Financial Modelling, Risk Management of Energy Instruments and the Role of Cryptocurrencies

Abstract

This paper empirically investigates whether cryptocurrencies might have a useful role in financial modelling and risk management in the energy markets. To do so, the causal relationship between movements on the energy markets (specifically the price of crude oil) and the value of cryptocurrencies is analysed by drawing on daily data from April 2013 to April 2019. We find that shocks to the US and European crude oil indices are strongly connected to the movements of most cryptocurrencies. Applying a non-parametric statistic, Transferring Entropy (an econophysics technique measuring information flow), we find that some cryptocurrencies (XEM, DOGE, VTC, XLM, USDT, XRP) can be used for hedging and portfolio diversification. Furthermore, the results reveal that the European crude oil index is a source of shocks on the cryptocurrency market while the US oil index appears to be a receiver of shocks.

Keywords: Energy Markets, Risk management, Crude Oil, Cryptocurrency, Transfer Entropy, Financial instruments.

JEL Classification: O31, G18, O32, O33

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I. Introduction

Climate change is one of the most crucial and hence widely debated issues over the last decade. The need to tackle it at the global scale provides a rationale to explore the role of energy

and environmental instruments in in reducing carbon emissions. The financial sector, with its crucial role in the economy and society, should play its part (Shahbaz et al 2018; Nasir et al 2019).

The oil price always conveys a large amount of information to researchers, investors and policymakers. Empirical research (Balke et al. 2002, Hamilton 2003, Barsky and Kilian 2004, Chen and Chen 2007, Kilian and Park 2009, Elder and Serletis 2010, Jo 2014, Degiannakis and Filis 2017) has confirmed that the uncertain movement of oil prices can have different effects on different economies and financial assets. It is highly likely that major economic indicators strongly rely on the crude oil market, which reflects all 'good-or-bad' information relating to global geopolitics. For example, the West Texas Intermediate (WTI) index peaked at around US$75 per barrel at the beginning of October 2018 and then fell to around US$40 per barrel at the beginning of January 2019. Keynes's (1923) seminal work in this area encourages researchers to study the stochastic dynamics in oil and commodity markets. Although there is plenty of theoretical and empirical research on oil price modelling to capture the uncertain movements in the oil price, oil prices movements still attract much scholarly attention, with more sophisticated empirical methods. As of July 2018, the cryptocurrency market accounted for over US$300 billion worth of market capitalization, with nearly 2,000 'coins' trading.

Crude oil shipments were worth *$486.3 billion* (from World's Top Exports) whereas the market capitalization for cryptocurrencies was worth *$171 billion* (from coinmarketcap.com, 26th April 2019). Given such a high level of investment in these two assets, we are interested in examining whether there are links between the crude oil and the cryptocurrency markets.

There are a number of other reasons to examine the causal relationship between crude oil indices and movements on cryptocurrency markets. *First*, recently, many countries have shown interest in issuing their own coins for oil trading, including Venezuela, Russia, and the United States. Nicolás Maduro, Venezuela's President, stated: "*In 2019, we have a schedule for [oil] to be sold for Petro (the name of cryptocurrency backed by crude oil prices) and in this way continue to free us from a currency that the elite of Washington uses*"[*]. Taking inspiration from the mechanisms of current cryptocurrency platforms (Bitcoin, Ethereum, Litecoin, etc.) many countries around the world are likely to introduce their own cryptocurrencies to trade oil and other commodities. *Second*, understanding of the co-movements is necessary in establishing the initial valuation of a new coin. Valuation models provide a preliminary pricing mechanism for those

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[*] https://www.ccn.com/cryptocurrency-accepted-venezuela-will-sell-oil-for-petro-maduro-says

interested in issuing new cryptocurrencies. *Third*, the phenomenal growth of the cryptocurrencies market has been attracting the attention of both individual and institutional investors, as cryptocurrencies provide an alternative investment platform for the hedging and diversification of investors' portfolios. We believe the next decade will see substantial research outputs on the linkage between crude oil and cryptocurrencies in different markets around the globe.

Several governments, including those of Russia, Iran and Venezuela, have already taken measures to regulate the oil markets by issuing their own coins. For instance, Igor Yusufov, former energy minister of Russia, announced that his country is in the final stages of issuing a cryptocurrency based on the fundamental of the petrodollar. Every cryptocurrency platform (Bitcoin, Ethereum, Litecoin, etc.) needs to possess the key characteristics of any strong fundamental coin. It is anticipated that the application of cryptocurrencies in trading crude oil will gradually become a normal method of payment for many governments and will be an enormously useful means to control their commodity prices. Many countries in Eastern Asia are currently facing conflicts, trade restrictions and economic sanctions from the United States, and these states are likely to adopt alternative payment platforms using cryptocurrencies by introducing their own petrol-coins[†]. Hence, understanding the dynamic relationship between a coin and crude oil is one of the initial steps in assessing the possibility of launching an oil trading currency. The rapid growth of the cryptocurrency market is an emerging area of research in the field of energy economics and finance, and has recently attracted much scholarly attention. Cryptocurrency is not only a trending financial investment but is also considered to be '*The decentralized transaction system empire*' (Ammous, 2018). The bitcoin standard: the decentralized alternative to central banking. John Wiley & Sons.Bitcoin was first introduced in 2009 with a market price of a few cents. Its price had climbed to over $14,000 by December 2017. More recently, the market capitalization of Bitcoin has surpassed US$200 billion, while around six million users have virtual wallets and nearly one billion confirmed transactions occur every day (Hileman and Rauchs, 2017).

Investors who choose cryptocurrencies as alternative investment platforms are likely to consider the linkage between these two markets. Why? To answer this, we need to empirically establish the nature of directional causality to understand how crude oil prices influence

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[†] Petrol-coins refers to the kind of cryptocurrency which is called 'Petrol' backed by crude oil.

cryptocurrencies and vice versa. Investors need to ascertain the determinants of this causal relationship to make wise investment decisions. A deep understanding of this connection between crude oil and the cryptocurrency market is of great importance in several ways. *First*, oil and cryptocurrencies are not homogenous assets and, currently, there are several kinds of internationally traded crude oils as well as a range of cryptocurrencies. The different varieties of oil commodities and cryptocurrencies offer a good opportunity to investigate the underlying relationship between these complex payment instruments and crude oil prices. *Second*, the movement of oil prices depends on macroscopic economic factors, which leads to the market experiencing many external exogenous shocks. Although the cryptocurrency market is a fairly new addition to the global financial system, and is relatively independent of macroeconomic factors in these early stages, over time prices of cryptocurrencies are likely to become increasingly connected with the global energy market. This implies that investors will tend to use cryptocurrencies to hedge against volatility in the oil markets. Thus, the investigation of this causal relationship will guide investments in financial instruments. *Third*, Laherrere (2006) showed the role of benchmark crude oil indices, such as Brent for Europe and WTI for the American market. These indices convey many prospective indicators used for economic and financial forecasting. While the rapid expansion of blockchain and cryptocurrency can be practically applied in oil trading, it is possible to examine the connections among these highly volatile assets. *Fourth*, the cryptocurrency market has similar features to the oil market, such as market risk (Koutmos, 2019), the network correlation with the other conventional markets (Giudici and Polinesi, 2019), technical trading and returns (Hudson and Urquhart, 2019). Therefore, it is necessary to consider the link between cryptocurrencies and energy markets.

