“Small things matter most”: The Spillover effects in the cryptocurrency market and hedging ability of Gold

Abstract

The cryptocurrencies with small market capitalization are often overlooked despite they can potentially be the source of shocks to other cryptocurrencies in market. To address this caveat, this paper attempts to investigate the spillover effects among 14 cryptocurrencies by employing *transfer entropy*. Our results suggest that among different types of cryptos, Bitcoin is still the most appropriate instrument for hedging, while Tether (USDT) which have a strong anchor with the US dollar is significantly volatile. Interestingly, we document that the small coins are more likely to be shock creators in the cryptocurrency market. Using the same approach, we further explored the link between gold prices and cryptocurrency prices. The results show that gold could be a good hedging instrument for cryptocurrencies due to its independence. In light of empirical results, it is advisable to carefully consider the coins with small capitalisation. Further, investors should conduct portfolio rebalancing by including gold to hedge against the unexpected movement in cryptocurrency market. Our paper not only contributes in terms of application of advanced empirical methodology but also provides evidence of interesting features of cryptocurrency market.

JEL Classification: Spillover effects, Cryptocurrency, Transfer Entropy, Gold.

Keywords: G12, G15, G23, Q02.

1. Introduction

Despite the controversy and debate which has surrounded the cryptocurrency market since its inception, this market has gradually become one of the significant alternative investments venue in the global financial system. While the Bitcoin (Nakamoto, 2008) is the pioneer of the cryptocurrencies being prosed as an asset class for investment activities (Corbet et al., 2018b), by the writing of this paper, there are about 2,144 types of cryptocurrencies which are currently traded in the market (coinmarketcap.com, 2019). In addition to the trading of cryptos, Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) have started to deal in a vast number of cryptos based financial instruments such as Bitcoin futures contracts (Corbet et al., 2018a). This remarkable growth is a manifestation of a new era of financialization based on virtual financial assets with a sense of big data and the fourth industrial revolution. Where these new markets have brought new sources of potential risks to investors, they are also providing more ways to manage the risks.

This study has two core objectives. Firstly, we employ the '*transfer entropy*' approach introduced by Schreiber (2000) and modified by Dimpfl and Peter (2013)[1] to investigate the spillover effects among cryptocurrency markets. This approach outperforms other techniques employed previously by considering asymmetric and nonlinear effects (Altiparmak and Dengiz, 2009). Hence, this method will be helpful in determining the performance of communication networks by informational flows transferred through returns changes. As *transfer entropy* focuses on information spillover dimension, the residual dimension (error terms) could be ignored (Ji et al., 2019). The previous approaches required the balanced dataset which avoids the spurious results while *transfer entropy* accepts the unbalanced and nonstationary data (Wollstadt et al., 2014).

Secondly, we focus on the question of the inclusion of gold and its position in cryptos portfolio. Often, it is desirable to include some precious metals such as gold for portfolio diversification. There are some studies which explored the link between financial assets and precious metals. For instance, Corbet et al. (2019) contributed to the existing literature by studying precious metals from a bibliometric and scientometric perspective. They argued that there are substantial areas of potential synergy which are yet to be unexplored. In another study, Wang et al. (2019) used a combination of the wavelet-based approaches and the GARCH-EVT-based value-at-risk (VaR) model to estimate the spillover effect in precious metals. Surprisingly, it showed that there was no contagion risk. In a comparative analysis which aimed to address the question that if Bitcoin is better safe-haven than gold and commodities, Shahzad et al. (2019) concluded that these kinds of assets are weak safe-haven for the global equity indices. In a study on overview of precious metals, Vigne et al. (2017) argued that the silver and gold have attracted the focus of researchers, however, it also acknowledged that silver, platinum and palladium do form a single asset class of homogeneous and interchangeable metals. With respect to gold, a comprehensive study by O'Connor et al. (2015) surveyed the literature on gold and concluded that gold has been an important investment class. Furthermore, despite the price, gold would remain an important aspect for future inquiry as well as attractive investment.

[1] Dimpfl and Peter (2013) modified the approach by incorporating Markov block bootstrap and repeated bootstrap.

The current study is critical in the sense that investigating volatility spillover among asset prices is an important topic which gains traction in the last few decades. For instance, Fowowe and Shuaibu (2016) and Zhang et al. (2019) focused on equity markets, Du et al. (2011) and Mensi et al. (2014) investigated spillover effects in commodity markets, Stevenson (2002) and Hoesli and Reka (2013) brought real estate market into analysis while Louzis (2015) analysed the spillover effects in the money market.

Moreover, the current study is crucial because the spillover effects in cryptocurrency markets are underexplored in the literature despite its growing popularity. Among very few studies which focused on the spillover effects in cryptocurrency market, Ji et al (2019a) followed the approached by Diebold and Yilmaz (2014) and examined the volatility transmission by using LASSO-VAR to estimate the volatility connectedness among different cryptos. In a contemporary study, Huynh (2019) employed the Vector Autoregressive as well as student-t's Copulas to estimate the spillover effects, which refers to the tail dependence structure to evaluate the possibility to cause volatility interconnectedness. Similarly, Koutmos (2018) employed a VAR framework to assert that Bitcoin is likely to be the dominant contributor, which triggers the volatility and return spillover in cryptocurrency market. Employing wavelet-based approach, Omane-Adjepong and Alagidede (2019) introduced the wavelet-based methods to investigate direction of volatility spillovers in cryptocurrency market. In the same vein, the study of Gkillas et al. (2018) and Gkillas, & Longin (2018) employs the extreme correlation and extreme price movement to examine the contagious risk among the cryptos market. They reported variation in the correlation of extreme returns under different market conditions (bull and bear markets). On a wider note, the current literature on cryptocurrency has been highly entrenched in the financial risk management (see, for instance, Aslanidis et al. (2019), Katsiampa et al. (2019), Charfeddine and Maouchi (2019), Canh et al. (2019), Bouri et al. (2018) and Baek et al. (2015)). These studies employed the traditional quantitative approaches to investigate systematic risks as well as the efficiency in cryptocurrency markets. However, in the informational context, an important aspect we must acknowledge is that the cryptocurrency markets are likely to have enormous layouts of information, which may result in negative bubbles (Fry and Cheah, 2016). Nonetheless, the employed framework was based on the econometric assumption of causality that the historical changes of the independent and dependent variable cause the current state of the dependent variable. Yet, the interconnectedness exposures among cryptocurrency markets can also prevail due to information flows. Therefore, previous studies are facing potentially biased conclusions due to anomalous distribution as well as cross-correlation in the time series. Interestingly, as argued by Corbet et al. (2019a) the only study which focused on 'market risk' is by Gkillas and Katsiampa (2018) that employed the extreme value theory to explain the tail behaviour of returns, although, the evidence suggests that the cryptocurrency markets have left-tail dependence structures (Canh, 2019; Huynh, 2019). More importantly, the cryptocurrency market is mainly driven by the investors' behaviours (Burggraf et al., 2020); therefore, the spillover risks should be carefully examined.

