Connectedness of Cryptocurrencies and Gold returns: Evidence from frequency-dependent quantile regressions

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Abstract

This paper explores the symmetric and asymmetric dependency structure of decomposed return series of Gold and eight cryptocurrencies to establish the hedging and diversification potentials of these asset classes. Daily data spanning 30 April 2013 to 18 April 2019 are employed within the Ensemble Empirical Mode Decomposition and Quantile-in-Quantile regression techniques. Our empirical results provide evidence that cryptocurrencies and Gold can both hedge and diversify for each other at different conditional distributions of their returns. We also find that cryptocurrencies are not purely speculative but can be driven by medium- and long-term fundamentals. In addition, both Gold and cryptocurrencies can be hedge and diversifiers for other traditional asset classes such as crude oil, fiat currencies, and other commodities.

Keywords: Gold; Cryptocurrencies; Ensemble Empirical Mode Decomposition; Quantile-on-Quantile; Regression

JEL classification: G11; G15; G28: O17

1. Introduction

Digital currencies which rely on cryptographic proofs for confirmation of transactions referred to as cryptocurrencies (cryptos) emerged in 1983 following the seminar paper of (Chaum, 1983). These currencies differ from fiat currencies by its unique combination of three features: ensuring limited anonymity, independence from a central authority, and double-spending attack protection. The interest on cryptos heightened following achievement of these three features by Nakamoto (2008) in the paper "A Peer to Peer Electronic Cash System" and the subsequent introduction of Bitcoin on 3 January 2009 (Lansky, 2018). As of April 2019, over 2000 cryptos were in existence compared to a little above 600 in January 2016 (Lansky, 2018) and 1622 as of May 2018 (Klein, Pham Thu, & Walther, 2018), with a total market capitalisation of over $240 billion. This signifies a rapid growth in a shor time span. According to Klein et al. (2018), cryptos have become attractive due to embodied innovative technology, high-security architecture, prosperity in functionalities, and investment opportunity as an asset. The emergence of cryptos has widened the investment and diversification platforms available to global investors. Cryptocurrencies have been likened to gold, which for years have been used as a hedge and safe-haven against assets like stocks, bonds, and other monetary assets (Baur & Lucey, 2010; Baur & McDermott, 2010, 2016; Klein et al., 2018). Research on the potential of some cryptos (usually Bitcoin) to act as a hedge and safe-haven similar to gold has emerged (Bouri, Gupta, Tiwari, & Roubaud, 2017; Bouri, Jalkh, Molnár, & Roubaud, 2017). They have become recognised as a new gold in digital form because of similarities in traits as highlighted in Dyhrberg (2016). These similarities between cryptos and gold include scarcity, the cost involved in the extraction, and non-interference or control by government. Cryptocurrencies, however, could differ from gold by exhibiting the characteristics of fiat currency, making them hybrid commodities. As a choice of alternative investment, Das & Kannadhasan (2018) posit that risk-averse investors may prefer gold, however, investors with speculative motive may opt for cryptocurrency, such as Bitcoin. Such dynamics occasion the need to explore further and generate better understanding of the dynamic interactions between cryptos and gold.

This has generated a plethora of studies examining the interdependency structure of some cryptos (mostly, Bitcoin) and gold prices (Das & Kannadhasan, 2018; Dyhrberg, 2016; Klein et al., 2018; Zwick & Syed, 2019). However, the price generation process involves multiple factors that relate to economic characteristics of the structure of these markets which make it difficult to understand (Di Matteo, Aste, & Dacorogna, 2003). The complexity of the price

generation process interrogates the validity of natural law of scale-invariance or fractals of a self-similar process to reflect the behavioural market theory known as the heterogeneous market hypothesis (HMH) (Müller et al., 1993). The HMH sees market participants as heterogeneous with different information, objectives, and varying investment horizons. Such market participants react to the information at different times, which makes market data mixed and noisy. This causes the price series of cryptocurrency and gold to exhibit non-linearity, non-stationarity, and long memory.

It is clear that the potential of non-linearity in the data generating process of these prices render the use of classical linear models inappropriate. The complex nature of such time series has increased time-frequency representations such as Short-time Fourier transform (Yunhong, Guosui, Xi, & Yiding, 1998), Wavelet transform (Hu, Liu, & Deng, 2009), and adaptive optimum kernel time-frequency representation (Liao, Guo, Wang, Zuo, & Zhuang, 2015; Wang et al., 2011) in modelling the behaviour of the series by determining the frequencies present, the strength of the frequencies, and their patterns over time (Nava, Di Matteo, & Aste, 2018b, 2018a). However, these methods have been found to be deficient in handling the complex dynamics of these types of time series. For example, Fourier analysis is effective in studying periodic and stationary time series whose properties do not change much over time while wavelet transform is inaccurate in detecting the event under noisy conditions (Xiao et al., 2017). In addition, these methods require a priori-basis selection which confounds the economic interpretation or meaning of the analysis.

Ostensibly, these methods have been used by previous studies in analysing the relationships between cryptos and gold prices in spite of the weakness outlined. For example, Das and Kannadhasan (2018) employed wavelet-based approach, Zwick and Syed (2019) used threshold regression model while Klein et al. (2018) utilized BEKK-GARCH to examine the relationship between Bitcoin and gold. This leads to inaccurate identification of hidden structures embedded in the data, the validity of a conclusion drawn from the analysis, and its policy implications.

Recently, the empirical mode decomposition (EMD) method (Huang, Shen, & Long, 1999; Huang, Masulis, & Stoll, 1996; Huang, 1998) for analysing the non-linear and non-stationary signal data is proposed. Unlike the previous methods, such as the wavelet analysis and spectrum analysis, EMD eliminates the need for an a-priori basis selection and addresses the

weakness of competing model to correctly identify the hidden structures embedded in the data. According to Huang (1998), the EMD technique assumes that the financial time series has many intrinsic mode functions (IMFs) of different oscillations which must satisfy two conditions: 1) it has the same number of extremum and zero crossing or differs by one at the most and 2) it is symmetric with the local zero mean. In spite of these strengths, the standard EMD suffers from mode-mixing making physical meaning of individual IMF unclear. As a way of improvement, the ensemble empirical mode decomposition (EEMD) which corrects the issue of mode-mixing is introduced (Wu & Huang, 2009). The EEMD has been recently applied to financial time series decomposition (Li, Li, Wu, Zhu, & Yue, 2018; Wu & Huang, 2009; Xu, Shang, & Lin, 2016; Zhang, Lin, & Shang, 2017).

The current study follows Bouri, Gupta, et al. (2017) and Das & Kannadhasan (2018) to analyse the asymmetric and symmetric dependency structure of decomposed series by quantile-in-quantile regression (QQR) but deviates from these studies by using EEMD instead of wavelets decomposition. The advantage of this method lies in the strength of EEMD to efficiently decomposed non-linear and non-stationary series which improve the quality of the decomposed series. The paper makes two contributions to literature. First, to our knowledge this the first paper to employ EEMD-based QQR to analyse the dependency structure of cryptos and gold. Second, although there are more than 2000 cryptos available, the extant literature concentrated on mostly Bitcoin, this study expands the discussion to seven other cryptos based on a longer span of data available.

Our empirical results reveals that cryptos and gold can both hedge and diversify for each other at different conditional distributions of their returns. We also find that cryptos are not purely speculative but can be driven by medium- and long-term fundamentals. In addition, both gold and cryptos can be hedge and diversifiers for other traditional asset classes such as oil, currencies, and other commodities.

2. Models and methodologies

2.1 Ensemble empirical mode decomposition (EEMD)

We employ the ensemble empirical mode decomposition (EEMD), QR, and QQR techniques for our analysis. This involves a two-step approach by which we extract intrinsic mode functions (IMFs) from gold and returns of the selected cryptos with EEMD. We then proceed

to estimate bi-directional regressions with QR the QQR methods at different frquencies. The IMFs, representing different time scales, are important in this study given the non-linearity and non-stationarity within our series (Ivanov, 2013).

As a potential successor of empirical mode decomposition (EMD), the EEMD improves the former by an objective intermittence test on a white noise-added signal (data) which allows the mean to be treated as the final true results (Wu & Huang, 2009). The EEMD sifts through the original series with a sufficient number of iterations. With the added white noise, it provides a uniform reference in the time-frequency space essential in this study and in line with the EEMD. We provide a brief description of the EEMD methodology based on Wu & Huang (2009).