Finally, this study adds to the existing and growing body of energy-finance literature relating to cryptocurrencies. The theoretical and empirical literature on cryptocurrencies has developed in various areas. A few studies have focused on the regulatory aspect of Bitcoin. For instance, Stokes (2012), Raymaekers, (2015), Böhme et al. (2015), Vandezande (2017), Pieters and Vivanco (2017) evaluated the regulatory framework of Bitcoin as a financial asset being traded on real markets. Other researchers discuss whether Bitcoin is likely to be treated as a speculative asset (Baur et al. 2018, Blau et al. 2017, Bouri et al. 2017, Dyhrberg 2016, Glaser et al. 2014, Yermack, 2015). Their results indicate that Bitcoin is a suitable investment for diversification, and has the potential to be used as a safe haven for hedging purposes. Bouri et al. (2017) further examine

whether Bitcoin can be considered a safe haven, hedge or a diversifier against volatility in a commodity index. Their findings indicate that Bitcoin is a safe haven and a strong hedge for energy commodities. Recent studies have also measured the relationship between Bitcoin volatility and its returns in the comparative international context (Balcilar et al. 2017, Katsiampa 2017, Peng et al. 2018). In addition, a few recent studies have examined the contagion risk and spillover effects among cryptocurrencies (for example, Ciaian and Rajcaniova 2018, Corbet et al. 2018, Symitsi and Chalvatzis 2018, Huynh et al. 2018, Huynh, 2019). Recently, researchers have also raised concerns about the efficiency of the cryptocurrency market (Urquhart 2016, Nadarajah and Chu 2017, Bariviera 2017, Sensoy 2019). However, few studies have investigated the influence of cryptocurrencies on crude oil markets or vice versa, and this study attempts to fill this gap in the energy-finance literature.

In this context, the aim of this paper is to examine information spillovers between a commodity asset (specifically oil) and a digital cryptocurrency (e.g., Bitcoin). Our data cover 80% of the market capitalization of cryptocurrency alongside two main oil indexes (US crude oil and European crude oil). With regard to methodology, we use an entropy approach to capture the direction of spillovers within the information network, from a static perspective. In contrast, previous studies have focused on lagged terms, for example within a Vector-Auto-Regression model. We employ different indicators to identify the importance of each cryptocurrency being studied within the global energy market.

The remainder of this paper is organized as follows. Section II reviews the literature and highlights our contribution. The methodology and data sources are explained in Section III. Section IV presents the preliminary data analytics and empirical findings. Finally, Section V concludes the paper with policy implications.

II. Literature Review

Regulatory bodies and investors, in particular, are concerned about excessive volatility and abnormal returns in the cryptocurrency market. Higher abnormal returns in these markets make investment in cryptocurrency more appealing to the investor community. Recent research on cryptocurrencies shows that investors can achieve substantial returns by diversifying across different cryptocurrencies (Liu, 2018).

A few studies have attempted to test the assumptions of market efficiency for cryptocurrencies. Examining the seasonality effect for cryptocurrencies, Kaiser (2018) could not observe robust and consistent calendar effects on cryptocurrency returns. He nevertheless found that the volatility and spreads, as well as trading volume, were generally lower on weekends and in January. Behavioural finance researchers have also raised concerns about the volatility of the cryptocurrency market. Investigating the widespread noise and sentiment-driven trading in the cryptocurrency market, Kallinterakis (2019) found a significant herding effect. He argued that the extreme noise and volatility in these markets had a destabilizing effect on associated financial markets.

In the energy research literature, Krugman's (1983) seminal work provides a solid foundation for understanding the economic perspectives on and implications of oil prices. He argued that volatility in oil prices can cause a reciprocal change in the foreign exchange markets in terms of multilateral relationships. A number of other studies have also contributed to the literature on oil prices and currencies. For instance, Lizardo and Mollick (2010) asserted that there is a significant relationship between positive oil shocks and subsequent depreciation of the US dollar. This result is similar to the work of Adler and Sosa (2011), Aloui et al. (2013), Reboredo (2012), Reboredo et al. (2014), Coudert and Mignon (2016), who all reported a strong relationship between oil prices and exchange rate volatility. Kunkler and MacDonald (2019) attempted to exclude the *numéraire* effect (see German et al. 1995 for the *numéraire* effect) in evaluating the co-movements between oil prices and G-10 countries' currencies. They examined the spillover and causal interference from the oil market to those currencies. Using intraday data, many recent studies (such as Andersen et al. 2007, Degiannakis 2008, Corsi et al. 2010, Bekaert and Hoerova 2014, Duong and Swanson 2015, Bollerslev et al. 2016, Wang et al. 2016, Tian et al. 2017, Gong and Lin 2018a) have found there is a causal relationship between oil prices and currency markets. Research on the return and volatility spillovers among 18 cryptocurrencies indicated that Bitcoin is a key contributor to return-volatility spillover across all cryptocurrencies, which implies a high degree of interconnectedness and interdependence amongst cryptocurrencies (Koutmos, 2018).

Another strand of literature investigates the relationship between oil prices and product prices. Serletis (1994) and Gjolberg and Johnsen (1999) reported the existence of a long-run equilibrium, while Adrangi et al. (2001) and Asche et al. (2003) emphasized the role of a unidirectional causal relationship. Generally, crude oil and product prices have strong dynamics. Product prices have played an important role in explaining short-run and long-run petroleum

markets. This effect is stronger in the European market than in the US market (Lanza et al., 2005). Using intraday oil prices, previous studies (see in Sévi 2014, Haugom et al. 2014, Prokopczuk et al. 2016, Phan et al. 2016, Wen et al. 2016, Gong and Lin 2017, Degiannakis and Filis 2017, Liu et al. 2017, Ma et al. 2017, Gong and Lin 2018b, Ma et al. 2019) sought to model oil's stochastic dynamics (including price and volatility)

When it comes to the connections between the different oil and other markets, several papers have contributed to the literature. For example, Lin and Tamvakis (2001) indicated the connection between NYMEX and International Petroleum Exchange (IPE) crude oil. They emphasized the spillover effects particularly when two markets are trading at the same time. Sadorsky (2012) proved that the MGARCH model would better than the conventional GARCH to detect contagion volatility and asymmetric effects on international oil markets. Similarly, Liu and Tu (2012) suggest the diversification from defining the correlation[‡] among five types of petroleum future contracts. This means that understanding the connection of these markets is important for the purpose of valuation of these assets. Moreover, Furió and Chuliá (2012) found dependency between Brent crude oil (known in Europe) and Zeebrugge natural gas forward prices and also reported a causal relationship in both markets. Furthermore, Jiao et al. (2007) and Chen et al. (2009) explored the economic transmission from the Chinese oil and international oil markets, which is considered to be of vital importance in understanding the interconnectedness of two different oil markets.