Our paper is related to the literature which employs *transfer entropy* to model information flow in financial markets. For instance, as Li et al. (2013) on Chinese bank system, Tungsong et. al (2017) on regional uncertainty spillovers in the global banking system, Lautier et al. (2019) on the oil market, Nam and Seong (2019) on Korean stock market, and Da Silva et al. (2019) studying the link between crude oil and some commodities used this approach. Most recently, Ji et al.

(2019a) also employed the time-varying *transfer entropy* approach to analyse the informational dependence between seven cryptocurrencies and commodity market (excluding gold or silver, they focused on agriculture, industrial and energy commodities).

Our paper is also related to prior studies examining transmittable channels between financial markets. There are two overarchingly typical ways in which connected networks prevails among cryptocurrencies. Firstly, most of the financial assets share the correlated-information layers, which may trigger the price-discovery process as well as the supply-demand dependence (Kodres and Pritsker, 2002). Secondly, the differences in risk premium can influence the investors' behaviour in decision regarding financial asset (Acharya and Pedersen 2005). Therefore, it is vital to account for the spillover effects while considering cryptocurrency market. Especially, the effects not only come from informational transferring processes but also from differences in the risk premium of specific coins. This is one of the motivations of this study.

An important contribution of this study is that we account for the fact that the cryptocurrencies with small market capitalization are often overlooked despite they can potentially be the sources of shocks to other cryptocurrency markets. Another contribution is our findings which suggest that among cryptos, Bitcoin is still the most appropriate instrument for hedging while USDT, which have a strong anchor with the US dollar, is a lot more volatile. Interestingly, the small coins are more likely to be shock creatures in the cryptocurrency market. The results also show that gold could be a good hedging instrument for cryptocurrency return movement due to its independence.

We also contribute to the growing literature in the perspective that employing advanced empirical methodology, the transfer entropy to analyze informational linkage among cryptocurrency markets and with gold. We utilize a set of rigorous methods to study complexity under network for nonlinear interactions in cryptocurrency markets.

The current paper has relevant implication for portfolio investors and policymakers. In light of empirical results, it is advisable to carefully consider the small market capitalisation coins. Further, investors should conduct portfolio rebalancing by including gold to hedge against the unexpected movement in cryptocurrency markets. The finding of volatility spillovers from small-capitalization coins to large capitalization coins is important for policymakers in maintaining a prudent and stabilized financial market.

The paper proceeds as follows. Section 2 entails a discussion on methodology and data. Section 3 presents the empirical findings and section 4 provides conclusion and policy implications.

2. Methodology - Transfer Entropy

Transfer entropy has a clear edge in over standard approaches which makes it superior in measuring information flows (Barnett, 2009). Particularly, standard econometrics is based on subject-specific assumptions and restrictions while *transfer entropy* allows for non-parametric estimation of time-series and do not require many assumptions regarding stochastic processes. In its essence, transfer entropy is an econophysics method, which measures the informational flows regarding the direction of a variable with respect to time, based on the theory of information. Transfer entropy was pioneered by Shannon (1948) as:

$$H_I = -\sum_i p(i).log(p(i)) \qquad \text{(Eq. 1)}$$

In which, *i* is a discrete random variable with probability distribution representing p(i). Moreover, *i* represents the possibilities of different form this variable can take. H is considered as the optimal function for the transformation process. H_I is called Shannon entropy. Shannon (1948) laid the foundation of this approach in terms of uncertainty and moving processes of a variable. Later, Kullback and Leibler (1951) modified the process by adding another factor (called process J). Interestingly, when we have more variables and more value, the Transfer entropy is understood as

$$\mathrm{h_I(k)} = -\sum_{\mathrm{i}} \mathrm{p}\left(\mathrm{i_{t+1}}, \mathrm{i_t^{(k)}}\right).\log\left(\mathrm{p}\left(\mathrm{i_{t+1}}\middle|\mathrm{i_t^{(k)}}\right)\right) \qquad \text{(Eq. 2)}$$

To be more detailed, marginal probability distribution p(i), p(j) and joint distribution p(i,j) should consequently be a stationary time series. Let assume that $i_t^{(k)} = (i_t, \dots, i_{t-k+1}). h_J(l)$ is considered analogously for process J. Kullback and Leibler (1951) integrated the generalized Markov process:

$$\mathrm{p}\left(\mathrm{i_{t+1}}\middle|\mathrm{i_t^{(k)}}\right) = \mathrm{p}\left(\mathrm{i_{t+1}}\middle|\mathrm{i_t^{(k)}}, \mathrm{j_t^{(k)}}\right) \qquad \text{(Eq. 3)}$$

as the probability that one variable receives information in the past and another factor (j_t). The fundamental concept of 'Transfer entropy' is to estimate the informational flows from two discrete and random variables. Schreiber (2000) provided the explanation for this methodology as (in which, I and J are two different processes). Transfer entropy from J to I = (Information for future process $I_{(t+1)}$ absorbed from the historical values of I and J) - (Information for future process $I_{(t+1)}$ absorbed from the historical values of only I). Finally, Transfer entropy implies:

$$\mathrm{T_{J\to I}(k,l)} = \sum_{\mathrm{i,j}} \mathrm{p}\left(\mathrm{i_{t+1}}, \mathrm{i_t^{(k)}} \mathrm{j_t^{(l)}}\right).\log\left(\frac{\left(\mathrm{i_{t+1}}\middle|\mathrm{i_t^{(k)}}, \mathrm{j_t^{(k)}}\right)}{\left(\mathrm{i_{t+1}}\middle|\mathrm{i_t^{(k)}}\right)}\right) \qquad \text{(Eq. 4)}$$

Where $T_{J\to I}$ consequently evaluates the information flow from J to I. Recently, Dimpfl and Peter (2013) innovated with Markov block bootstrap and repeated bootstrap. The null hypothesis is that there is no information transferred.

$$\mathrm{RT_{J\to I}(k,l)} = \frac{1}{1-\mathrm{q}}\log\left(\frac{\sum_{\mathrm{i}} \phi_{\mathrm{q}}\left(\mathrm{i_t^{(k)}}\right) \mathrm{p^q}\left(\mathrm{i_{t+1}}\middle|\mathrm{i_t^{(k)}}\right)}{\sum_{\mathrm{i,j}} \phi_{\mathrm{q}}\left(\mathrm{i_t^{(k)}}, \mathrm{j_t^{(k)}}\right) \mathrm{p^q}\left(\mathrm{i_{t+1}}\middle|\mathrm{i_t^{(k)}}, \mathrm{j_t^{(k)}}\right)}\right) \qquad \text{(Eq. 5)}$$

In which, J and I are two processes whereas q is weighting parameter q > 0 for individual probability function p(.) for calculation. In which, i_n is the n^{th} component of the time series I and j_n is component the n^{th} component of time series of variables J. It is noted that $\phi_{\mathrm{q}}(\mathrm{j}) = \frac{\mathrm{p^q(j)}}{\sum_{\mathrm{j}} \mathrm{p^q(j)}}$ and φ_q is the escort distribution given by $\varphi_{\mathrm{q}}(\mathrm{i}) = \frac{\mathrm{p^q(i)}}{\sum_{\mathrm{i}} \mathrm{p_i^q}}$. The main reason to put the Markov process is to estimate the probability to change from one stage to another stage under the transferring information. Furthermore, the Markov process also supports to estimate the possible scenarios of matrix transition. Based on the (Eq. 5), one may refer to Bekiros at al. (2017) to define the l = k = 1 (or the process of de-noise of the dataset) and Transfer entropy could capture the asymmetric movement of the pair (X and Y) and (Y and X). Hence, using *transfer entropy* can be insightful for information flows' movements between two time-series. In nutshell, the *transfer entropy* is based on the concept of the logarithm of the number of trials, which could occur based on a specific probability distribution.