The EEMD defines the IMF components as the mean of an ensemble of trials, where each is made of the signal (data) and a white noise of finite amplitude. In generic terms, all data $x(t)$ are a sum of signal (that is actual data, $s(t)$) and noise $n(t)$ so that

$$x(t) = s(t) + n(t). \tag{1}$$

While many data analysis techniques have failed to remove this noise component, the EEMD adds white noise in order to remove weak signals (to keep the true signal). This is based on inspirations from Flandrin, Rilling, & Goncalves (2004) and Gledhill (2003). Wu & Huang's (2009) EEMD improves upon EMD and the works of the above authors by using the cancellation (effects) principle[1] associated with an ensemble of noise-added cases to improve results. This improvement stems from overcoming the problems of scale separation and mode mixing[2] associated with the EMD without a subjective test (known as noise-assisted data analysis (NADA)) on the original data. Scale separation is a problem linked to the intermittency test aimed at fixing mode mixing problem based on a subjective election of scales (Wu & Huang, 2009).

From Eq. (1) an i^{th} artificial observation,

$$x_i(t) = x(t) + \omega_i(t) \tag{2}$$

[1] See de Cheveigné (2005) for further details.

[2] Any IMF consisting of oscillations of dramatically disparate scales caused by intermittency of the driving mechanism (Wu & Huang, 2009).

is realised by adding a white noise of different realisations, $\omega_i(t)$ which avoids mode mixing which provides a relatively uniform reference scale distribution to facilitate EMD.

The development of EEMD relies on the properties of EMD of Huang et al. (1998) and Huang, Shen, & Long (1999) as follows:

1. add a white noise to the targeted data to arrive at $x_i(t)$
2. decompose $x_i(t)$ into IMFs
3. iterate 1 and 2 with varying white noise series and
4. obtain the (ensemble) means of corresponding IMFs of the decomposition as the final result.

The desirable features of the EEMD are that the randomly added white noise series will cancel out each other in the final rendition of the respective IMFs. Hence, mean IMFs reside within the natural dyadic filter windows which sidesteps the mode mixing problem. The largest number of IMFs s_i (and one residual r) of a data set is approximately $log_2 N$ where N denoted the total number of data points. Thus, r can be represented as $s_i - (s_i - 1)$.

2.2 The QR and QQR approaches

The QQR technique is the non-parametric version of quantile regression that empirically justifies the conditional quantile relationship between two or more variables. The QQR technique is assumed to combine one of quantile regression and non-parametric estimators. In order to study bearish and/or bullish relationship between gold and cryptocurrencies, the QQR technique seems appropriate. In terms of price patterns, quantiles can describe asymmetry between high and low returns as well as capturing possible non-stationarity in the series. In this study we look at this nexus starting with

$$GR_t = \beta^{\theta}(CR_t) + u_t^{\theta} \qquad (3)$$

where GR_t and CR_t denote the gold and cryptocurrency returns at period *t*, θ is the θth quantile of the conditional distribution of GR_t and u_t^{θ} is the error quantile whose θth conditional quantile is made-up to be zero, and $\beta^{\theta}(\cdot)$ represents slope of this relationship. One can view Eq. (3) as the quantile regression, from which QQR can be derived.

The Eq. (3) can be extended by a first order Taylor expansion of a quantile of CR^{τ} as follows:

$$\beta^{\theta}(CR_t) \approx \beta^{\theta}(CR^{\tau}) + \beta^{\theta'}(CR^{\tau})(CR_t - CR^{\tau}) \quad (4)$$

where $\beta^{\theta'}$ explains the partial derivative of $\beta^{\theta}(CR_t)$, indicative of a marginal effect as the slope. We see that θ is the functional form of $\beta^{\theta}(CR^{\tau})$ and $\beta^{\theta'}(CR^{\tau})$ while τ is the functional form of EX and EX^{τ}, hence θ and τ are the functional forms of $\beta^{\theta}(CR^{\tau})$ and $\beta^{\theta'}(CR^{\tau})$. If we represent $\beta^{\theta}(CR^{\tau})$ and $\beta^{\theta'}(CR^{\tau})$ by $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$, respectively, then

$$\beta^{\theta}(CR_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(CR_t - EX^{\tau}) \quad (5)$$

can suffice. By substituting Eq. (5) into Eq. (3), we arrive at the Eq. (6) as follows:

$$GR_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(CR_t - CR^{\tau})}_{(*)} + u_t^{\theta} \quad (6)$$

where, (*) gives the conditional quantile of θth of gold returns. Further, it reveals the actual association between the quantile of cryptocurrency returns (θth) and the quantile of gold returns (τth) of parameters β_0 and β_1 with indices of θ and τ. As in ordinary least squares (OLS), a similar minimisation is applied to arrive at Eq. (7)

$$\min_{b_0,b_1} \sum_{i=1}^{n} \rho_{\theta}\left[GR_t - b_0 - b_1\left(\widehat{CR}_t - \widehat{CR}^{\tau}\right)\right] K\left(\frac{F_n(\widehat{CR}_t)-\tau}{h}\right) \quad (7)$$

where $\rho_{\theta}(u)$ is the quantile loss function representing as $\rho_{\theta}(u) = u\big(\theta - I(u<0)\big)$, i is the function of indicator, $K(\cdot)$ is the kernel density function and h denotes kernel density function bandwidth parameter. The kernel function weights the observations of EX^{τ} where the minimal weights are negatively related to distribution function of $\widehat{CR}_t$ as $F_n\left(\widehat{CR}_t\right) = \frac{1}{n}\sum_{k=1}^{n} I(\widehat{CR}_k < \widehat{CR}_t)$. In line with Sim and Zhou (2015) we use $h = [0.05\ to\ 0.95]$ for empirical QQ analysis which is the bandwidth for the quantiles. The bandwidth is the partition of the quantiles and determines the smoothness of the estimation results. Smaller bandwidths are preferred to larger ones as the latter may induce bias in the estimated coefficients. We note that in the case where gold is the independent variable the equations can be modified accordingly.

By using QR and QQR to quantify the relationship between gold and cryptos with IMFs as inputs, not only are we able to capture the time-varying non-linear non-stationary link, we are also able to infer the nexus during both bear and bull return episodes at short-, medium-, and long-terms. As the first of a few studies of this nature, our paper provides fresh insights for different types of gold investors to satisfy their profit-maximising or risk-minimising goals.

3. Data and preliminary analysis

We present the sampled cryptos in Table 1. Selection is based on a large span of available data for which the same number of IMFs are obtained. We also consider the market capitalisation in the selection of crytos. For example, Bitcoin (64%), Ethereum (22%), Ripple (5%), Litecoin (2%), and others (8%) (Zhang, Chan, Chu, & Nadarajah, 2019). All cryptos data are gleaned from CoinMarketCap[3] but gold data is taken from the Bloomberg Terminal; and are quoted in USD. For the purposes of this study, gold is matched with each cryptocurrency according to time span and trading days. The return series are decomposed into a number of IMFs depending on the length of series and they represent short-term, medium-term, and long-term dynamics. We select IMF 1, IMF 5, and IMF Residual to represent short-, medium-, and long-term dynamics, respectively, in line with the extant literature.

We present the summary statistics of gold and returns of the selected cryptos and the number of IMFs in Table 2. We find both left and right skewness and excess kurtosis are corroborated by the Shapiro-Wilk test of normality. These confirm asymmetries in the distributions of the series. We also find similar patterns for the IMFs across the time-scales. Further, IMFs seem to be useful as inputs for the regression techniques in the light of frequency-variations in the time series. These provide further motivation to employ quantile-based regressions to analyse the gold-cryptos nexus. The times series plots presented in Figure 1 (in the Appendices) also show volatility clusters and thus an indication of time-varying risk emanating from the series.

Table 1: Summary of sample data

Cryptocurrency	Period	No. of IMFs
Bitcoin (BTC)	30/04/2013 – 18/04/2019	10
Dash (DASH)	17/02/2014 – 18/04/2019	10
Ethereum (ETH)	10/08/2015 – 18/04/2019	10
Litecoin (LTC)	30/02/2014 – 18/04/2019	10
Monero (XMR)	22/05/2014 – 18/04/2019	10
NEM (XEM)	02/04/2015 – 18/04/2019	10
Ripple (XRP)	05/08/2013 – 18/04/2019	10
Stellar (XLM)	06/08/2014 –18/04/2019	10

Note: Cryptocurrencies are arranged in alphabetical order.

4. Empirical results: asymmetric regression results

[3] https://coinmarketcap.com/

4.1 QR results

In this study we surmise a bi-directional nexus between gold and cryptocucurries and we perform regressions accordingly. For clarity of presentation and want of space we elect to plot the regression coefficients, rather than present the actual coefficients in tables[4]. These are presented in Figure 2. We note that both QR (lines in wine colour) and QQR (lines in blue colour) estimates are in the same plots. Apart from Figure 2 providing a pictorial representations of the gold-cryptos link in terms of magnitude and direction, it also engenders a basis to validate estimates from the QQR technique – this is further explained in Section 4.2. In the plots we note that the pair with Gold as the first variable and a crypto as the second variable (e.g. Gold-Bitcoin) implies Gold is the dependent variable and Bitcoin is the independent variable (hereafter referred to as *from*). The reverse is true (hereafter referred to as *to*). Thus, in the QR Gold-Bitcoin implies the quantile returns of Gold are regressed on the returns of Bitcoin. But for QQR, the quantile returns of Gold are regressed on the corresponding quantile returns of Bitcoin. The same analogy applies for Bitcoin-Gold, for instance.