Indeed, there is a large amount of empirical evidence on the role of oil in economic activities. For example, Pindyck (2003), Brown and Yucel (2008), Zamani (2016), Jadidzadeh and Serletis (2017), Serletis and Rangel-Ruiz (2004), Bachmeier and Griffin (2006), Ramberg and Parsons (2010), Brigida (2014) and Atil et al. (2014) investigated the relationship between crude oil prices and natural gas prices. Although there are inconsistent results in terms of strong evidence or weak evidence, these studies suggest crude oil can be a market dominant for natural gas.

The relationship between crude oil and other commodities and currencies is well established in the energy literature. With the emergence of the new cryptocurrencies, a handful of studies have investigated the relationship between cryptocurrencies and oil prices. Van Wijk (2013) found that Bitcoin had a negative relationship to oil prices. Employing the Vector Error Correction Model, this author also examined the relationship of Bitcoin to other types of financial assets. However,

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[‡] The investors are advised to minimize the variance by adding the opposite direction of correlation indices.

these relationships were explored for only that particular cryptocurrency, ignoring other prominent cryptocurrencies. Most cryptocurrencies have been developed using the first version of Bitcoin or using a decentralized version (version 2.0) such as Ethereum (ETH) or Ripple (XRP) or Litecoin (LTC). Therefore, an examination of causal relationships is necessary to explain the spillover or contagion effects across these markets. Wang et al. (2016a) found that trading activities on oil markets influenced Bitcoin returns and volatilities. However, Wang et al. (2016b) focused on only one kind of cryptocurrency and their methodology was mainly based on linear assumptions. Guesmi et al. (2018) argue that Bitcoin can be used for hedging. If investors have the option to add assets to their portfolio of gold, oil and equities, Bitcoin will be an optimal option to minimize the overall risk of the portfolio. Using quantile-and-quantile regression and CoVaR, Selmi et al. (2018) argued that, by using Bitcoin, investors may earn higher returns in the hedging process than they can with oil and gold. Recently, Gajardo et al. (2018) employed the Multifractal Asymmetric Detrended Cross-correlation analysis method to examine the relationship between Bitcoin and stock (through DJIA), gold and several major currencies. The results showed that Bitcoin has an asymmetric correlation with other financial assets; however, this phenomenon is evident only in the short run. Symitsi and Chalvatzis (2019) presented new insights relating to the economic value of Bitcoin. They found that an oil portfolio consisting of Bitcoin generates higher risk-adjusted returns.

With the growing momentum of research on cryptocurrencies and energy products, we will briefly summarize here the current literature on the linkage between cryptocurrency and crude oil. First, Gronwald (2019) considered whether Bitcoin could be considered a commodity asset or not. If so, a co-movement with the commodity market would be expected. Using jump-GARCH and short-run supply-demand shocks, Gronwald drew the conclusion that Bitcoin has the characteristic of an exhaustible commodity resource, similar to crude oil. This could result in the co-movement of these two kinds of assets. Although Giudici and Abu-Hashish (2019) found that oil has no link to Bitcoin prices, several studies have reported a relationship between these two assets, for example Gajardo et al (2018), using cross-correlation dependence. Similarly, Jin et al. (2019) concluded that Bitcoin prices are susceptible to price fluctuations from oil by using MF-DCCA and MV-GARCH. Therefore, we can conclude that the evidence on the relationship between Bitcoin and crude oil is inconclusive. In addition, this paper not only examines the directional impact of Bitcoin but also considers the other main cryptocurrencies.

In brief, a vast amount of empirical work has examined the relationship between oil prices and other kinds of financial/non-financial assets. Nevertheless, the relationship between cryptocurrencies (as monetary currencies) and crude oil has received limited academic attention. Using a more sophisticated estimation ('Entropy Transfer'), this paper contributes to the embryonic literature on the transmission channel from oil shocks to the cryptocurrency market.

III. Empirical Methodology and Data

In this section we present our main estimation approach. Because of the complexity of data or stochastic processes, methods previously used to calculate information transfer have been mainly derived from assumptions of specific subjects (or sometimes the process-built restrictions). An important challenge faced by energy researchers is to quantify the informational flow, as the Vector Auto Regression (VAR) approach cannot estimate this relationship. Therefore, we employ 'Entropy Transfer', which is considered a more robust method (Schreiber, 2000) to overcome the methodological concerns raised over previous approaches. In addition, Granger (1988) causality underperform for structural models. Thus, Transfer Entropy is used here to measure the large amount of asymmetric information and large networks in non-parametrically directed processes. For example, if we consider two processes, I and J, the Transfer Entropy is defined as:

Transfer entropy from J to I = (Information for future observation $I_{(t+1)}$ absorbed from historical values of I and J) - (Information for future observation $I_{(t+1)}$ absorbed from the historical value of only I) $\quad$ (1)

Then, Shannon (1948) entropy was defined as the independently encoded drawing:

$$H_J = -\sum_j p(j).\log(p(j)) \qquad (2)$$

in which, J is a discrete random variable with probability distribution p(j) and j stands for the different outcomes that this variable can take. Therefore, H is considered the optimal value. However, Shannon's formula works well under uncertainty. Combined with the theoretical framework of Kullback and Leibler (1951), the Shannon process was further expanded into two processes, I and J, with the strict assumption that the time series should be stationary, for marginal probability distribution p(i), p(j) and joint distribution p(i,j). Following this, the average number of encoded observations for (t+1) and value (k):

$$h_I(k) = -\sum_i p\left(i_{t+1}, i_t^{(k)}\right).\log\left(p\left(i_{t+1}\middle|i_t^{(k)}\right)\right) \qquad (3)$$

where $i_t^{(k)} = (i_t, \ldots, i_{t-k+1})$. $h_J(l)$ is considered analogously for process J. Then, with the generalized Markov process $p\left(i_{t+1}\middle|i_t^{(k)}\right) = p\left(i_{t+1}\middle|i_t^{(k)}, j_t^{(k)}\right)$ from Kullback and Leibler (1951). We then have the Shannon (1948) transfer entropy given as:

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

where $T_{J \to I}$ evaluates the information flow from J to I.

Applying the 'Transfer Entropy' process, we generalize information flows from variable Y to variable X in the following formula:

$$TE_{Y \to X}(k, l) = \sum_{i_{n+1}, i_n^k, j_n^l} p(i_{n+1} i_n^k, j_n^l) \log_2 p(i_{n+1}|i_n^k, j_n^l)$$

$$- \sum_{i_{n+1}, i_n^k, j_n^l} p(i_{n+1} i_n^k, j_n^l) \log_2 p(i_{n+1}|i_n^k)$$

$$= \sum_{i_{n+1}, i_n^k, j_n^l} p(i_{n+1} i_n^k, j_n^l) \log_2 \frac{p(i_{n+1}|i_n^k, j_n^l)}{p(i_{n+1}|i_n^k)} \quad (5)$$

in which i_n is the nth component of the time series of variable X and j_n is component n of the time series of variable Y.