The *transfer entropy* is an alternative approach to traditional causality methods such as Granger (1969) causality in measuring causal influence. To reiterate, it captures the model-free measurement of information flow, does not rely on data structure or linearity and robust again spurious association (Lizier et al., 2011). In addition, this approach allows for the estimation of information flow between two time series. Even though there are some critiques regarding this approach (James, 2016), this method gains traction and is widely employed in various fields. In finance and economics, Kwon and Yang (2008) employed to analyse transmission from the US and European markets to the Asia Pacific region, Peter et al. (2011) for information flow from CDS (Credit Default Swap) market to corporate bond, Kim et al. (2013) to analyse interconnectedness between macroscopic determinants and banking systems. The subject study attempts to apply the transfer entropy to cryptocurrency market to account for enormous information flow.

2.2 Data

Our daily dataset covers the period from April 2013 to April 2019. The data is collected from the coinmarketcap.com database. At first, we collected all the cryptos on the exchange to estimate the risk transmission. Currently, there are around 1,000 coins while there are some coins which have missing information or are publicized too late. Therefore, we choose to obtain coins who have at least 1000 observations to store enough information for our estimations. To reiterate, one of the advantages of using *transfer entropy* is that it does not require balanced dataset. The sample accounts for over 80% market capitalization of the cryptocurrency market. In order to eliminate the unexpected noise, we follow the approach by Gandal et al. (2018) and perform the logarithmic transformation of each cryptocurrency's closing prices. The summary of descriptive statistics is provided in Table 1.

Table 1. Summary of statistics description

Variables	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB
BTC	0.0016	0.0433	-0.2674	0.3614	-0.1108	11.0616	5878***
LTC	0.0013	0.0668	-0.5192	0.8245	1.700	27.7714	570000***
ETH	0.0030	0.0763	-1.3739	0.4034	-4.051	83.2739	360000***
XEM	0.0035	0.0876	-0.5025	1.0684	1.969	23.8385	27000***
DASH	0.0034	0.0777	-0.4204	1.0668	2.529	31.6831	66000***
DOGE	0.0009	0.0808	-0.6257	1.0625	1.550	29.0534	56000***
XMR	0.0018	0.0740	-0.4404	0.5676	0.5846	9.0181	2789***
VTC	0.0010	0.1118	-0.6141	1.0923	2.234	19.9729	24000***
XVG	0.0044	0.1722	-0.9162	1.9169	1.169	16.0909	12000***

DGB	0.0012	0.1024	-0.6035	1.1522	1.858	20.8781	26000***
XLM	0.0021	0.0793	-0.3334	0.7040	1.928	17.8684	17000***
USDT	-0.0001	0.0120	-0.1822	0.1511	-2.397	110.783	730000***
MAID	0.0012	0.0694	-0.4020	0.4643	0.1711	7.0397	1235***
XRP	0.0019	0.0758	-0.6017	1.0109	2.0258	30.2785	66000***

The last column is the Jarque-Bera test to check whether data characteristics are normally distributed. (*), (**), (***) reflected statistically significance of the corresponding coefficients at the 10%, 5% and 1% level.

The results in Table 1 show that our data are not normally distributed. Therefore, employing the traditional statistics methods which require distributional assumptions and ignoring the layout of informational flows may result in biased results. Interestingly, only the Tether (USDT) has average negative return while all other cryptos exhibit the positive value. The main reason might be that the USDT is the coin which has a strong anchor with USD as the exchange currency. Due to this feature, investors can use this coin as a vehicle to invest in crypto linked to the USD.

4.1 Analysis and Findings

Although stationary is not a necessary requirement and the *transfer entropy* approach can ensure probability density functions as a single realization (Wollstadt et al. 2014), we still conducted the stationary test. The results presented in Table 2 indicate that all variables are stationary at level.

Table 2. Stationary test

Variables	Dickey-Fuller t-statistics	Conclusions
BTC	-46.438***	
LTC	-45.736***	
ETH	-34.781***	
XEM	-42.069***	
DASH	-43.387***	
DOGE	-40.463***	
XMR	-42.506***	All our variables are stationary at 1% significance level.
VTC	-41.902***	
XVG	-53.220***	
DGB	-43.755***	
XLM	-38.836***	
USDT	-26.252***	
MAID	-47.360***	
XRP	-42.666***	

The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% level.

We first examine the correlation among the cryptocurrency markets by using the correlation matrix. As seen in Figure 1, the link between USDT and other cryptocurrency is quite weak based on the linearity assumption. In addition, MAID has a connection with the other coins. One of the noticeable points from the correlation matrix is that all cryptocurrencies share positive dependence. This means that cryptocurrency markets have the same directional co-movement.