We advise the reader that the plots in Figure 2 are constructed with the background that the bi-directional gold-cryptos link at the composite level (returns without decomposition) and in the short-term (IMF1) are mostly insignificant at the conventional[5] levels of significance. Significance is attained in the medium-term (IMF5) and long-term (IMFR). We further observe that, in the case of Ethereum, there is no significant link with gold throughout. This may be quite surprising given the place of Ethereum in the cryptos space. For instance, it has attracted a great deal of attention and rivaled Bitcoin as the second ranking crypto in their early years (Mensi, Al-Yahyaee, & Kang, 2018). Therefore, we present the results for all gold-cryptos pairs in the medium- and long-terms except for Ethereum.

[4] All regression tables are available upon request to the corresponding author.
[5] That is 1%, 5%, and 10% significance levels.

Table 2: Summary statistics of Gold and cryptocurrencies returns and their IMFs

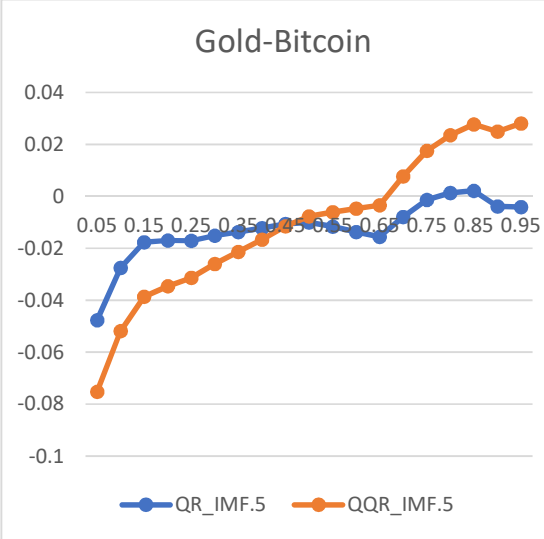
Statistic	Gold	BTC	Gold_IMF1	Gold _IMF5	Gold _IMFR	BTC_IMF1	BTC_IMF5	BTC_IMFR
Obs.	1500	1500	1500	1500	1500	1500	1500	1500
Mean	-0.0001	0.0016	0	-0.0001	-0.0002	0.0003	0.001	0.001
Std. Dev.	0.01	0.05	0.01	0.00	0.00	0.04	0.01	0.00
Skewness	0.03	-0.14	-0.05	0.07	-1.16	0.02	0.53	-0.91
Kurtosis	3.95	7.99	0.75	0.31	0.28	5.32	2.67	-0.47
Normtest.W*	0.96	0.88	0.99	1.00	0.84	0.94	0.91	0.84
	Gold	**DASH**	**Gold_IMF1**	**Gold _IMF5**	**Gold _IMFR**	**DASH_IMF1**	**DASH_IMF5**	**DASH_IMFR**
Obs.	1299	1299	1299	1299	1299	1299	1299	1299
Mean	0	0.0031	0	0	0	-0.0004	-0.0009	0.0038
Std. Dev.	0.01	0.08	0.01	0.00	0.00	0.06	0.01	0.01
Skewness	0.20	3.32	-0.04	0.08	-0.94	0.39	-1.53	0.54
Kurtosis	2.47	49.06	0.45	0.43	-0.42	14.90	10.43	-0.96
Normtest.W*	0.97	0.77	0.99	1.00	0.83	0.88	0.81	0.91
	Gold	**ETH**	**Gold_IMF1**	**Gold _IMF5**	**Gold _IMFR**	**ETH_IMF1**	**ETH_IMF5**	**ETH_IMFR**
Obs.	928	928	928	928	928	928	928	928
Mean	0.0002	0.0036	0.0001	0	0	-0.0002	-0.0007	0.0047
Std. Dev.	0.008	0.0708	0.0063	0.001	3.00E-04	0.052	0.0124	0.0074
Skewness	0.366	0.635	-0.074	0.086	0.516	0.081	-0.196	0.595
Kurtosis	2.939	4.173	0.575	0.270	-1.027	1.039	1.661	-0.900
Normtest.W*	0.965	0.930	0.995	0.996	0.908	0.991	0.975	0.905
	Gold	**LTC**	**Gold_IMF1**	**Gold _IMF5**	**Gold _IMFR**	**LTC_IMF1**	**LTC_IMF5**	**LTC_IMFR**
Obs.	1500	1500	1500	1500	1500	1500	1500	1500
Mean	-0.0001	0.0006	0	-0.0001	-0.0002	0.0007	0.0002	0.0002
Std. Dev.	0.01	0.07	0.01	0.00	0.00	0.05	0.01	0.00
Skewness	0.03	1.84	-0.05	0.07	-1.16	-0.02	0.05	0.03
Kurtosis	3.95	24.58	0.75	0.31	0.28	8.16	5.38	-1.24
Normtest.W*	0.96	0.77	0.99	1.00	0.84	0.89	0.88	0.95
	Gold	**XMR**	**Gold_IMF1**	**Gold _IMF5**	**Gold _IMFR**	**XMR _IMF1**	**XMR _IMF5**	**XMR _IMFR**
Obs.	1233	1233	1233	1233	1233	1233	1233	1233
Mean	0	-0.0001	0.0001	-0.0001	-0.0001	-0.0003	0	-0.0022
Std. Dev.	0.01	0.08	0.01	0.00	0.00	0.06	0.01	0.01
Skewness	0.21	0.36	-0.06	0.09	-0.96	0.05	0.09	-0.59
Kurtosis	2.60	4.85	0.55	0.51	0.00	1.50	0.37	-0.92

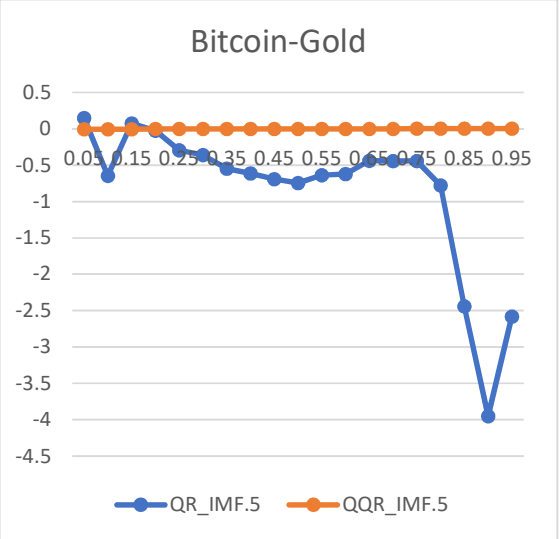
Normtest.W*	0.97	0.93	0.99	0.99	0.88	0.98	0.99	0.91
	Gold	**XEM**	**Gold_IMF1**	**Gold _IMF5**	**Gold _IMFR**	**XEM_IMF1**	**XEM_IMF5**	**XEM_IMFR**
Obs.	1016	1016	1016	1016	1016	1016	1016	1016
Mean	0.0001	0.0053	0	0	0	-0.0005	0	0.0077
Std. Dev.	0.01	0.09	0.01	0.00	0.00	0.07	0.02	0.01
Skewness	0.33	2.05	-0.05	0.05	-0.47	-0.09	0.10	-1.03
Kurtosis	2.76	18.10	0.43	-0.22	-1.24	3.81	1.82	-0.13
Normtest.W*	0.97	0.86	1.00	1.00	0.88	0.96	0.96	0.85
	Gold	**XLM**	**Gold_IMF1**	**Gold _IMF5**	**Gold _IMFR**	**XLM_IMF1**	**XLM_IMF5**	**XLM_IMFR**
Obs.	1181	1181	1181	1181	1181	1181	1181	1181
Mean	0	0.0017	0.0001	-0.0001	0	-0.0005	0.0003	0.0028
Std. Dev.	0.008	0.080	0.006	0.001	0.000	0.062	0.014	0.003
Skewness	0.220	1.345	-0.050	0.012	-0.815	-0.132	0.224	-0.893
Kurtosis	2.612	10.710	0.518	0.540	-0.626	3.490	2.652	-0.501
Normtest.W*	0.969	0.868	0.995	0.993	0.857	0.954	0.947	0.841
	Gold	**XRP**	**Gold_IMF1**	**Gold _IMF5**	**Gold _IMFR**	**XRP_IMF1**	**XRP_IMF5**	**XRP_IMFR**
Obs.	1433	1433	1433	1433	1433	1433	1433	1433
Mean	0	0.0026	0	0	0	-0.0006	0.0004	0.0032
Std. Dev.	0.009	0.077	0.007	0.001	0.000	0.061	0.014	0.004
Skewness	0.249	2.124	-0.048	-0.013	-1.106	-0.047	0.426	1.181
Kurtosis	2.781	32.901	0.669	0.296	0.283	19.051	3.271	0.249
Normtest.W*	0.967	0.733	0.993	0.996	0.859	0.801	0.915	0.824