The joint probability of X and Y is defined as:

$$p\left(i_{n+1}, i_n^{(k)}, j_n^{(l)}\right) = p(i_{n+1}, i_n, \ldots, i_{n-k+1}, j_n, \ldots, j_{n-l-1}) \quad (6)$$

Then, Erdös and Rényi (1970) introduced a new approach based on this with weighting parameter $q > 0$ for individual probabilities p(j).

$$H_J^q = \frac{1}{1-q} \log\left(\sum_j p^q(j)\right) \quad (7)$$

As $q \to 1$, Rényi entropy will converge to Shannon entropy while $0 < q < 1$ means low probability with more weight. Otherwise, $q > 1$ means a higher initial probability for preference of outcome j. Endowing the escort distribution, Beck and Schlögl (1993) indicated the parameter $\phi_q(j) = \frac{p^q(j)}{\sum_j p^q(j)}$, with $q > 0$ in order to normalize the weighted distribution. Jizba et al. (2012) developed the Rényi entropy, which we employed as follows:

$$RT_{J \to I}(k, l) = \frac{1}{1-q} \log \left(\frac{\sum_i \phi_q\left(i_t^{(k)}\right) p^q\left(i_{t+1} \middle| i_t^{(k)}\right)}{\sum_{i,j} \phi_q\left(i_t^{(k)}, j_t^{(k)}\right) p^q\left(i_{t+1} \middle| i_t^{(k)}, j_t^{(k)}\right)} \right) \quad (8)$$

The process of Shannon and Rényi *Transfer Entropy* is based on discrete random data. Then, the process is based on the Markov block bootstrap (Dimpfl and Peter, 2013) and repeated by bootstrap. Finally, the null hypothesis for transferring entropy states that no information is transferred. We also generalize the Rényi Transfer Entropy:

$$RTE_{Y \to X}(k, l) = \frac{1}{1-q} \log_2 \frac{\sum_{i_{n+1}, i_n^k} \varphi_q(i_n^k) p^q(i_{n+1} | i_n^k)}{\sum_{i_{n+1}, i_n^k} \varphi_q(i_n^k, j_n^l) p^q(i_{n+1} | i_n^k, j_n^l)} \quad (9)$$

where φ_q is the escort distribution given by:

$$\varphi_q(i) = \frac{p^q(i)}{\sum_i p_i^q} \quad (10)$$

The methodology of '*Transferring Entropy*' is not only used by computer science researchers (e.g. Lizier et al. 2008, Lizier and Mahoney 2013), but has also been applied in many other interdisciplinary fields, for example in: neurosciences to detect neural cortex (Sumioka et al. 2007, Faes et al. 2013), social network and behaviors (Ver Steeg and Galstyan 2012); mathematical statistics (Barnett and Bossomaier 2012, Liu et al. 2014); and, especially, in thermodynamics (Prokopenko et al. 2013).

The applications of '*Transferring Entropy*' in economics and finance is an emerging methodological development. Next, we briefly evaluate the application of this method in economics and finance. Marschinski and Kantz (2002) introduced this method to evaluate the information flow from the S&P500 Index (USA)DAX (Germany). They found it provided more efficient and consistent estimations compared with other approaches as it subtracts the effects of noise as well as high volatility in the time series. Baek et al. (2005) employed this method to investigate the impact of energy industry returns on the overall health of an economy. Their sample covered 135 firms listed on the New York Stock Exchange over the period 1983 to 2003, and they found that energy companies significantly influence the national economy. Interestingly, these results are in line with the paper by Kwon and Yang (2008) which reported on information flows from the US and European markets to the Asia Pacific region. Furthermore, Jizba et al. (2012) reexamined the work of Marschinski and Kantz (2002) with the integration of two methodological approaches (Shannon's entropy and Rényi's entropy). They also investigated the non-parametric distribution in terms of information transfer. Similarly, Dimpfl and Peter (2013) and Peter et al.

(2011) investigated the information flow from the CDS (Credit Default Swap) market to the corporate bond market by applying the '*Transfer Entropy*' approach. The results reveal a dynamic relationship of market risk (measured by CBOE Volatility Index - VIX) among different financial assets. Kim et al. (2013) analysed a set of variables including the equity index, consumer price index, real exchange rate, trade balance and industrial production index, representing macroeconomic determinants, from 18 economies over the period 1990-2000. They studied the interconnectedness among their samples and showed the US market was a net sender of information flows, whereas Europe appeared to be a passive recipient. Li et al. (2013) adapted this new perspective of '*Transferring Entropy*' to investigate the contagion risks among Chinese banks by simulating the spillover risks of networks, and concluded that Chinese banks are likely to be stable under market risks.

In brief, several previous studies have applied Transfer Entropy to investigate causal relationships in different institutional and market settings. However, we are not aware of any study that has applied Transfer Entropy to investigate connections between the crude oil markets and the cryptocurrency markets. Therefore, our paper extends the application of this quantitative technique to investigate the causal relationship between the US and European crude oil returns and 14 different cryptocurrencies.

Our daily returns data are sorted into two main groups: First, oil returns data for the US index (DCOILWTICO) and European index (DCOILBRENTEU) are collected from Federal Reserve Economic Data (https://fred.stlouisfed.org/). Noticeably, we focus on the developed regions only, specifically, the US and EU crude oil markets due to the large proportion of these developed economies in global crude oil market (Chuliá et al., 2019). Furthermore, Jin et al. (2012) also indicated that Dubai crude oil has similar properties to Brent. Most importantly, WTI crude oil which has been traded in the New York Mercantile Exchange (NYME), the biggest commodity futures. This is the most crucial pricing benchmarks in the global crude oil which could be considered as an important criterion for investors. In a recent study, Liu and Gong (2020) confirmed that WTI plays a prominent role in the international crude oil markets. Concomitantly, examining the relationship between the two largest crude oil markets and an inclusive sample of cryptocurrency coins by employing new econometrics models would provide us with deeper insights into the spill-over effects.

Second, data on 14 cryptocurrencies are collected from coinmarketcap.com. These currencies are: BTC (Bitcoin), LTC (Litecoin), ETH (Ethereum), XEM (Nem), DASH (Dash),

DOGE (Dogecoin), XMR (Monero), VTC (Vertcoin), XVG (Verge), DGB (Digibyte), XLM (Stellar), USDT (Tether), MAID (MaidSafeCoin), XRP (Ripple). Our sample period covers data from 29th April 2013 to 06th April 2019, though not all cryptocurrencies were in existence over the whole period. We chose a long horizon to cover as much information as possible. In addition, one of Transfer Entropy's advantages is that is allows unbalanced datasets to be used to estimate causal relationships. From the available pool of all cryptocurrencies, we selected those that met three main criteria: (i) continuous trading; (ii) having an equal number of or more observations than DCOILWTICO and DCOILBRENTEU; and (iii) accounted for at least 80% market capitalization of the cryptocurrency market. Further information regarding market capitalization, circulating supply and date of issue are provided in Appendix (ii). In Table 1, we report the descriptive statistics for our sample.

Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
DCOILWTICO	1,168	0.0005	0.0221	-0.0905	0.1128	0.2535	5.8424
DCOILBRENTEU	1,168	0.00004	0.0200	-0.0690	0.0989	0.4333	5.7238
BTC	2,169	0.0016	0.0433	-0.2674	0.3614	-0.1108	11.0616
LTC	2,169	0.0013	0.0668	-0.5192	0.8245	1.7000	27.7714
ETH	1,338	0.0030	0.0763	-1.3739	0.4034	-4.0516	83.2739
XEM	1,466	0.0035	0.0876	-0.5025	1.0684	1.9692	23.8385
DASH	1,877	0.0034	0.0777	-0.4204	1.0668	2.5294	31.6831
DOGE	1,938	0.0009	0.0808	-0.6257	1.0625	1.5506	29.0534
XMR	1,781	0.0018	0.0740	-0.4404	0.5676	0.5846	9.01816
VTC	1,902	0.0010	0.1118	-0.6141	1.0923	2.2348	19.9729
XVG	1,624	0.0044	0.1722	-0.9162	1.9169	1.1696	16.0909
DBG	1,885	0.0012	0.1024	-0.6035	1.1522	1.8588	20.8781
XLM	1,705	0.0021	0.0793	-0.3334	0.7040	1.9281	17.8684
USDT	1,501	-0.0001	0.0120	-0.1822	0.1511	-2.3979	110.783
MAID	1,804	0.0012	0.0694	-0.4020	0.4643	0.17116	7.03972
XRP	2,071	0.0019	0.0758	-0.6011	1.0109	2.0258	30.2785

Notes: Transfer Entropy allows us to estimate the causal relationship based on the unbalanced data. Our sample covers the period from 29th April 2013 to 06th April 2019 with different observations for our variables.

Following Miller & Scholes (1972). [§], we continued data processing to calculate the index return by logarithm return[**]. Table 1 presents the characteristics of WTI and BRENT EU indices returns as well as 14 cryptocurrencies in terms of daily trading activities. Overall, the mean daily return is approximately zero. Except for Bitcoin, Ethereum and USDT, the other variables show positive skewness, which indicates that these coins have positive extreme values in the datasets. Bitcoin, Ethereum and USDT are likely to have negative extreme values. With regard to kurtosis analysis, all variables have a heavy tail distribution, with the probability of extreme values in both tails. Surprisingly, Ethereum has the highest kurtosis value (83.27397) whereas the oil prices (in the US and Europe) have the lowest values (5.842435 and 5.723816, respectively). We therefore reject all the assumptions relating to normal distribution, implying there is an interconnectedness in the abnormal distribution of variables. Therefore, we employ the entropy approach to investigate the causal relationship between crude oil markets and cryptocurrencies.

To define the data structures as well as their characteristics, plots are combined into a plot matrix. We then need to employ *Transfer Entropy* for further quantitative testing. Hence, *Transfer Entropy* is employed to capture the informational flows among these markets, assuming that the vast majority of information will have interacted. These results are likely to be robust, owing to the correction of selecting information by crude oil markets to cryptocurrencies through tensor of blockchains of these cryptocurrencies. Clearly, the anomalous distributions among our variables raises concerns that we need to employ the econphysics technique to estimate the informational flows to eliminate the outliers, and that we need to employ data transformation in order for our results to be robust.

[§] $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$ in which P_t is the index at time t

[**] Many recent papers have applied this methodology for Bitcoin returns, but see in particular Jiang et al. (2018) and Sensoy (2019).

Figure-1: Data Distribution and Correlation between the US Crude Oil Index and each Cryptocurrency
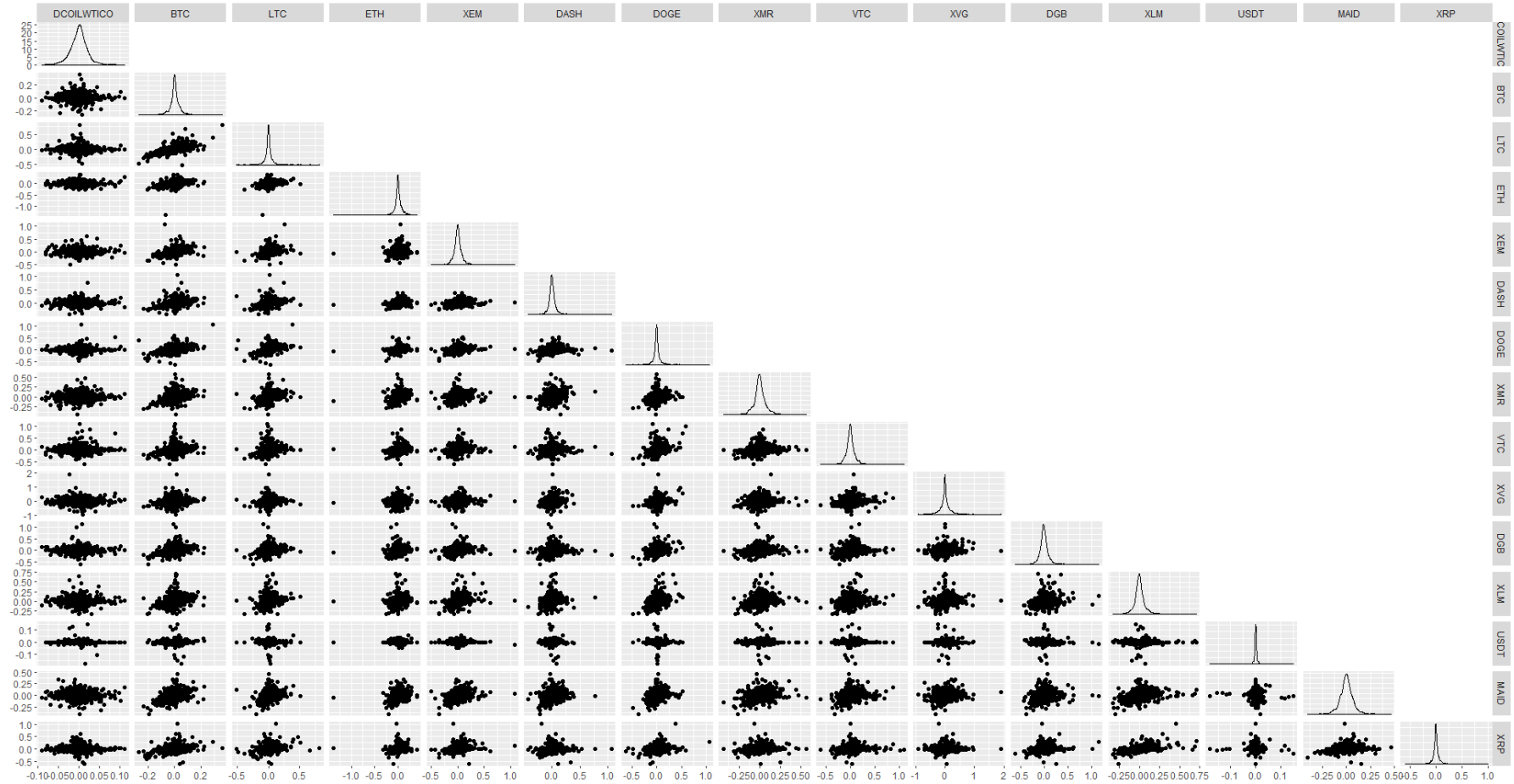
Note: The correlation data have non-normal distribution (not linear). Furthermore, some dataset structures are skewed and heavy-tailed. Interestingly, there are some outliers correlated with the US crude oil index, which means that the dots are at a distance from the sample plot.