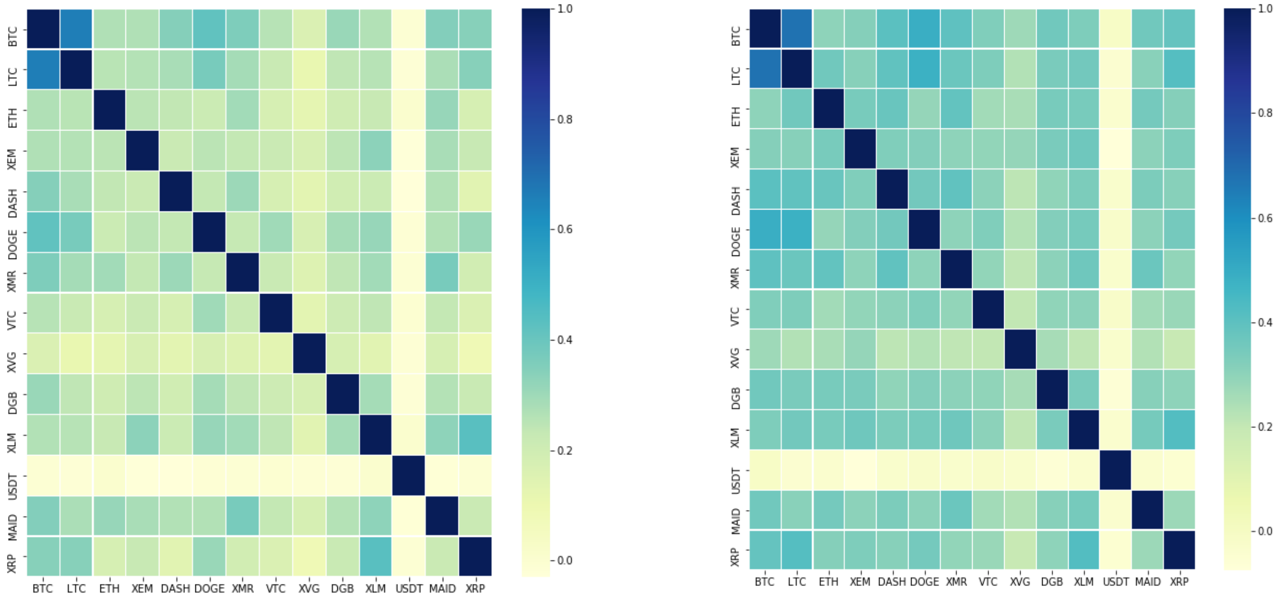
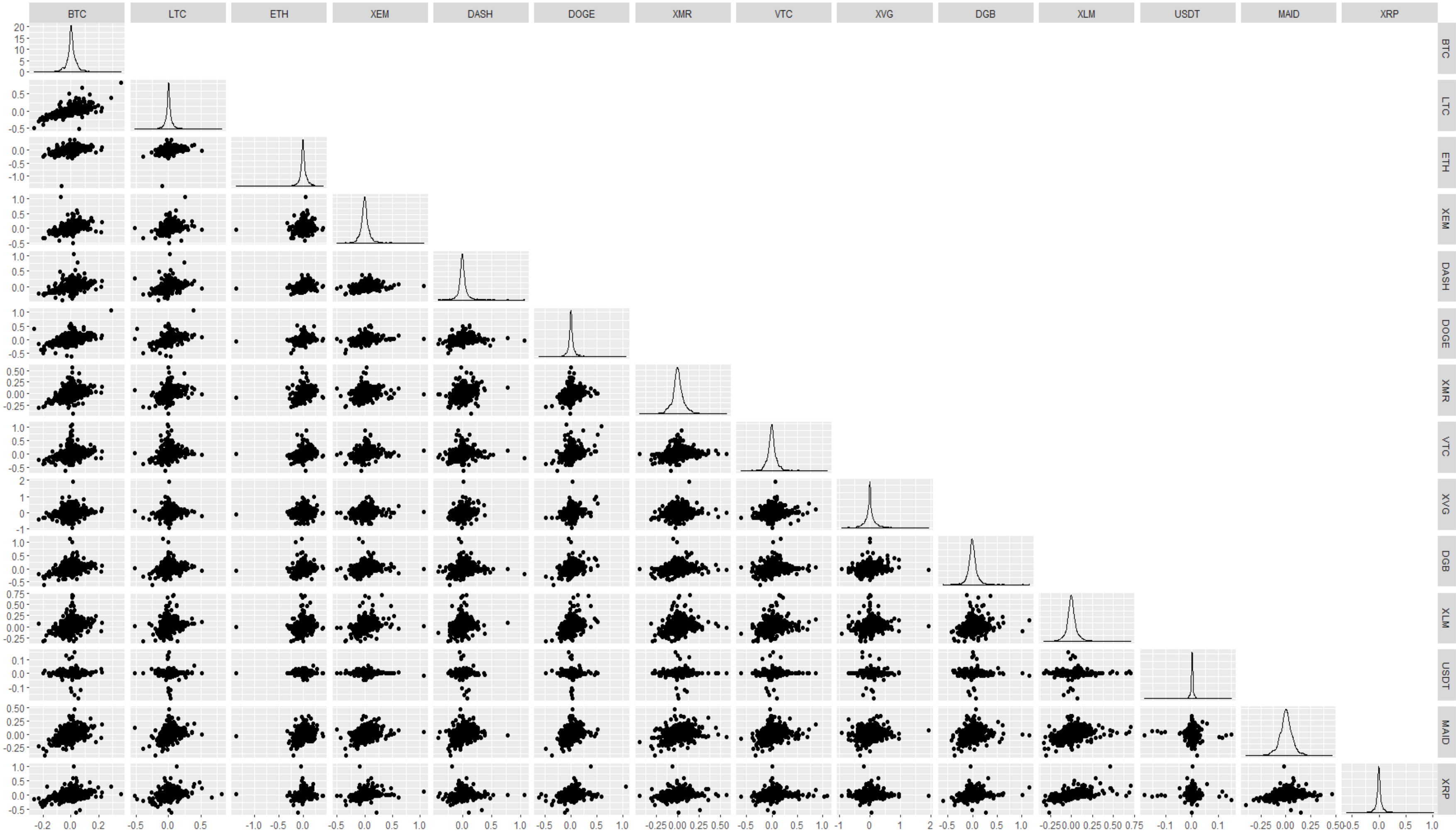


Figure 1. Correlation among coins in cryptocurrency markets
Notes: The left figure presents the Pearson correlation while the right figure exhibits the Spearman correlation.

One of the disadvantages of using Pearson correlation is based on linear symmetric and parametric comparison. However, as viewed in Table 1, the distribution of our variables follows the non-normal shape. Therefore, the application of the Pearson correlation might lead to biased conclusions. To ensure consistency, we still perform this method to have a further comparison with Transfer entropy. The Spearman correlation demonstrates that the cryptocurrency world has more strong correlation than Pearson correlation does. Figure 2 gives us further insight into the data distribution and correlation structure of these variables.



Based on the Emerson et al. (2013) suggestion for scatterplot matrix of our data, we recognized that all variables are skewed and heavy tail. Noticeably, Ethererum is likely to be right-skewness whereas the remaining ones are left-skewed. In addition, the plotted correlations of these cryptocurrencies are witnessed by some outliers and without linear shapes. Once again, we suggest using Transfer entropy to evaluate the causally informational flows.

Figure 2. The data distribution and correlation structure

4.2 Spillover effects in cryptocurrency market

We estimate *transfer entropy* values and the results are presented in Table 1. We must acknowledge that these values do not represent the directional or signal relationship as correlations or coefficients. These figures can be interpreted as the values of *transfer entropy* from '*Sender*' to '*Receiver*' which represent information flow between the two series.

Our results show that overarchingly, there are spillover effects among cryptocurrency markets as measured by the Transfer entropy approach. Interestingly, the coins having low market capitalization are likely to be more sensitive than the ones with high capitalisation. For example, DOGE (ranked 28th) and DASH (ranked 13th) are the successfully highest receiver and sender, respectively. Meanwhile, the largest market capitalization coins shown be sending and receiving quite less.

Since Bitcoin represents close to 50% of the market capitalisation of all cryptocurrencies, our results show similar patterns as the study of Canh et al. (2019). Bitcoin is likely to have great connectedness with XMR, XRP, DBG and XLM. This also suggests that Bitcoin could be considered as a '*safe heaven*' for hedging because of its dependence. Our results also complement some of the findings by Vidal and Ibañez (2018), Dyhrberg (2016a), Dyhrberg (2016b) and Su et al. (2018). Besides that, the results show that MAID coin has shown to be quite independent by not receiving any effect from the cryptocurrency market.