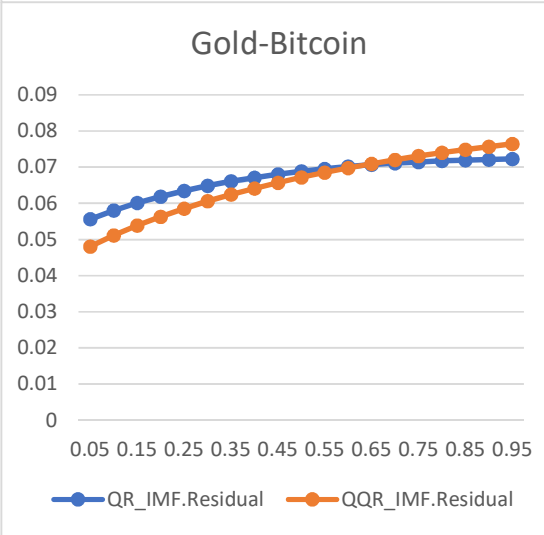
Note: Normtest.W indicates Shapiro-Wilk test of normality which is rejected at all conventional levels of significance.*

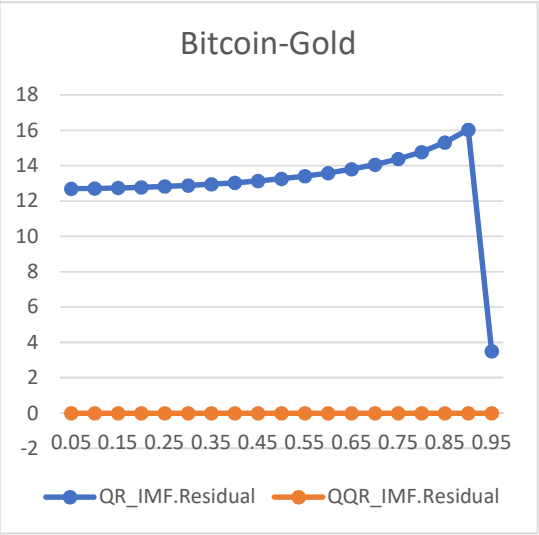
It is clear from the coefficient estimates that composite and short-term gold-cryptos links can be spurious. Investors may be caught in the frenzy about cryptos (especially Bitcoin) as the new gold (Dyhrberg, 2016) in the short-term. Further, from an econometric perspective, a claim by Klein et al. (2018) that Bitcoin does not bear a resemblance to any other conventional asset, may be supported. Nonetheless, if we follow definition of a hedge by Baur & Lucey (2010), we can deem these insignificant coefficients to imply that gold and crytocurrrencies are uncorrelated, which suggests that gold and cryptos can hedge each other at the compotite level and in the short-term. Further, we may see the unconditional connectedness between cryptos and gold as negligible as found by (Kurka, 2019). However, with the passage of time investors may rebalance their portfolios with after a careful assessment of the market. This may serve as reminder that Weber's (2016) Bitcoin standard may be far-fetched. But this could support the assertion that cryptos may not be adopted by states by reason of their risks (Lansky, 2018). Notwithstanding, this scenario corroborates the findings of Bouoiyour, Selmi, Tiwari, & Olayeni (2016), using EMD that Bitcoin, for instance, is driven by long-term fundamentals as opposed to being labelled as a purely speculative asset class. Further, Kristoufek (2015) find Bitcoin to possess both speculative and standard financial asset properties (see also, Zwick & Syed, 2019). Thus, we surmise that it takes some time and detailed analysis for noteworthy relationships between gold and cryptos to be revealed; as we have done in this study.

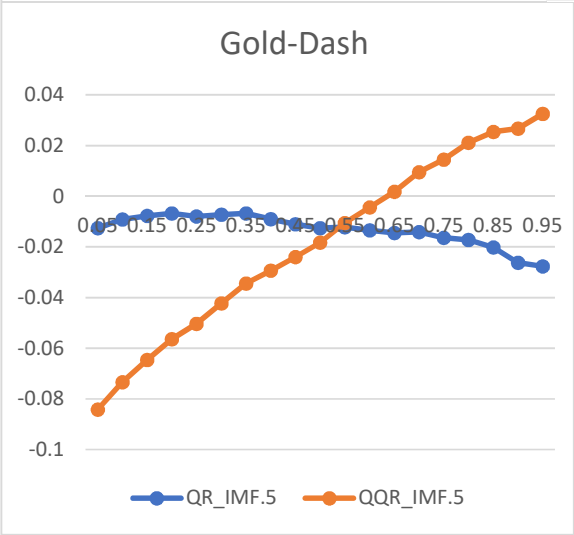
At this juncture, we analyse the QR estimates. We refer to blue colour plots in Figure 2. We observe that *from* and *to* share similar pattern in the medium- and long-terms. The coefficients of the former are smaller and the plots are smoother than those of the former. However, *to* estimates are somewhat smooth until the 75th quantile and take jumps afterwards. In the extreme upper tails we realise the links are strongest. In general, we find that the magnitude of both *from* estimates rise from lower quantiles through to upper quantiles, except for Dash, Litecoin, and Ripples (which exhibit a reverse pattern). But for *to* estimates, links fall from lower quantile to upper quantiles; and are steeper after the 75th. Exceptions are noted for Dash, Litecoin, NEM (rise steadily), Stellar (in the long-term), Monero (fall, rise, and fall again), and Ripple (fall steadily and rise in the medium-term). These patterns show us how the two asset classes are linked as per trends in the market. So we see the asymmetric nature of the nexus which should be instructive, in generic terms, for investment strategies involving these asset classes.

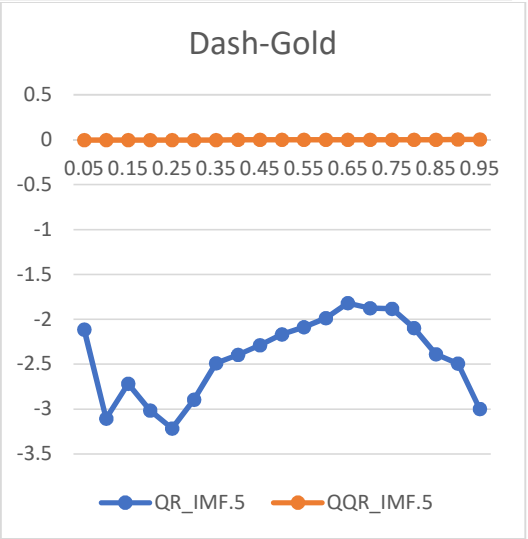

Gold-Bitcoin
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5

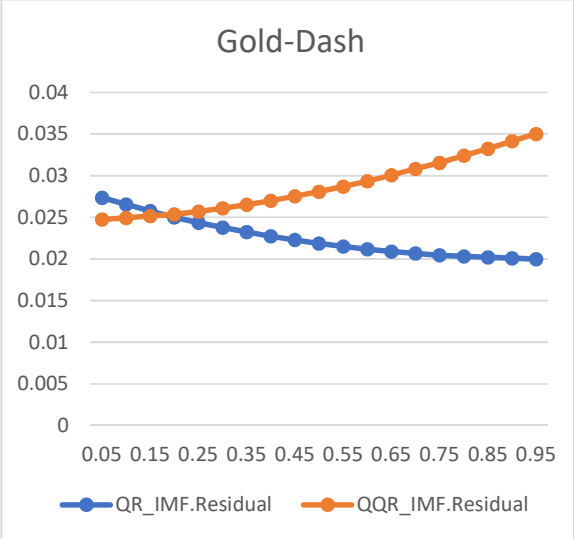

Bitcoin-Gold
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
-4.5
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5