Figure-2: Data Distribution and Correlation between the European Crude Oil Index and each Cryptocurrency
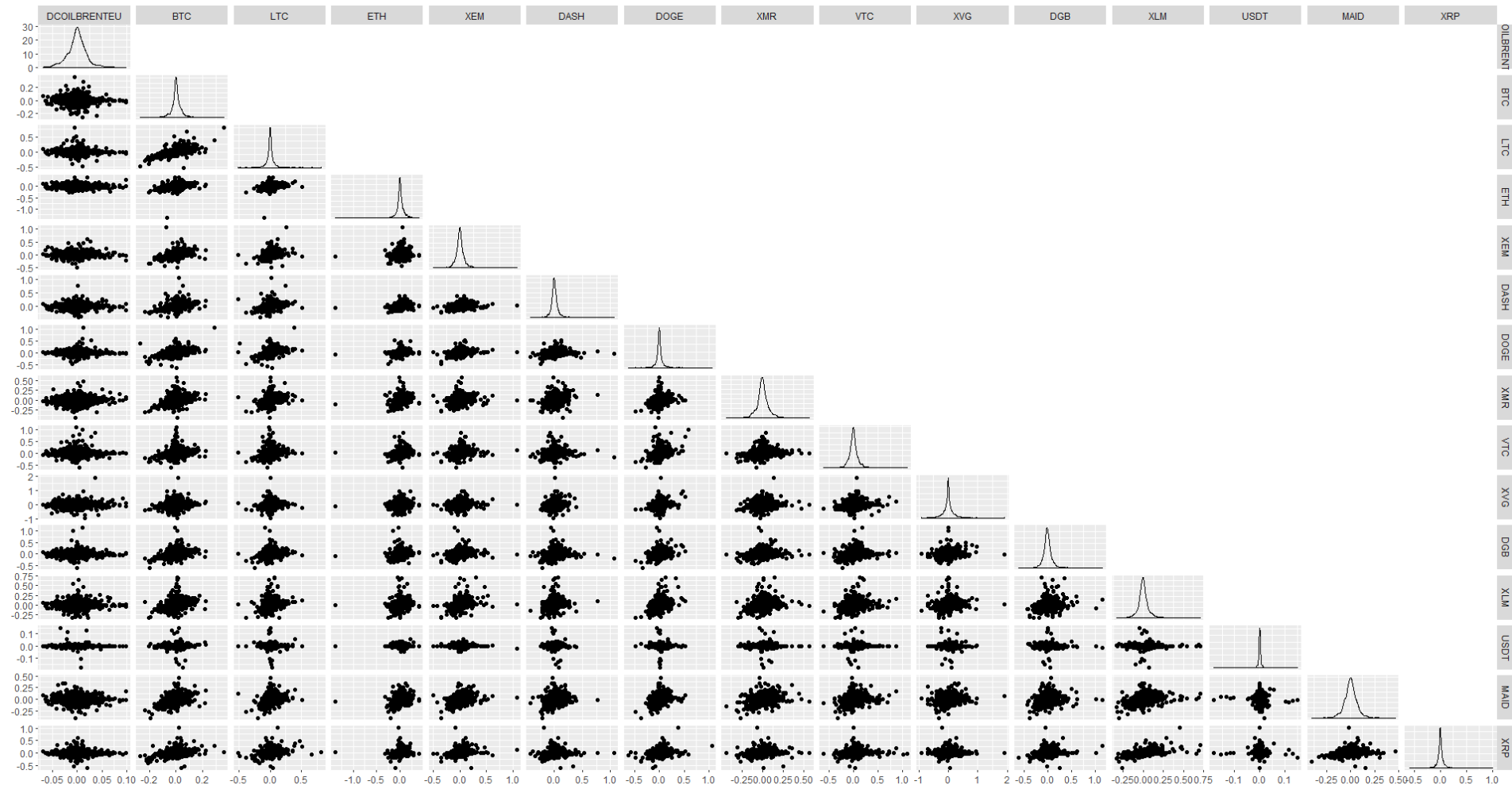
Note: The correlation data have a non-normal distribution (not linear). Furthermore, some dataset structures are skewed and heavy-tailed. Interestingly, there are some outliers correlated with the European crude oil index, which means that the dots are at a distance from the sample plot.

IV. Empirical Findings and Discussion

IV.I. Linear Correlation Analysis

First, we employed the linear correlation using a Bonferroni-adjusted significance level and the empirical results are reported in Table 2. Table 2 shows the empirical linear correlations between DCOILWTICO, DCOILBRENTEU and the 14 cryptocurrencies.

Table-2: Linear Correlation Analysis

Cryptocurrencies	DCOILWTICO	DCOILBRENTEU
BTC	0.0041	-0.0262
LTC	-0.0012	-0.0333
ETH	-0.0019	-0.0258
XEM	-0.0032	-0.0084
DASH	0.0516	0.0252
DOGE	0.0446	0.0411
XMR	0.0120	0.0494
VTC	0.0319	0.0183
XVG	-0.0158	0.0323
DBG	0.0202	0.0073
XLM	-0.0020	0.0331
USDT	-0.0283	-0.0179
MAID	-0.0312	-0.0281
XRP	-0.0193	-0.0221

Note: None of the correlations is statistically significant even at the 10% level.

There is no correlation between crude oil returns and cryptocurrency values. The correlation values are around zero and statistically insignificant. The results from linear correlation therefore suggest there is no connection between crude oil and cryptocurrencies. However, in fact, the transmission of information still happens. Therefore, we need to further investigate the connections among these relationships (including itself and between oil(s) and cryptocurrencies).

IV.II. Unit Root Analysis

Before employing further estimation techniques, we need to test the stationary of all the variables. Table 3 gives a summary of stationarity tests such as Augmented Dickey-Fuller and Phillips-Perron. The purpose of having the stationary time series datasets is to ensure the results are unbiased and not spurious.

Table 3: Unit Root Analysis

Variables	Augmented Dickey-Fuller	Phillips-Perron
DCOILWTICO	-32.920***	-32.796***
DCOILBRENTEU	-28.557***	-28.580***
BTC	-46.438***	-46.466***
LTC	-45.736***	-45.798***
ETH	-34.781***	-34.743***
XEM	-42.069***	-41.977***
DASH	-43.387***	-43.393***
DOGE	-40.463***	-40.378***
XMR	-42.506***	-42.511***
VTC	-41.902***	-41.898***
XVG	-53.220***	-52.886***
DBG	-43.755***	-43.780***
XLM	-38.836***	-38.884***
USDT	-26.252***	-24.939***
MAID	-47.360***	-47.374***
XRP	-42.666***	-42.933***

Note: The symbols *, **, and *** denote the level of significance at the 10%, 5%, and 1% levels, respectively.

All variables are stationary at the 1% significance level from the original series. This shows that crude oil and cryptocurrency returns are integrated at I(0).

IV.III. Transfer Entropy Analysis

In Table 4, we present the results of Renyi and Shannon (threshold) Transfer Entropy between the US crude oil index (DCOILWTICO) index returns and the 14 cryptocurrencies.