Noticeably, USDT is the most sensitive coin among our 14 selected coins. This coin also sends and receives shocks. Adding to the existing literature, we also added USDT in this study due to the reason that it attempts to be tied to the US dollar. By this reason, this coin is likely to the most sensitive with the changes of other coin prices.

We see from Table 3 that Litecoin is likely to send only 2 shocks from other coins. One of the possible explanations for this phenomenon is that Litecoin is the new fork of the market-leading Bitcoin. Therefore, when the investors might be more cautious when buy or sell this coin, thereby reducing the possibility to cause shocks by this coin. To elaborate it further, we can refer to some of the relevant concepts. As argued by Backus et al (2018), the 'entropy' denotes the risk premium of the asset. Therefore, it can intuitive argue that one of the features of cryptocurrency market is the intra-market transfer of risk premium. Putting it differently, each coin has a specific trait, which results in the difference in asset (coin) pricing. Backus et al. (2018) further calibrated these gaps for equities that contain economic information. Relying on their explanation, we also consider the risk premium gap among these coins which leads to the price movement in the cryptocurrency market. Another perspective, we would like to link the price changes in the cryptocurrency market with 'entropy' is the 'news'. On this aspect, employing the 'Transfer entropy' on the stock to explain the price movements, Glasserman and Mamaysky (2019) argued that 'Entropy' in the stock market comes from new information. Hence, if the market is efficient (Fama, 1970) and reflects a coin price movement which also results in the price movements of other coins, resulting from information transfer caused by the first coin in the cryptos market. Concomitantly, through this mechanism, 'transfer entropy' can explain and estimate spillover effects through price changes.

Table 3. Transfer entropy matrix

		SENDER													
		BTC	**LTC**	**ETH**	**XEM**	**DASH**	**DOGE**	**XMR**	**VTC**	**XVG**	**DGB**	**XLM**	**USDT**	**MAID**	**XRP**
RECEIVER	**BTC**		0.0039 [0.0014]	0.0043 [0.0025]	0.0070 [0.0022]	0.0040 [0.0017]	0.0056 [0.0014]	0.0033 [0.0018]	0.0050 [0.0016]	0.0055 [0.0020]	0.0014 [0.0017]	0.0105** [0.0019]	0.0127*** [0.0021]	0.0085** [0.0017]	0.0049 [0.0014]
	LTC	0.0040 [0.0015]		0.0088 [0.0022]	0.0045 [0.0021]	0.0088** [0.0018]	0.0071* [0.0015]	0.0046 [0.0017]	0.0078* [0.0017]	0.0063 [0.0020]	0.0049 [0.0018]	0.0052 [0.0019]	0.0062 [0.0020]	0.0070 [0.0016]	0.0068* [0.0016]
	ETH	0.0049 [0.0023]	0.0041 [0.0024]		0.0036 [0.0024]	0.0041 [0.0024]	0.0055 [0.0024]	0.0076 [0.0022]	0.0062 [0.0025]	0.0106* [0.0027]	0.0055 [0.0023]	0.0041 [0.0023]	0.0092* [0.0023]	0.0067 [0.0023]	0.0041 [0.0024]
	XEM	0.0087 [0.0024]	0.0060 [0.0022]	0.0057 [0.0023]		0.0073 [0.0021]	0.0030 [0.0022]	0.0057 [0.0022]	0.0057 [0.0020]	0.0084 [0.0021]	0.0038 [0.0022]	0.0059 [0.0021]	0.0050 [0.0023]	0.0048* [0.0021]	0.0037 [0.0022]
	DASH	0.0026 [0.0019]	0.0038 [0.0018]	0.0144*** [0.0022]	0.0101** [0.0020]		0.0108*** [0.0016]	0.0074 [0.0018]	0.0087* [0.0018]	0.0092** [0.0019]	0.0067 [0.0018]	0.0062 [0.0017]	0.0108*** [0.0019]	0.0072* [0.0017]	0.0053 [0.0018]
	DOGE	0.0038 [0.0017]	0.0030 [0.0019]	0.0138** [0.0026]	0.0077 [0.0023]	0.0124*** [0.0018]		0.0037 [0.0019]	0.0075* [0.0017]	0.0056 [0.0021]	0.0036 [0.0017]	0.0067 [0.0019]	0.0143*** [0.0022]	0.0031 [0.0019]	0.0059 [0.0018]
	XMR	0.0077* [0.0017]	0.0058 [0.0017]	0.0069 [0.0023]	0.0095** [0.0020]	0.0070 [0.0018]	0.0088** [0.0017]		0.0058 [0.0018]	0.0062 [0.0019]	0.0033 [0.0017]	0.0034 [0.0019]	0.0068 [0.0021]	0.0059 [0.0017]	0.0087** [0.0017]
	VTC	0.0057 [0.0017]	0.0059 [0.0018]	0.0094 [0.0028]	0.0039 [0.0023]	0.0060 [0.0016]	0.0081** [0.0016]	0.0039 [0.0018]		0.0055 [0.0018]	0.0096** [0.0017]	0.0043 [0.0019]	0.0055 [0.0021]	0.0040 [0.0019]	0.0058 [0.0019]
	XVG	0.0051 [0.0020]	0.0056 [0.0020]	0.0072 [0.0023]	0.0056 [0.0022]	0.0044 [0.0022]	0.0036 [0.0022]	0.0055 [0.0020]	0.0041 [0.0021]		0.0082* [0.0021]	0.0048 [0.0020]	0.0065 [0.0019]	0.0045 [0.0019]	0.0128*** [0.0020]
	DGB	0.0080* [0.0018]	0.0061 [0.0017]	0.0088 [0.0024]	0.0042 [0.0021]	0.0096** [0.0019]	0.0072 [0.0018]	0.0075 [0.0019]	0.0064 [0.0018]	0.0056 [0.0021]		0.0054 [0.0018]	0.0141*** [0.0021]	0.0052 [0.0017]	0.0068 [0.0017]
	XLM	0.0101** [0.0020]	0.0073 [0.0020]	0.0041 [0.0025]	0.0011 [0.0022]	0.0089* [0.0019]	0.0092* [0.0020]	0.0056 [0.0020]	0.0044 [0.0019]	0.0096** [0.0019]	0.0064 [0.0019]		0.0096** [0.0020]	0.0058 [0.0018]	0.0081* [0.0018]
	USDT	0.0116** [0.0022]	0.0120*** [0.0021]	0.0098 [0.0025]	0.0100* [0.0022]	0.0154*** [0.0022]	0.0134*** [0.0021]	0.0090* [0.0021]	0.0048 [0.0021]	0.0056 [0.0020]	0.0085 [0.0021]	0.0147*** [0.0023]		0.0063 [0.0022]	0.0145*** [0.0019]
	MAID	0.0052 [0.0017]	0.0064 [0.0016]	0.0063 [0.0025]	0.0084 [0.0020]	0.0057 [0.0019]	0.0044 [0.0017]	0.0067 [0.0018]	0.0032 [0.0016]	0.0052 [0.0017]	0.0053 [0.0019]	0.0036 [0.0019]	0.0075 [0.0021]		0.0052 [0.0018]
	XRP	0.0115*** [0.0016]	0.0080** [0.0016]	0.0054 [0.0022]	0.0063 [0.0022]	0.0079* [0.0017]	0.0105** [0.0017]	0.0108** [0.0020]	0.0056 [0.0018]	0.0094** [0.0020]	0.0051 [0.0017]	0.0067 [0.0021]	0.0140*** [0.0020]	0.0044 [0.0018]	

(*), (**), (***) reflect statistical significance of the corresponding coefficients at the 10%, 5% and 1% level whereas standard errors of the corresponding coefficients are reflected in square brackets. The outputs of main values are defined as the Shannon transfer entropy as the study of Dimpfl & Peter (2013) with n = 300 (the number of bootstrap replications for each direction of the estimated transfer entropy) and we dropped k = 50 (the beginning of the bootstrapped Markov chain), known as the burning values. Noted that the number of shuffles are chosen randomly as 100 observations.

