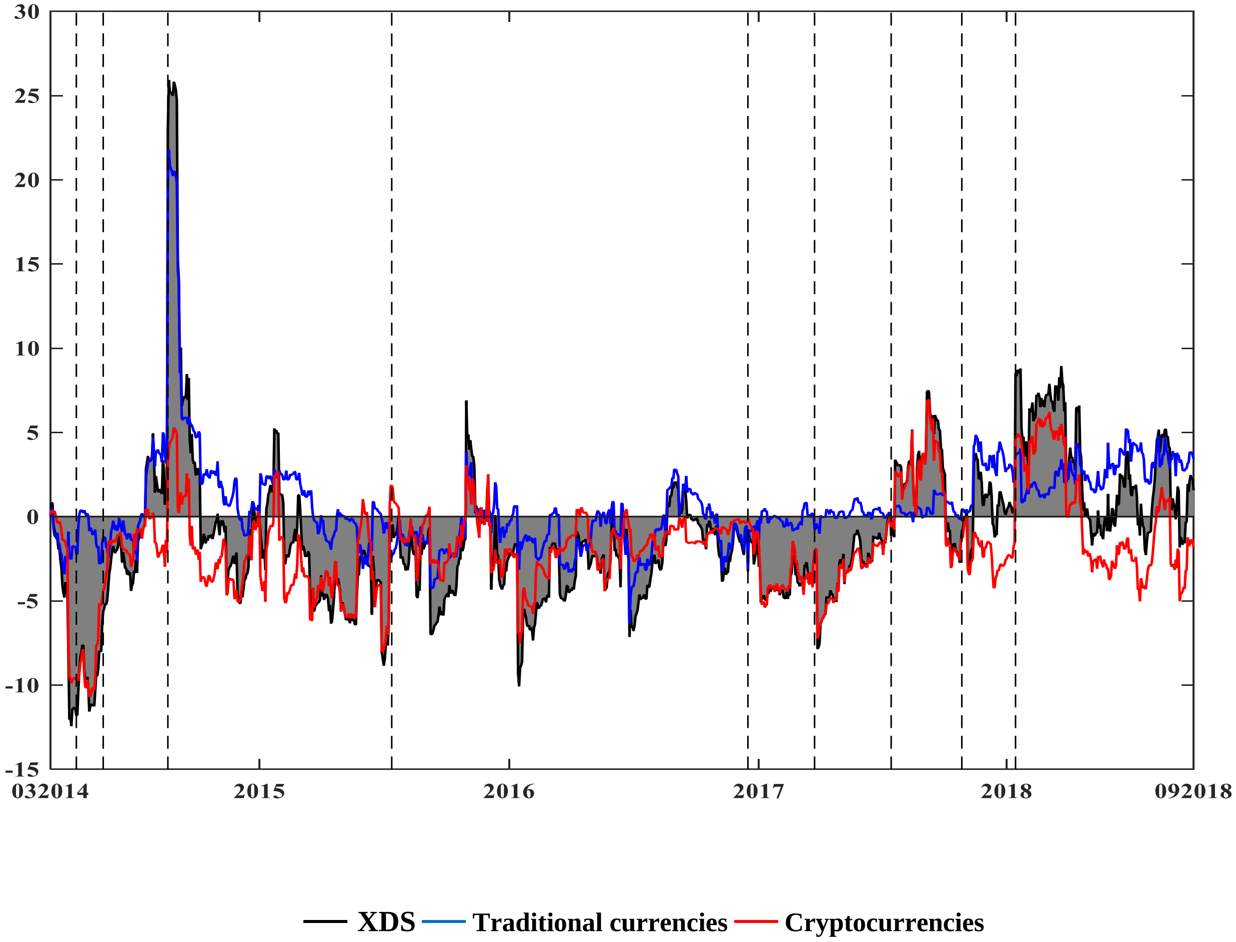

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3g: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for XLT**