Table-4: Renyi and Shannon Transfer Entropy Results from DCOILWTICO to Cryptocurrency Markets

Causality	Renyi Transfer Entropy	Shannon Transfer Entropy
DCOILWTICO → BTC	0.0083 [0.0027]	0.0080
BTC → DCOILWTICO	0.0081 [0.0025]	
DCOILWTICO → LTC	0.0117* [0.0028]	0.0116
LTC → DCOILWTICO	0.0042 [0.0024]	
DCOILWTICO → ETH	0.0268*** [0.0043]	0.0267
ETH → DCOILWTICO	0.0055 [0.0042]	
DCOILWTICO → XEM	0.0145 [0.0040]	0.0144
XEM → DCOILWTICO	0.0089 [0.0037]	
DCOILWTICO → DASH	0.0171** [0.0032]	0.0170
DASH → DCOILWTICO	0.0140* [0.0033]	
DCOILWTICO → DOGE	0.0109 [0.0028]	0.0108
DOGE → DCOILWTICO	0.0102 [0.0030]	
DCOILWTICO → XMR	0.0136*	0.0136

	[0.0032]	
XMR → DCOILWTICO	0.0052 [0.0036]	
DCOILWTICO → VTC	0.0076 [0.0031]	0.0076
VTC → DCOILWTICO	0.0045 [0.0031]	
DCOILWTICO → XVG	0.0132* [0.0033]	0.0131
XVG → DCOILWTICO	0.0184** [0.0035]	
DCOILWTICO → DGB	0.0104 [0.0032]	0.0103
DGB → DCOILWTICO	0.0065 [0.0031]	
XLM → DCOILWTICO	0.0070 [0.0036]	0.0069
DCOILWTICO → XLM	0.0103 [0.0032]	
DCOILWTICO → USDT	0.0122 [0.0036]	0.0122
USDT → DCOILWTICO	0.0075 [0.0038]	
DCOILWTICO → MAID	0.0107* [0.0031]	0.0106
MAID → DCOILWTICO	0.0056 [0.0035]	
DCOILWTICO → XRP	0.0094 [0.0027]	0.0093
XRP → DCOILWTICO	0.0103 [0.0027]	

Note: The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Interestingly, only six cryptocurrencies have a causal relationship with DCOILWTICO. Only two cryptocurrencies have a bilateral relationship, with shocks from US crude oil to DASH and XVG, and vice versa. DASH is a bitcoin-based currency featuring instant transactions, decentralized governance and budgeting, and private transactions. Consequently, DASH has similar characteristics as Bitcoin but comes with more advanced features such as private information and transactions. Therefore, it is cogent to use it as a payment method. Furthermore, the XVG is a technological platform based on the Tor Project[6]. Interestingly, the Tor project was received a lot of offers from the United States National Agencies for developing their platforms; for example, The National Security Agency (NSA) (Guardian, 2013). Therefore, the effects of XVG on the US crude oil could be explained by the broad interest of technological and advanced platform which is designed.

In terms of transmission from the US crude oil market returns on cryptocurrency returns, the findings of Shannon transfer entropy estimation indicate a significant information flow from the US crude oil to six of the cryptocurrencies (LTC, ETH, DASH, XMR, XVG and MAID). This is evidence of information flows from the US crude oil market returns to cryptocurrency markets. It supports the proposition that the macroscopic economic value of the US crude oil has an effect on the cryptocurrency markets.

The process of transferring entropy from the US crude oil market to the cryptocurrency market lies in the range 1.1% (weakest at Litecoin) to 2.6% (strongest at Ethereum). Taking the Rényi's transfer entropy through these graphs (in **Figure 3**), we can further investigate this relationship. From the results presented in Figure 3, there is a possibility to reweight the probabilities under Erdös and Rényi's (1970) methodology (mentioned in the previous section). The value of q will converge to 1 (q → 1). As can be seen, the value of transfer entropy of Litecoin and Ethereum is highest at the smallest value of (q) and decreases as q increases. Finally, it will converge in Shannon's TE.

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[6] Please see more at https://www.torproject.org/

Figure 3: Rényi Transfer Entropy with different values of q from the US Crude Oil Market
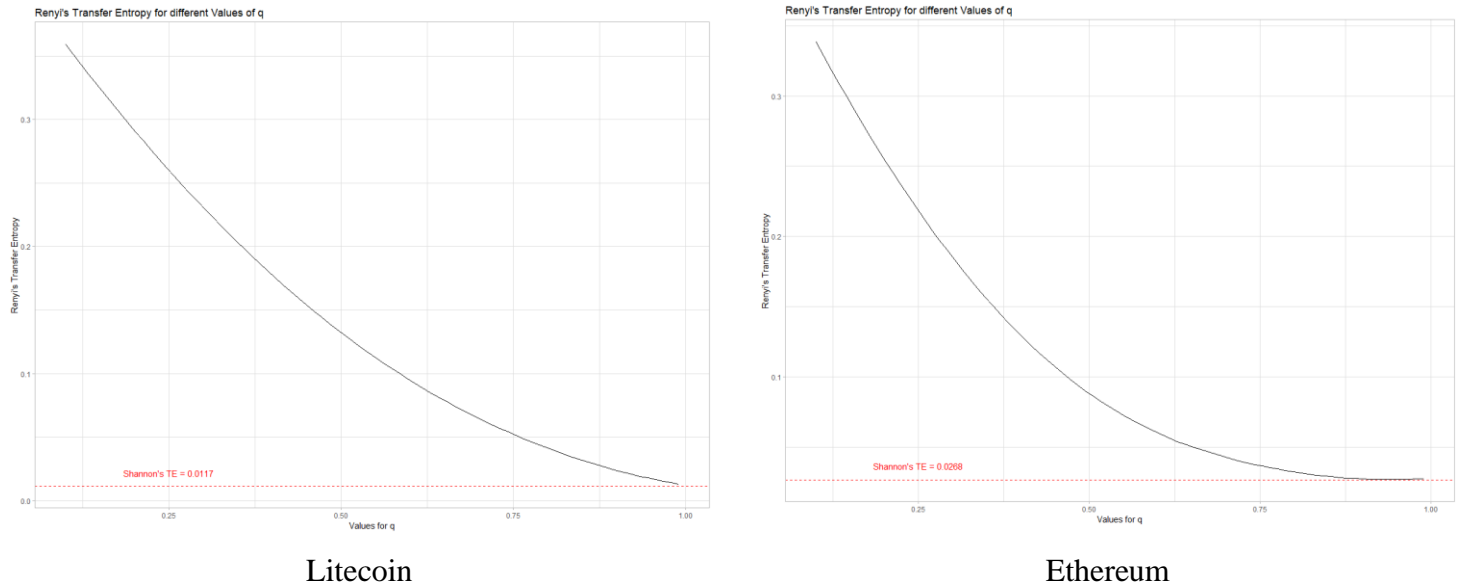

Litecoin

Ethereum

Table 5 demonstrates the results of Renyi and Shannon (threshold) Transfer Entropy between DCOILBRENTEU index returns and the 14 cryptocurrencies.