Regarding the interdependence among different cryptocurrencies, our findings complement previous work by Fry and Cheah (2016), Ciaian and Rajcaniova (2018), Corbet et al. (2018) and Katsiampa (2018). The results are also in line with the Balcilar et al. (2017) and Bouri et al. (2019) which used Granger causality to reveal the interconnectedness in cryptocurrency markets with fewer currencies. Following this line of work, our study provides further insight by showing that the small coins cause more movements because their standard deviations of returns are quite large, compared with the dominant players (ie. Bitcoin, Ethereum and Litecoin). Furthermore, our study also reveals some interesting findings related to the 'sending-receiving' effects in cryptocurrency market. Considering cryptocurrencies with small capitalization, this study shows that they are likely to play an important role in shaping the dependent structure of the overall market. Therefore, our finding contributes to the current literature by reflecting on one of the drivers of the cryptocurrency market.

Previously, Aste et al. (2010) and Song et al. (2012) claimed that non-economic factors can drive cryptocurrency market, which is uncommon in other financial markets. It is suggested that cryptocurrency market could have an underlying complex structure and standing beyond traditional approaches of their network. The current study reflects on these aspects and interconnectedness among different cryptos.

Table 3. Summary of sending and receiving signs

Causal relationship	Effects	Causal relationship	Effects
BTC →	4	**→ BTC**	3
LTC →	2	**→ LTC**	4
ETH →	2	**→ ETH**	1
XEM →	3	**→ XEM**	1
DASH →	5	**→ DASH**	7
DOGE →	7	**→ DOGE**	4
XMR →	2	**→ XMR**	4
VTC →	3	**→ VTC**	2
XVG →	4	**→ XVG**	2
DGB →	2	**→ DGB**	3
XLM →	2	**→ XLM**	6
USDT →	6	**→ USDT**	9
MAID →	3	**→ MAID**	0
XRP →	5	**→ XRP**	7

Notes: This table summarizes the number of causal relationship by the sending and receiving signal through Transfer entropy estimation. Total causal effects are counted as 50 while the total recipient effects are 53.

The results also indicate that Bitcoin may not be the strongest source of volatility for other cryptocurrencies. Perhaps, with respect to coins with large market capitalisation, Ripple tends to be more volatile and this tends to cause shocks and bear shocks from others.

4.2. The role of gold in driving cryptocurrency returns

In this part, we examine the role of gold and its association with the cryptocurrency returns. In more recent studies, Rosales (2019) and Ferdiansyah et al. (2019) argued that gold could be a good hedging instrument against adverse movements in cryptocurrency markets. Furthermore, Adebola et al. (2019) examined the convergence (or divergence) of cryptocurrencies when putting gold in the portfolio. Although these recent studies sparked the debate by mostly focusing on equilibrium relationships between gold and coin, this paper attempts to explain how gold plays a role in terms of informational transferring among a large number of cryptocurrencies with different degree of capitalisation. Apparently, if gold leads to changes in the structure of probability of a cryptocurrency, we can conclude that gold price movements significantly affects the returns of this cryptocurrency using Transfer entropy approach. We explain the link between cryptocurrency and gold prices via the aggregate market risk. The study of Huynh et al (2020) has indicated that the gold may play a proxy role for economic risk, which causes the movements in cryptocurrency, particularly Bitcoin. This mechanism explains how the gold and cryptos prices are strongly connectedness. To make it clearer, we retrieved data of gold prices from London Bullion Market Association (LBMA) from 23rd May 2013 to 30th April 2020. We also transformed the prices to logarithm return for further estimations. The results are presented in Table 4.

Table 4. Role of gold in driving cryptocurrency returns

Sending effects	Parameters	Receiving effects	Parameters
BTC → Gold	0.0036 [0.0014]	Gold → BTC	0.0069** [0.0014]
LTC → Gold	0.0041 [0.0013]	Gold → LTC	0.0027 [0.0014]
ETH → Gold	0.0059 [0.0025]	Gold → ETH	0.0042 [0.0025]
XEM → Gold	0.0043 [0.0022]	Gold → XEM	0.0094* [0.0022]
DASH → Gold	0.0045 [0.0016]	Gold → DASH	0.0067 [0.0018]
DOGE → Gold	0.0032 [0.0016]	Gold → DOGE	0.0076 [0.0019]
XMR → Gold	0.0050 [0.0016]	Gold → XMR	0.0063 [0.0019]
VTC → Gold	0.0029 [0.0016]	Gold → VTC	0.0028 [0.0018]
XVG → Gold	0.0059 [0.0020]	Gold → XVG	0.0049 [0.0022]
DGB → Gold	0.0028 [0.0017]	Gold → DGB	0.0066 [0.0019]
XLM → Gold	0.0087** [0.0018]	Gold → XLM	0.0044 [0.0021]
USDT → Gold	0.0049 [0.0022]	Gold → USDT	0.0039 [0.0022]

MAID → Gold	0.0054 [0.0017]	Gold → MAID	0.0047 [0.0017]
XRP → Gold	0.0086*** [0.0014]	Gold → XRP	0.0056 [0.0015]

(*), (**), (***) reflect statistical significance of the corresponding coefficients at the 10%, 5% and 1% level whereas standard errors of the corresponding coefficients are reflected in square brackets. The outputs of main values are defined as the Shannon transfer entropy as the study of Dimpfl and Peter (2013) with n = 300 (the number of bootstrap replications for each direction of the estimated transfer entropy) and we dropped k = 50 (the beginning of the bootstrapped Markov chain), known as the burning values. Noted that the number of shuffles are chosen randomly as 100 observations.

Overall, we find that the movement of cryptocurrency return is quite independent of gold return using the *transfer entropy* approach. Based on our results in Table 4, only two kinds of cryptocurrency which have shocks on Gold are XLM and XRP. Interestingly, both coins were used password-based key derivation function from Bitcoin Gold (one specific coin in cryptocurrency). Bitcoin Gold is a currency unit which allows investors using gold to exchange Bitcoin. Therefore, the interconnectedness between these cryptocurrencies and gold is intuitive. Furthermore, the study of Huynh et al (2020) argued that the investors tend to move their capital from the risky assets to the safer investment options when the market shakes. Therefore, the coins which are generated to refer to gold trading might suffer the 'flight-to-quality'. Saying differently, this process is likely to reflect the alternative investment under ambiguous decisions. However, when it comes to Bitcoin and gold, Bitcoin reflects its prima facie dominant position as it is the only coin which has '*receiving effect*' from gold prices. By employing a novel approach, we confirmed that gold could be safe-haven, especially the small market capitalization coins, which mostly cause shocks in the crypto markets.