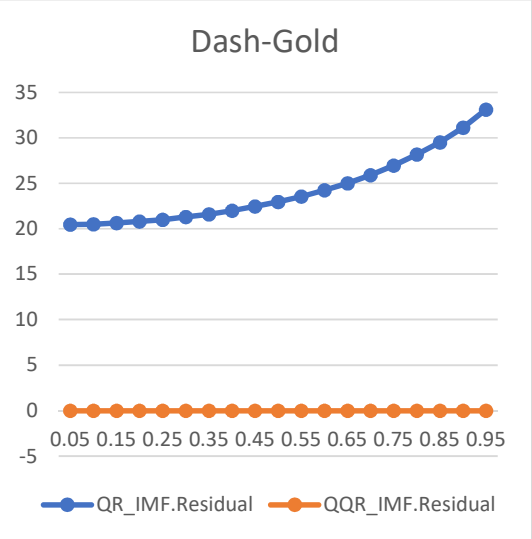

Gold-Bitcoin
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual

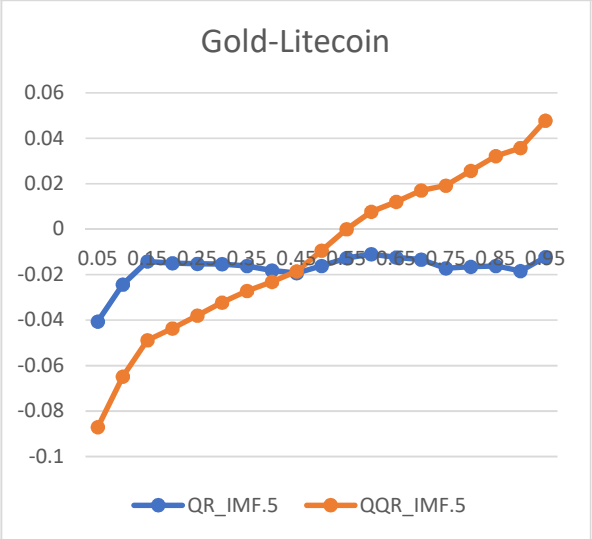

Bitcoin-Gold
18
16
14
12
10
8
6
4
2
0
-2
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual

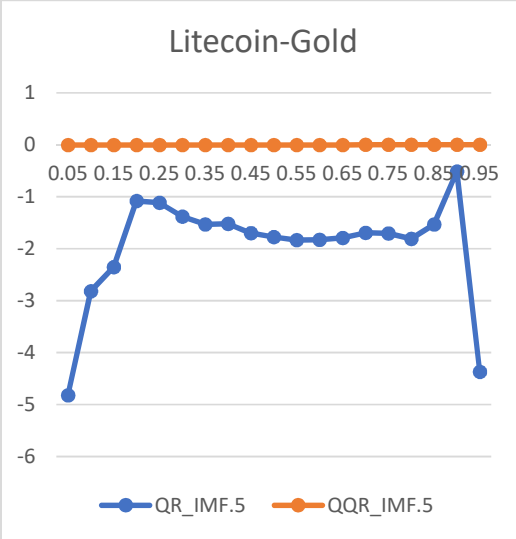

Gold-Dash
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5

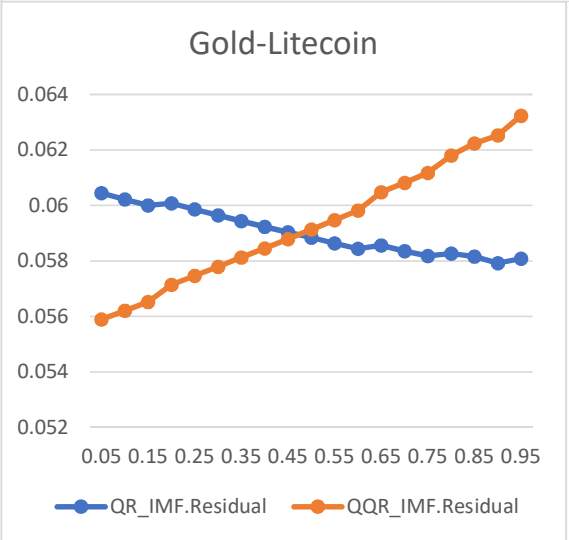

Dash-Gold
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5

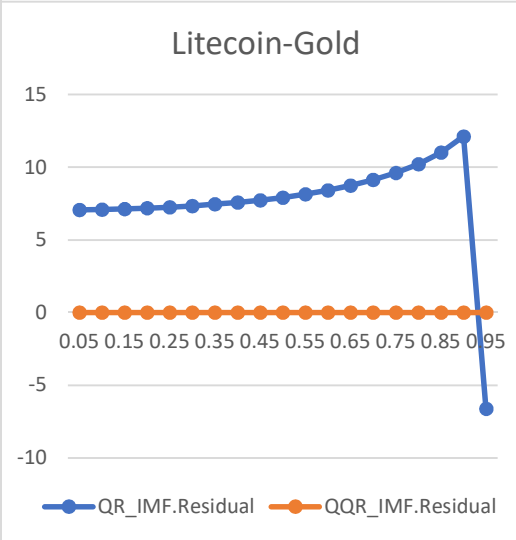

Gold-Dash
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual

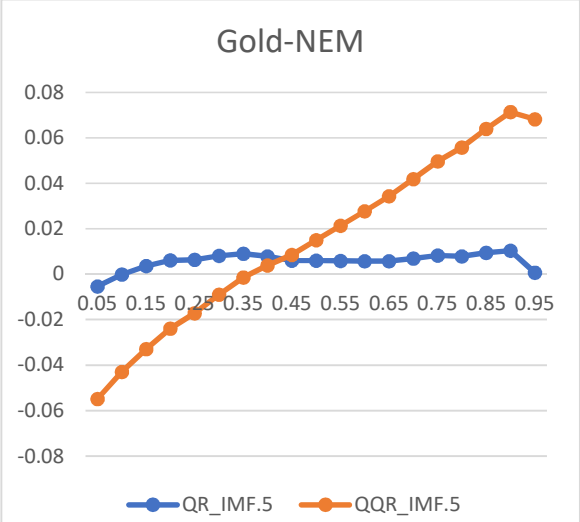

Dash-Gold
35
30
25
20
15
10
5
0
-5
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual

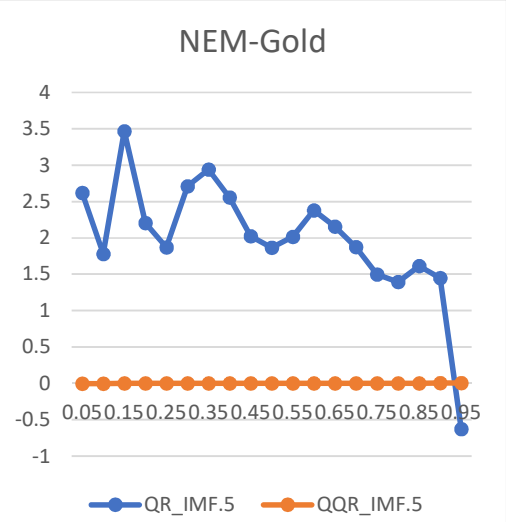

Gold-Litecoin
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
QR_IMF.5
QQR_IMF.5

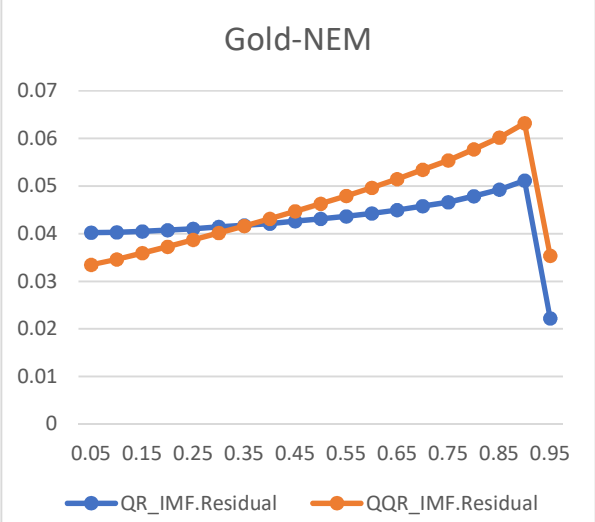

Litecoin-Gold
1
0
-1
-2
-3
-4
-5
-6
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5

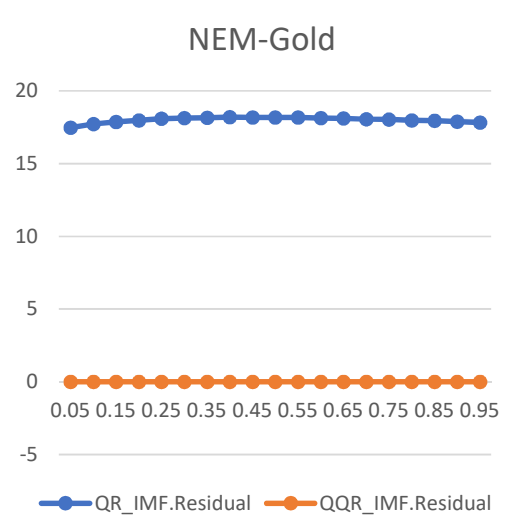

Gold-Litecoin
0.064
0.062
0.06
0.058
0.056
0.054
0.052
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual

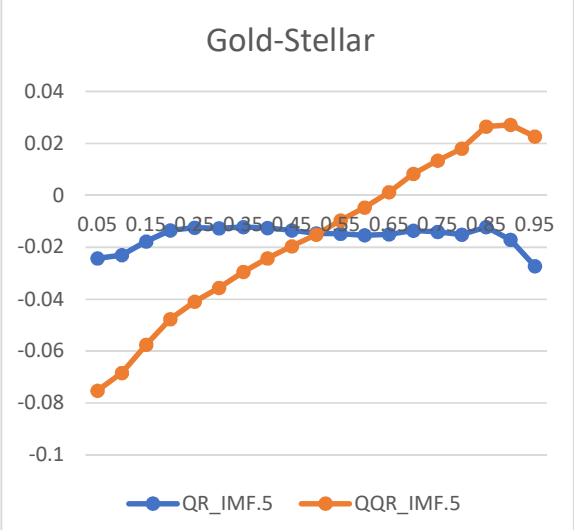

Litecoin-Gold
15
10
5
0
-5
-10
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual

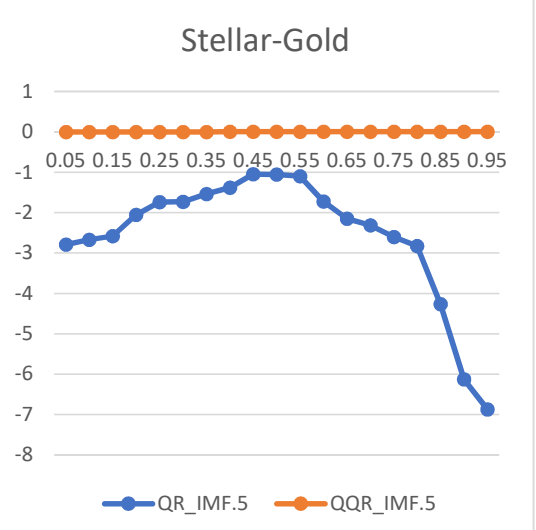

Gold-NEM
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5

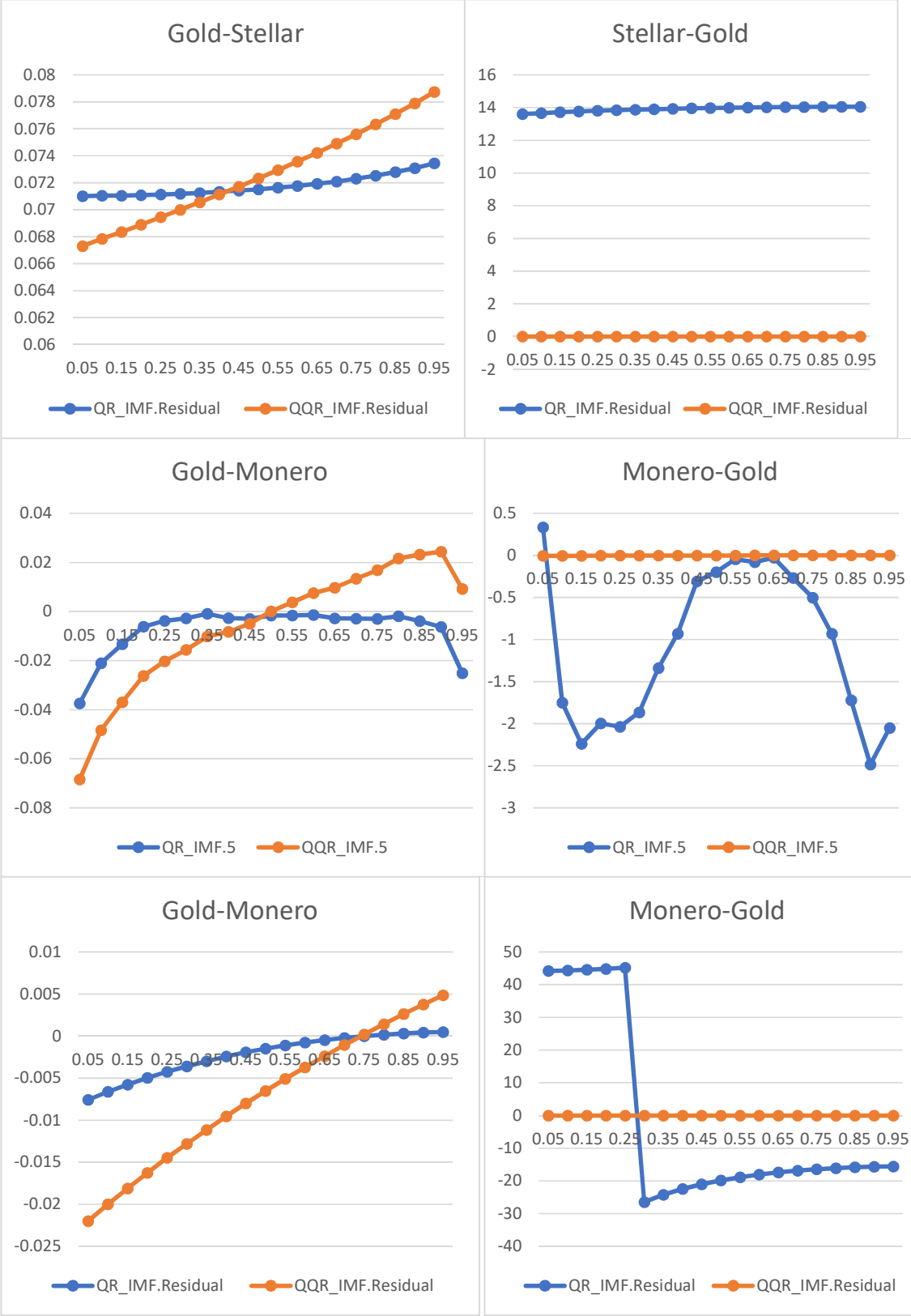

NEM-Gold
4
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
-1
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5


Gold-NEM
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual


NEM-Gold
20
15
10
5
0
-5
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual


Gold-Stellar
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5


Stellar-Gold
1
0
-1
-2
-3
-4
-5
-6
-7
-8
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5


Gold-Stellar
0.08
0.078
0.076
0.074
0.072
0.07
0.068
0.066
0.064
0.062
0.06
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual
Stellar-Gold
16
14
12
10
8
6
4
2
0
-2
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual
Gold-Monero
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5
Monero-Gold
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.5
QQR_IMF.5
Gold-Monero
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
-0.025
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual
Monero-Gold
50
40
30
20
10
0
-10
-20
-30
-40
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95
QR_IMF.Residual
QQR_IMF.Residual