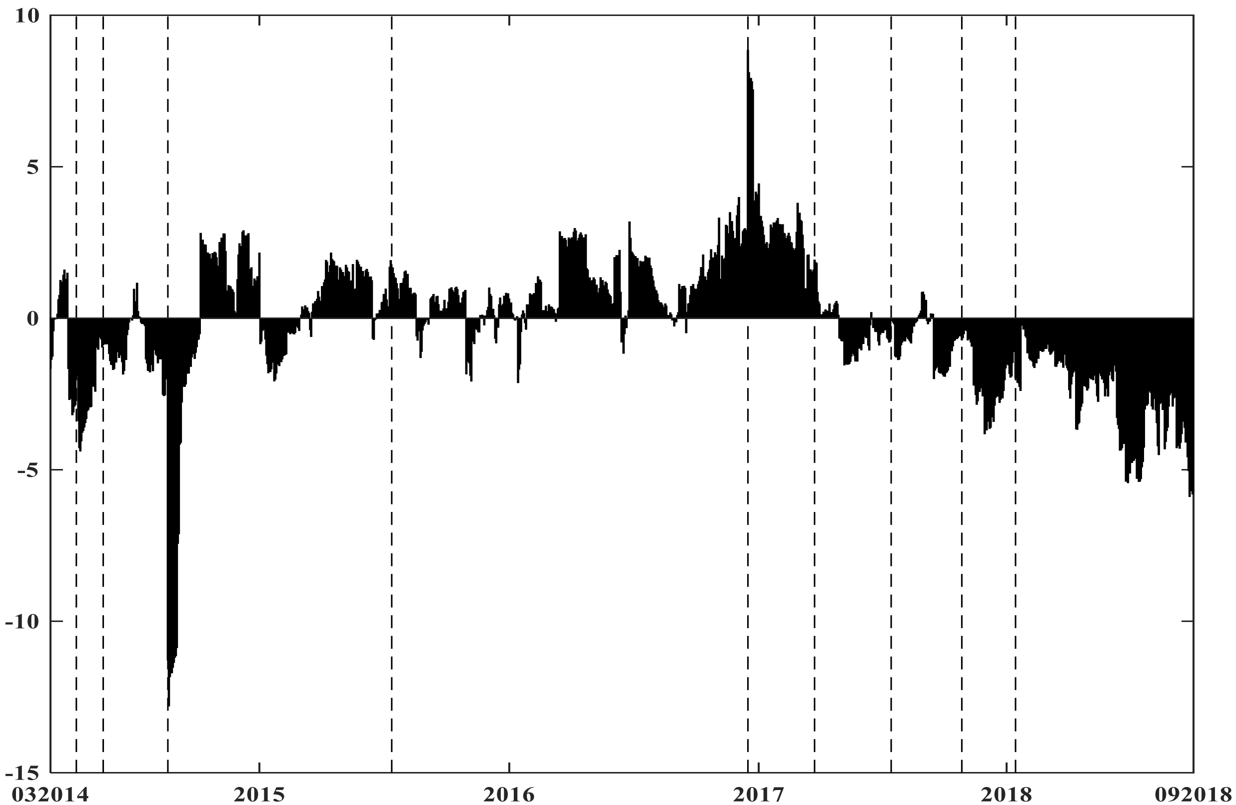

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 3h: Net directional connectedness and net pair-wise directional connectedness by blocks of currencies for XDS**



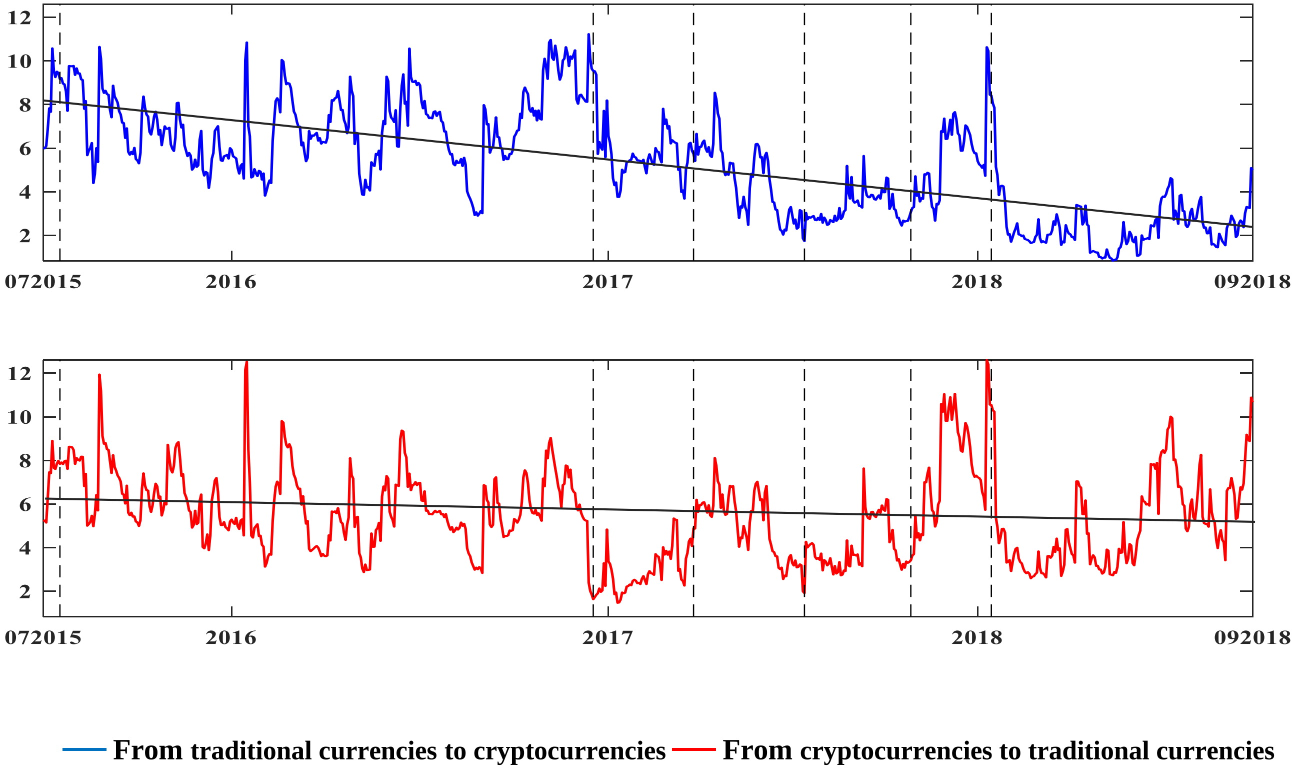

Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 4: Dynamic net connectedness from the block of traditional currencies to the block of cryptocurrencies**




Note: The vertical lines delimit the following episodes: I: March 2014-April 2014; II: April 2014-May 2014, III: May 2014-August 2014, IV: August 2014-July 2015, V: July 2015-November 2016, VI: November 2016-March 2017, VII: March 2017-July 2017, VIII: July 2017-October 2017, IX: October 2017-January 2018, X: January 2018-Sep 2018.

**Figure 5: Dynamic directional volatility connectedness from the block of traditional currencies to the block of cryptocurrencies and vice versa**




Note:

The vertical lines delimit the following episodes: I: July 2015-November 2016, II: November 2016-March 2017, III: March 2017-July 2017, IV: July 2017-October 2017, V October 2017-January 2018, VI: January 2018-Sep 2018.

The black straight lines represent the trends in both directional connectedness.

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