5. Conclusion and implications

In the context of the current debate on cryptocurrencies as an investment asset, the current study sheds further light on their spillover effects between different types of cryptocurrencies and their association with gold prices. Specifically, the current study also provides insight into the interconnectedness among 14 cryptocurrencies and their linkages with gold prices by employing *transfer entropy*. This paper contributes to the cryptocurrency literature by employing a novel approach of using the information to investigate the cryptocurrency return movement based on unstructured and asymmetric data. We find that the cryptos intended to be tied to the US dollar is likely to be volatile by sending and receiving shocks. Apparently, if anchored to the US dollar, USDT is prone to be chosen for exploiting investment opportunity in trading.

Our results provide strong evidence supporting the linkage between the traditional liquidity asset (USD) and the cryptocurrency (USDT). In our study, we demonstrate the fiat currency linked crypto (USDT) could be a consequent coin, which triggers and receives a number of flows. It also shows that the movements of the largest market capitalization coins are caused by smaller ones. The results also deliver some implications for portfolio investments. In particular, the investors can gain from using coins which are weak dependence in our test such as ETH (received 1), XEM (received 1) or MAID (received 1).

With respect to Bitcoin, there is evidence of a gradual decline in the dominant position in cryptocurrency due to the evolution increasing market competitiveness. The Transfer entropy estimates also show that the signals received are larger than the ones which are sent (at 5% significance level). It can be inferred that the cryptocurrency market has 'noise effects'. Some transmitted flows are cancelled out during the process of causing shocks. However, the coins also receive more shocks from their peers. This supports the notion that the Bitcoin could be used as a hedged instrument.[2]

Given that the cryptocurrency markets are unregulated, our study raise three main perspectives about policy recommendations and investment strategies. First, the hedge funds and institutional investors using the cryptos as investment classes ought to model the risk factors (for example, the threshold of bearing the downside event). By doing this, they might be cautious to avoid the sudden and extreme losses in an unexpected adverse event. Second, In the monetary digitalization strategy of many governments (for instance, China is planning to issue the digital coin[3]), it would be suggested to use the stable platform to issue the digital currency. Otherwise, the monetary system might be vulnerable to spillover risk shocks. Third, our study draws the attention of investors to not overlook the unusual movement of small-capitalization coins, which induce the systematic risk among the market. It is worth noting that the diversification would be a useful strategy to apply; especially, adding a marginal proportion of gold might improve the quality of the portfolio.

Cryptocurrencies with small market capitalisation which were mostly rolled out after Bitcoin, Ethereum, Litecoin, need to rely on the stable platforms. The leading coins in the past show stable characteristics. Especially, in the booming year of 2017, many coins built their network based on Ethereum. Nonetheless, a large number of coins in their Initial Coin Offering (ICO) process were based on Ethereum. This might have made Ethereum less volatile and receptor of the shocks. As the market is likely to move under the anchor of cross-sectional dependence coins, the big coin could be the good safe-haven for the investors in terms of the external shocks.

By using *transfer entropy*, we found that gold is still a good investment for investors who want to hedge the cryptocurrency movement. However, in so doing, it is important to differentiate among different cryptos. Only a few coins have connections with gold, such as Stellar and Ripple, because their platforms of payment were built on Bitcoin gold. Recently, Corbet et al. (2020a) found that Stellar is likely to be the least influenced altcoins in the COVID-19 pandemic, reflecting the market stress. Notwithstanding our findings, the recent study of Corbet (2020b) pronounces that gold should be not considered as hedged, safe-haven instrument in this tough time. Therefore, the connectedness returns in trading between gold and cryptocurrency could be a catalyst of amplifying of contagion. This matter was confirmed by the extant literature by Canh et al. (2019) about the systematic risk of Stellar among the cyptocurrency market. Therefore, our findings also provide the empirical evidence that the connectedness between cryptocurrency and gold exists in the financial risk management context. Noticeably, intuitively they are affected by gold price dynamics, thought the remaining coins are still independent of gold movements. Interestingly, the

[2] Bouri, and Dyhrberg (2016), Bouri et al. (2017)
[3] https://www.theguardian.com/world/2020/apr/28/china-starts-major-trial-of-state-run-digital-currency

Bitcoin turned to reflect its dominant position when showing the weak interconnectedness with gold. Therefore, the implication for investors is to put some gold in the portfolio to hedge against unexpected movement (Lucey, 2018).

Considering the progressive nature of cryptocurrencies and financial innovation, further research is clearly important to enhance our understanding. As possible venues for future research, the specific portfolios can be constructed with some weights to cryptocurrency by following approaches such as inverse volatility (IV), minimum variance (MV), l2-norm constrained minimum variance (NMV), l2-norm constrained maximum decorrelation (NMC), maximum diversification (MD) and risk parity (RP).[4] Future studies can also focus on spillover effects between cryptos and other assets including crude oils and equities.

[4] Burggraf (2019)

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Appendix

This appendix provides the insights of each cryptocurrency in terms of name, market capitalization, total supply and all-time high in the exchange.

Symbol	Name	Market capitalization (USD)	Total Supply (unit)	All time high
BTC	Bitcoin	136,759,360,511	18,090,100	20,089.00 USD (Dec 17, 2017)
LTC	Litecoin	2,942,027,900	63,796,046	375.29 USD (Dec 19, 2017)
ETH	Ethereum	16,312,224,993	108,840,701	1,432.88 USD (Jan 13, 2018)
XEM	NEM	327,406,637	8,999,999,999	2.09 USD (Jan 04, 2018)
DASH	Dash	483,921,015	9,199,322	1,642.22 USD (Dec 20, 2017)
DOGE	Dogecoin	273,697,461	122,382,571,496	0.018773 USD (Jan 07, 2018)
XMR	Monero	954,237,270	17,344,656	495.84 USD (Jan 07, 2018)
VTC	Vertcoin	11,203,694	52,457,522	10.00 USD (Dec 06, 2017)
XVG	Verge	72,823,892	16,094,431,829	0.300588 USD (Dec 23, 2017)
DGB	DigiByte	82,446,542	12,576,220,133	0.142889 USD (Jan 07, 2018)
XLM	Stellar	1,102,769,405	50,000,000,000	0.938144 USD (Jan 04, 2018)
USDT	Tether	4,147,833,131	4,207,771,504	1.21 USD (May 27, 2017)
MAID	MaidSafeCoin	52,042,087	452,552,412	1.20 USD (Jan 02, 2018)
XRP	Ripple	9,864,151,928	99,991,237,614	3.84 USD (Jan 04, 2018)