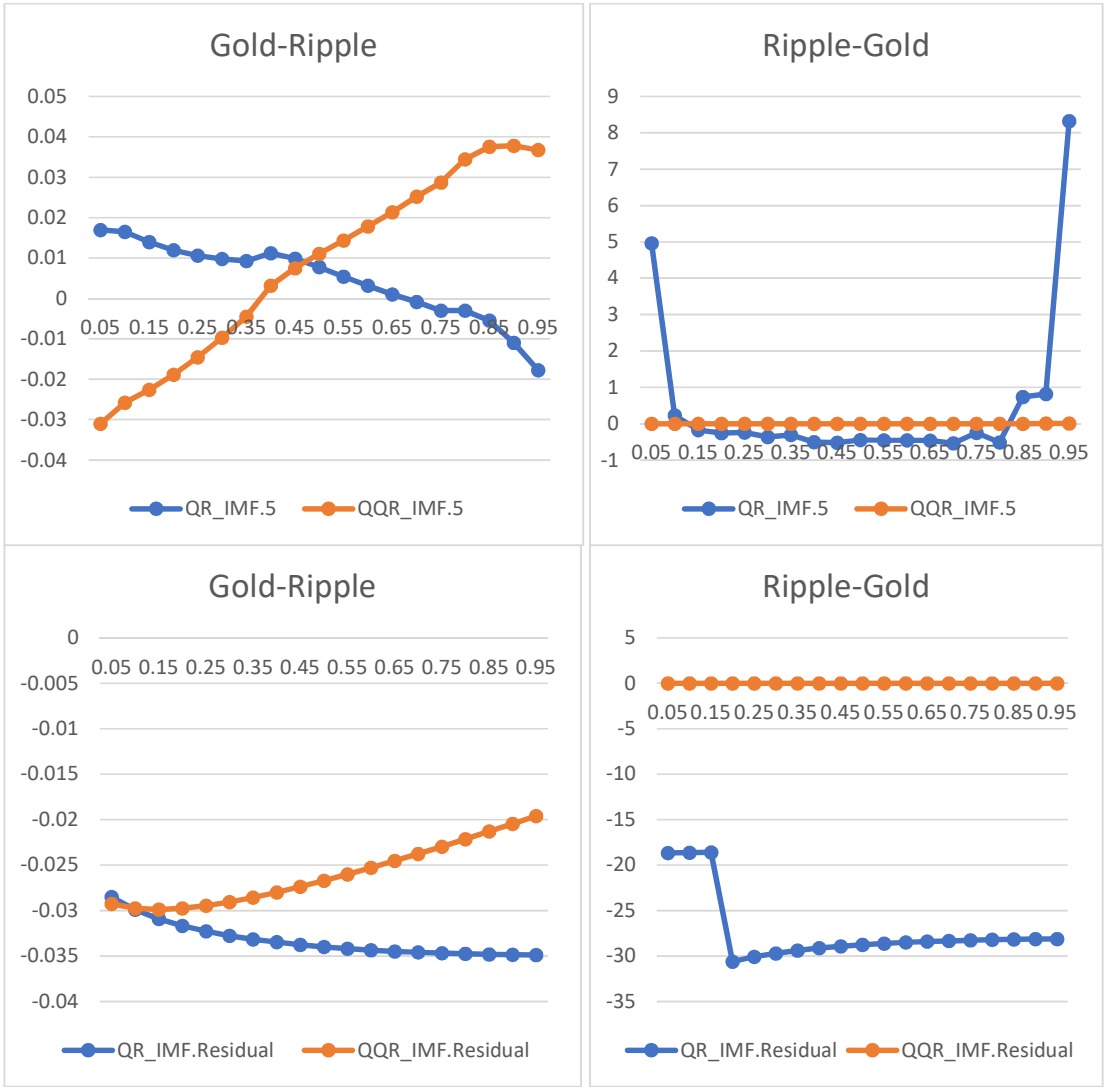


Figure 2: Bi-directional gold and cryptos QR and QQR

Having established hedging potential between gold and cryptos (uncorrelated) in the short-term and at composite level, we now analyse the direction of the nexus to provide insight into diversification possibilities. In this regards, we consider a negative coefficient or inverse relationship as one that provides diversification potential but positive coefficient does not. However, Baur & Lucey (2010, p. 219) distinguish between hedge and diversifier as follows: *"A hedge … uncorrelated or negatively correlated …"* and *"A diversifier … positively (but not perfectly correlated) …"* These two do not possess the specific property risk reduction market turmoils and so cannot be safe haven. Therefore, we follow the definitions of Baur & Lucey (2010) to identify specific quantiles where gold and cryptos can hedge or diversify for each other.

In the *from* context, we observe hedging possibilities mostly in the medium-term except for NEM which shows only diversifier prospects in both medium-and long-terms. In the long-term gold and cryptos mostly have positive relationships and thus may diversify each other. But Monero can hedge in the long-term up to the 75th quantile. The specific quantiles where inverse relationships are observed (hedging) are as follows: Bitcoin (lower half of distribution), Dash and Stellar (across all quantiles but small in magnitude as compared to the others), Monero (up to 15th quantile and after the 85th), and Ripple (only after the 65th quantile). It follows that the other quantiles offer diversifications instead.

The *to* link is comparable with *from* nexus in the sense that gold and cryptos are hedgers of each other mostly in the medium-term but diversifies in the long-term. There are, however, a few exceptions. For instance, Ripple cannot hedge at the tails of the distribution in the medium-term but it can diversify in the long-term. Monero can also hedge in the long-term in the upper third of the distribution. Lastly, NEM can also hedge only at the extreme tails of the distribution, but can otherwise diversify.

Our findings corroborate other studies that find cryptos to act as a hedge under different circumstances. For instance, Bouri et al. (2017) support the view under global uncertainty at higher quantiles and in the short-term. Bouri et al. (2017) also reveal hedge and diversifier properties for Bitcoin against commodities in a time-varying manner. For gold, in particular, Zwick & Syed (2019) find both hedge and diversifier features of Bitcoin.

Further, our findings reveal that gold and cryptos, on the hand can hedge or be safe haven under market uncertainties. For instance, Selmi, Mensi, Hammoudeh, & Bouoiyour (2018) find Bitcoin and gold, rather than oil, as safe haven under global uncertainty. Once more, Al-Yahyaee, Mensi, Al-Jarrah, Hamdi, & Kang (2019) document the diversification benefits of Bitcoin and gold for oil and Standard & Poor Goldman Sachs Commodity Index (S&P GSCI). Furthermore, given that our variables are denominated in US dollars, we can relate our findings to Kliber, Marszałek, Musiałkowska, & Świerczyńska (2019) who find Bitcoin as a weak hedge in all US dollar-denominated investment markets.

We further observe from Figure 2 that, the *to* (i.e. crypto-gold) links are stronger than *from* (i.e. gold- crypto) links. In other words, when cryptos are the dependent variables they hedge or

diversify better than when gold is the dependent variable, both in the medium- and long-terms. This implies that the conditional quantiles of gold provide stronger hedging and diversification potentials on cryptos than the conditional quantiles of cryptos have on gold. We suggest that bearish and bullish gold prices are better indicators for hedging and diversification strategies than rising and plummetting prices of cryptocurrencies.

We have established the importance of asymmetric dependence connection between gold and cryptos for investment strategies. Our finding, however, contravenes that of Charles & Darné (2019) who find GARCH-type models to be inappropriate for modelling dynamic asymmetric Bitcoin returns. In terms of the hedging ability of cryptos, Kurka (2019) holds a different opinion, that market disruptions may be transmitted from Bitcoin to the traditional economy.

4.2 QQR results

The QQR is a non-parametric technique which provides us with no significance of the regression coefficients. However, it is possible to infer the validity of the QQR from the QR. Bouri et al. (2017) suggest the QQR approach "decomposes" the QR estimates into the specific quantiles of the explanatory variables. In Figure 2 we observe that while the QQR and QR estimates are not the same, they show similar patterns for the most part. For the gold-crypto link we find much more resemblance, but QQR estimates are subsumed under the QR estimates in the crypto-gold link. From these we can reinforce the validity of the QQR technique in the context of this study. That means the analysis pertaining to QR in terms of hedging and diversification apply to the QQR estimates as well, only differing in magnitudes.

Specifically, we observe that in the long-term QQR estimates are essentially zeros as compared to QR estimates. Further, in the lower half of the distribution, QR lies above QQR but in the upper half the reverse is true. This holds for the gold-crypto links, except for Ripple. The QR and QQR plots diverge after the 15^{th} quantile with QQR rising and QR falling, in the long-term.

5. Conclusions and recommendations

In this study we examined the asymmetric frequency-varying connection between gold and major cryptocurrencies to identify hedging and diversification possibilities between the two

asset classes. With daily return series we decomposed the series into short-, medium- and, long-term frequencies using EEMD and employed the QR and QQR techniques. The EEMD does not only delineate the series into time horizons, but also reduces the noise that may be present in the series. The QR and QQR also capture the asymmetries in the relationship at different portions of the return distributing over the time scales (see also Troster, Tiwari, Shahbaz, & Macedo, 2018). Our sampled period spanned 30/04/2013 to 18/04/2019.

We found both QR and QQR as valid models to examine the relationship between gold and cryptos at different time-frequency scales. In one sense, our study is unique among many that use noise reduction in the context of frequency-dependent asymmetric analysis. Thus, we make improvement upon several studies whose important patterns may be shrouded noise in the data or proffer inaccurate results. Among other things, we confirm the HMH in the context of dynamic asymmetric, hedge, diversifier as opposed to the efficient market hypothesis (EMH). This partially corroborates Nadarajah & Chu (2017) who find only a weak form of efficiency in Bitcoin after an odd integer power transformation of the returns. Without this transformation Bitcoin was starkly inefficient.

Following Baur & Lucey's (2010) definitions of hedge and diversification, we find that both gold and cryptos can hedge and diversify for each other within the medium- and long-terms. However, we do not find any significant link between gold and Ethereum at all time scales and in the unconditional and conditional distributions of the returns. Our findings corroborate the notion of cryptos and gold possessing hedge and diversifier properties under different scenarios (see Bouri, Gupta, et al., 2017, 2017; Kliber et al., 2019; Zwick & Syed, 2019; etc.). Notwithstanding, Klein et al. (2018) and Kurka (2019) discount these properties for Bitcoin, among others.

Further, we support Liu's (2019) assertion that portfolio diversification across different cryptos can improve investment outcomes. Our results indicate that cryptos and gold (together), on the one hand can hedge and diversify for other traditional assets, on the other hand. This assertion is corroborated by Selmi et al. (2018) and Al-Yahyaee et al. (2019), among others. In the nutshell, we find that there are possibilities of increased reward or risk-reduction in portfolios constructed with gold different cryptos. It should, however, be noted that these phenomena are

asymmetric and occur at different time horizons. Hence, investment decisions should be wary of these dynamics.