Note: The information in this table is up to 8th December 2019 and is retrieved from coinmarketcap.com

Table: VAR Granger causality among cryptocurrencies

Granger causality	Chi2	Granger causality	Chi2
ALL -> btc	43.363**	eth -> maid	10.932***
ALL -> dash	62.594***	gold -> xmr	4.8998*
ALL -> dgb	79.391***	ltc -> maid	5.2586*
ALL -> doge	56.16***	ltc -> usdt	5.3832*
ALL -> ltc	61.775***	ltc -> vtc	5.5871*
ALL -> maid	60.215***	ltc -> xem	15.445***
ALL -> usdt	58.619***	ltc -> xlm	4.8262*
ALL -> vtc	64.701***	ltc -> xrp	15.643***
ALL -> xem	60.909***	maid -> btc	9.1096**
ALL -> xlm	75.434***	maid -> xem	5.9077*
ALL -> xrp	76.941***	usdt -> btc	5.2926*
ALL -> xvg	78.064***	usdt -> dash	14.588***
btc -> dash	8.2946**	usdt -> dgb	4.6966*
btc -> doge	4.6777*	usdt -> ltc	12.016***
btc -> eth	4.8063*	usdt -> xem	7.3909**
btc -> usdt	7.2729**	usdt -> xmr	8.4808**
btc -> vtc	4.7108*	vtc -> doge	18.427***
btc -> xem	8.3805**	vtc -> ltc	5.2256*
btc -> xlm	12.651***	vtc -> xvg	8.7873**
btc -> xrp	6.1177**	xem -> dgb	10.216***
dash -> btc	8.1914**	xem -> usdt	5.9755*
dash -> maid	5.3709*	xem -> xlm	5.7485*
dash -> xlm	5.1112*	xlm -> dgb	4.8528*
dash -> xrp	11.663***	xlm -> vtc	5.9711*
dgb -> ltc	6.0525**	xlm -> xvg	4.7071*

dgb -> maid	6.5776**	xmr -> dgb	5.1627*
dgb -> usdt	4.9661*	xmr -> doge	6.9596**
dgb -> vtc	4.8593*	xmr -> maid	6.0621**
dgb -> xem	15.513***	xmr -> vtc	7.693**
dgb -> xrp	4.6894*	xmr -> xlm	12.102***
dgb -> xvg	5.779*	xmr -> xrp	4.9934*
doge -> dash	9.2618**	xrp -> dash	5.5299*
doge -> dgb	23.344***	xrp -> doge	6.7342**
doge -> ltc	6.3992**	xrp -> ltc	7.6896**
doge -> usdt	6.9898**	xrp -> maid	6.4255**
doge -> xlm	5.6147*	xrp -> usdt	9.0608**
doge -> xmr	4.9387*	xrp -> xlm	6.2428**
doge -> xrp	13.685***	xvg -> dgb	4.6644*
doge -> xvg	10.209***	xvg -> ltc	5.4168*
eth -> dash	12.498***	xvg -> xrp	4.6004*

Note: *, ** and *** denote the significance level at 10%, 5% and 1%.

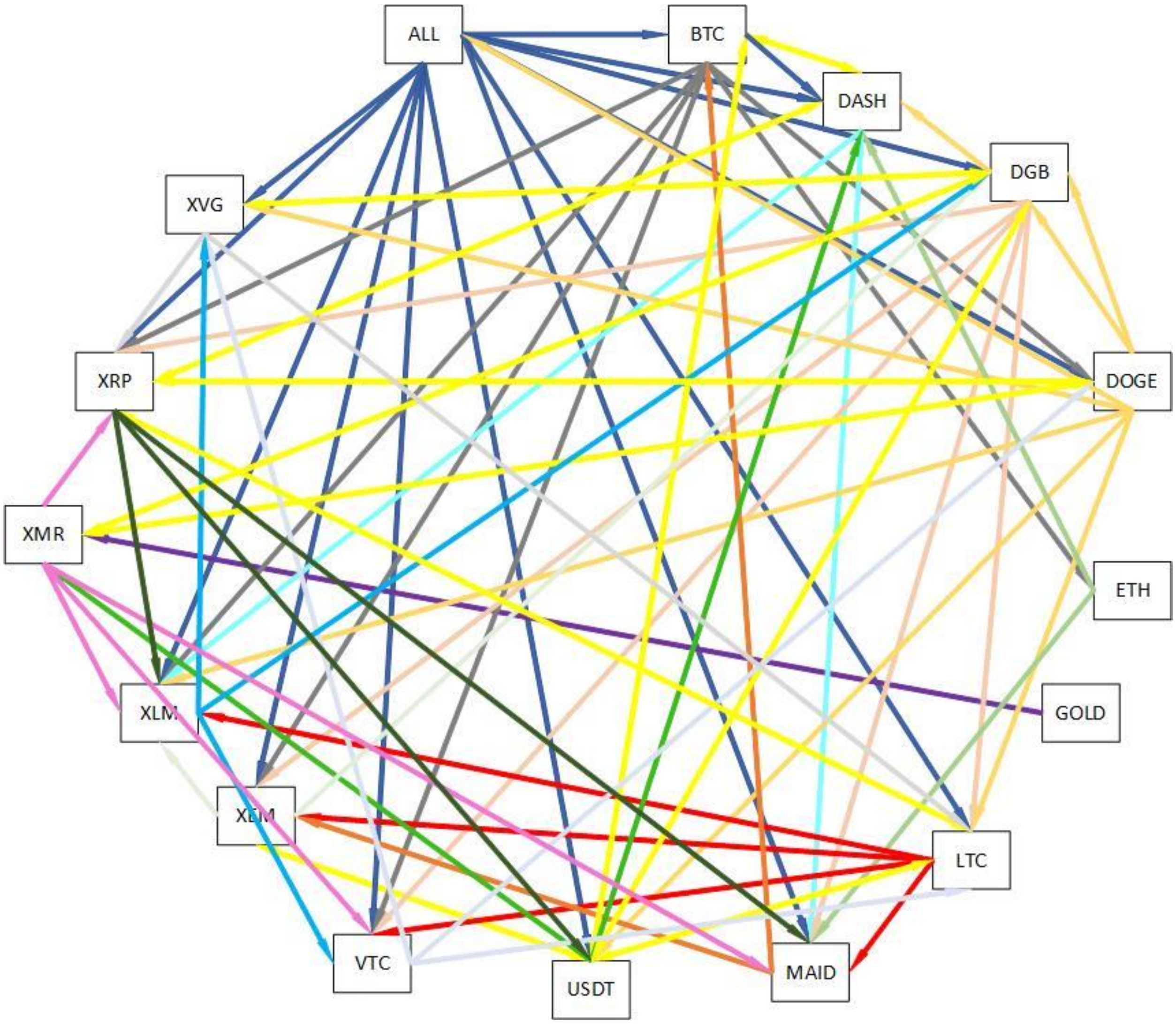

Fig. VAR Granger Causality among cryptocurrencies

Note: The single arrows are the significant Granger causality, the yellow double arrows are the significant bilateral Granger causality among them.