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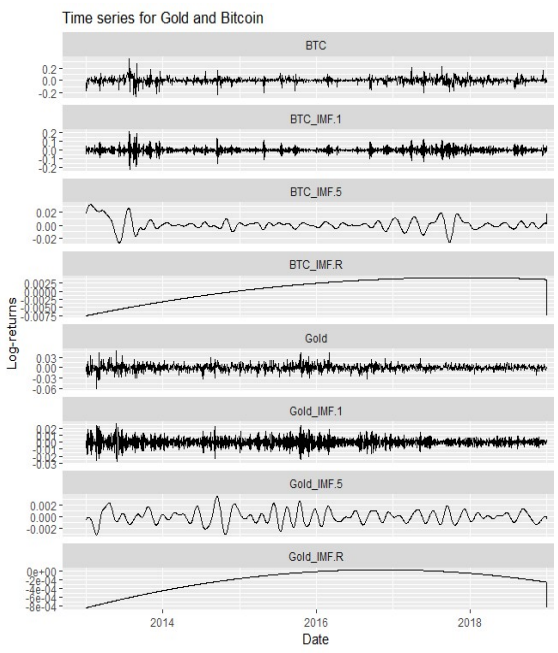
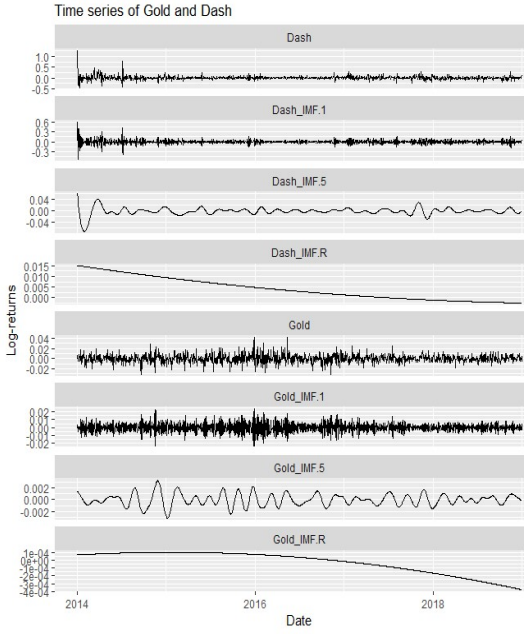
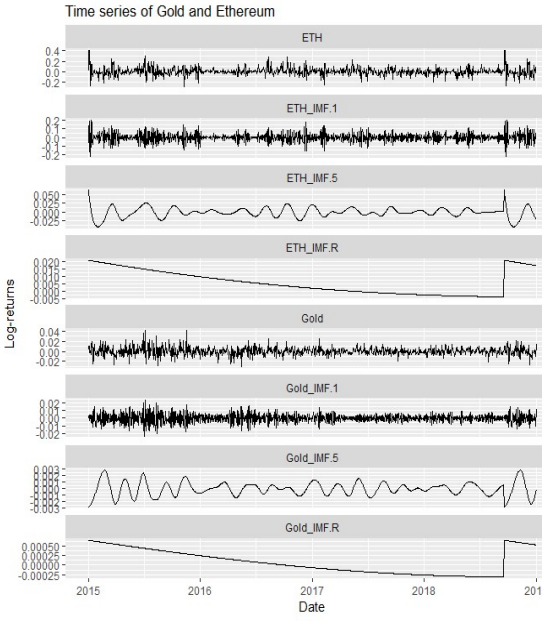
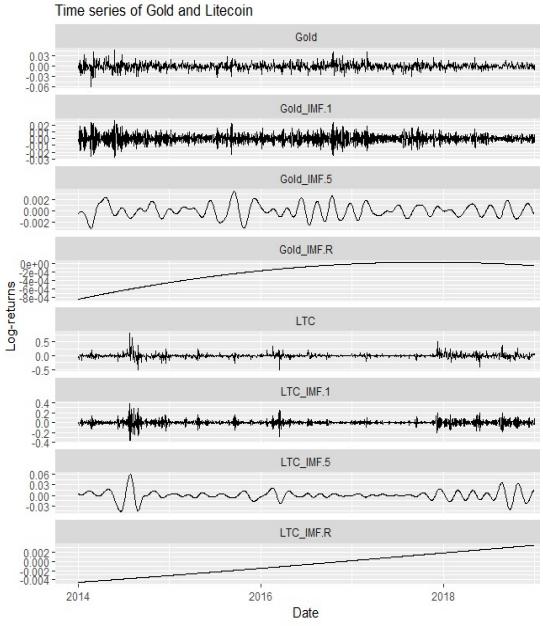
Appendices


Time series for Gold and Bitcoin
BTC
BTC_IMF.1
BTC_IMF.5
BTC_IMF.R
Gold
Gold_IMF.1
Gold_IMF.5
Gold_IMF.R
Log-returns
2014
2016
2018
Date


Time series of Gold and Dash
Dash
Dash_IMF.1
Dash_IMF.5
Dash_IMF.R
Gold
Gold_IMF.1
Gold_IMF.5
Gold_IMF.R
Log-returns
2014
2016
2018
Date


Time series of Gold and Ethereum
ETH
ETH_IMF.1
ETH_IMF.5
ETH_IMF.R
Gold
Gold_IMF.1
Gold_IMF.5
Gold_IMF.R
Log-returns
2015
2016
2017
2018
Date


Time series of Gold and Litecoin
Gold
Gold_IMF.1
Gold_IMF.5
Gold_IMF.R
LTC
LTC_IMF.1
LTC_IMF.5
LTC_IMF.R
Log-returns
2014
2016
2018
Date

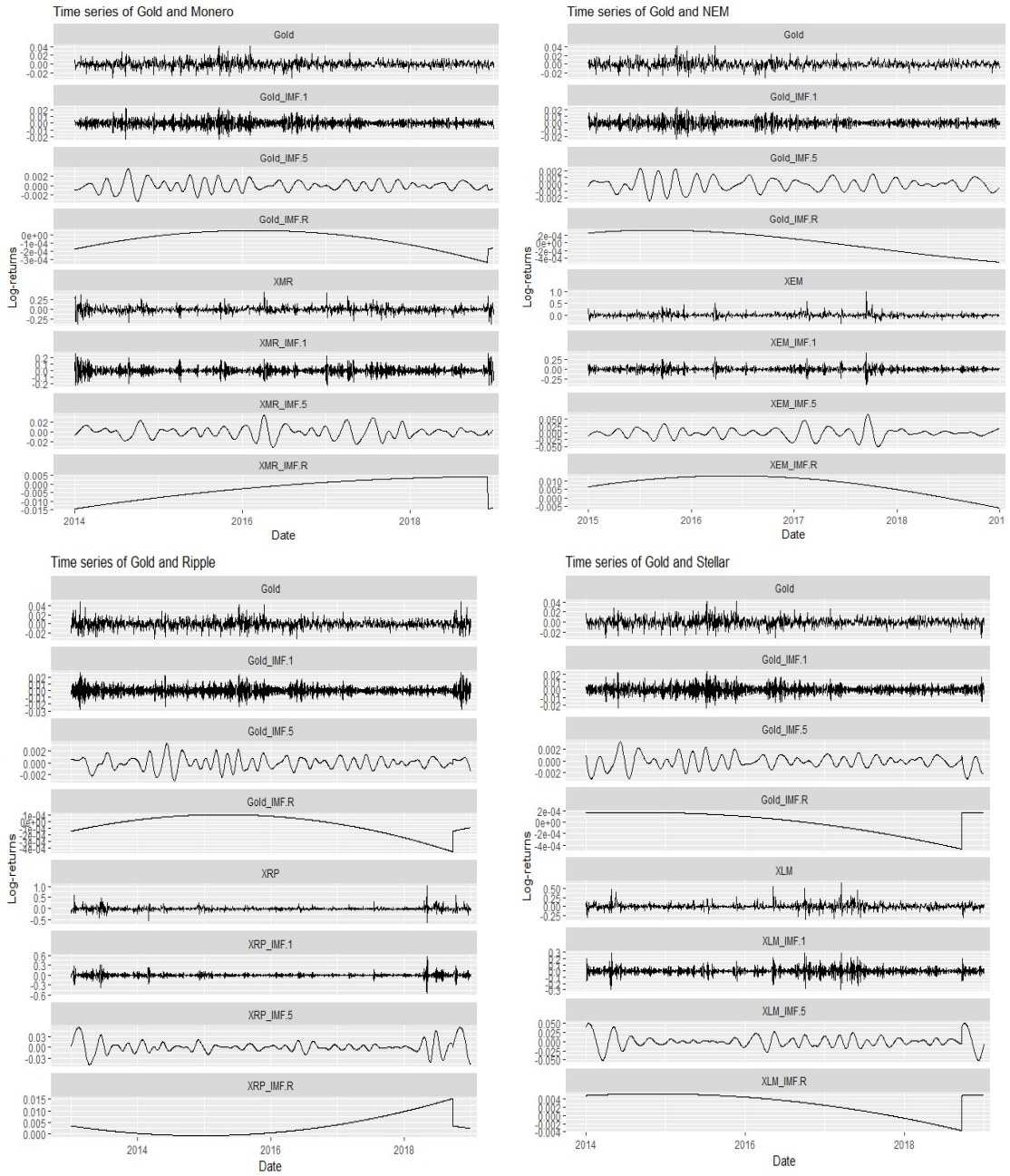


Figure 1: Return and IMF plots of gold and cryptocurrencies