Table 5: Renyi and Shannon Transfer Entropy Results from DCOILBRENTEU to Cryptocurrency Market

Causality	Renyi Transfer Entropy	Shannon Transfer Entropy
DCOILBRENTEU → BTC	0.0113* [0.0025]	0.0112
BTC → DCOILBRENTEU	0.0106* [0.0026]	
DCOILBRENTEU → LTC	0.0116* [0.0028]	0.0115
LTC → DCOILBRENTEU	0.0075 [0.0027]	
DCOILBRENTEU → ETH	0.0177** [0.0041]	0.0177
ETH → DCOILBRENTEU	0.0138 [0.0041]	

DCOILBRENTEU → XEM	0.0088 [0.0038]	0.0087
XEM → DCOILBRENTEU	0.0080 [0.0038]	
DCOILBRENTEU → DASH	0.0118 [0.0028]	0.0117
DASH → DCOILBRENTEU	0.0108 [0.0029]	
DCOILBRENTEU → DOGE	0.0089 [0.0031]	0.0089
DOGE → DCOILBRENTEU	0.0058 [0.0031]	
DCOILBRENTEU → XMR	0.0128* [0.0032]	0.0127
XMR → DCOILBRENTEU	0.0042 [0.0035]	
DCOILBRENTEU → VTC	0.0112 [0.0031]	0.0111
VTC → DCOILBRENTEU	0.0052 [0.0029]	
DCOILBRENTEU → XVG	0.0093 [0.0034]	0.0093
XVG → DCOILBRENTEU	0.0056 [0.0034]	
DCOILBRENTEU → DGB	0.0076 [0.0031]	0.0076
DGB → DCOILBRENTEU	0.0152** [0.0031]	
XLM → DCOILBRENTEU	0.0063 [0.0033]	0.0062

DCOILBRENTEU → XLM	0.0063 [0.0036]	
DCOILBRENTEU → USDT	0.0137 [0.0037]	0.0137
USDT → DCOILBRENTEU	0.0077 [0.0037]	
DCOILBRENTEU → MAID	0.0120* [0.0032]	0.0120
MAID → DCOILBRENTEU	0.0065 [0.0033]	
DCOILBRENTEU → XRP	0.0061 [0.0028]	0.0061
XRP → DCOILBRENTEU	0.0081 [0.0030]	

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

Among the 14 cryptocurrencies, six have interconnectedness with DCOILBRENTEU. They are BTC, LTC, ETH, XMR, DGB, and MAID. Among them, only Bitcoin has a bilateral causal relationship with the European crude oil market, which means that there is a strong connection from Bitcoin to DCOILBRENTEU, and vice versa.

Generally, all the shocks from the European crude oil market lead to shocks on the cryptocurrency market, as evidenced by the single direction from DCOILBRENTEU to specific coins. It makes sense to say that DCOILBRENTEU is an indicator of the economic situation, and so offers investors to carefully watch these indices for their movements.

Four coins (LTC, ETH, XMR, MAID) are considered the receiver from the two markets. There are some common characteristics of these coins, including: (i) a decentralization system, (ii) providing a platform for petrol-dollars in the future, and (iii) automatic confirmation of transactions. We also observe that the process of transferring entropy from the European crude oil market to the cryptocurrency market lies in the range of 0.76% (weakest at DGB) and 1.7% (strongest at Ethereum). Similarly, Ethereum also receives the highest transfer entropy from the US crude oil shocks. Therefore, we can conclude that Ethereum is likely to be the most passive receiver in the two crude oil markets. Concurrently, Ethereum is evaluated as the most innovative

coin, as it allows many networks to be built on it, such as petrol coins or smart contracts in oil trading. Hence, there is likely to be greater information transfer from these two crude oil markets for Ethereum.

Figure 4 demonstrates the process of Rényi transfer entropy with different values of q from the European crude oil market.

Figure 4: Rényi Transfer Entropy with different values of q from the European Crude Oil Market
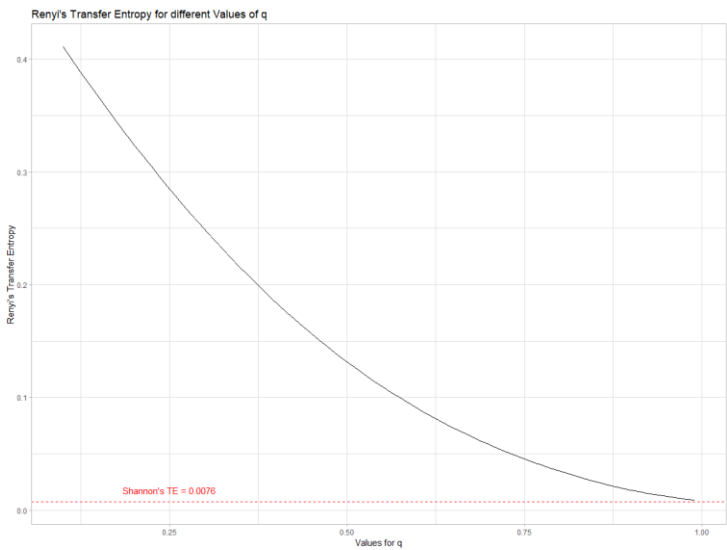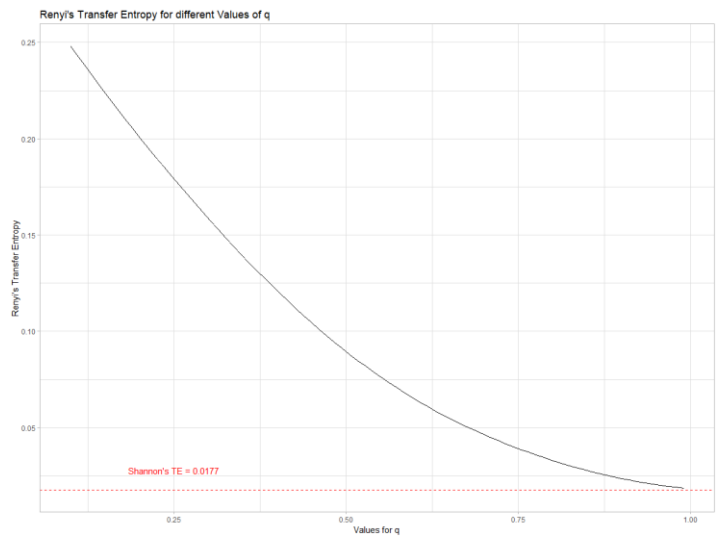
DGB   Ethereum

These graphs are similar to those for the transfer entropy process from the US crude oil market. At the highest q value, the transfer entropy value is lower. The highest transfer entropy values are at the lowest values of q.

The value of q will converge to 1 (q → 1). In Figure 4, the transfer entropy value of DGB and Ethereum is highest at the smallest values of q and decreases as q increases. Finally, it will converge in Shannon's TE.

## IV.IV. The Causal Relationship between US and European Crude Oil Markets

Table-6: Renyi and Shannon Transfer Entropy Results from DCOILWTICO to DCOILBRENTEU

Causality	Renyi Transfer Entropy	Shannon Transfer Entropy
DCOILWTICO → DCOILBRENTEU	0.0214*** [0.0029]	0.02138667
DCOILWTICO → DCOILBRENTEU	0.0126** [0.0027]	

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

We find strong evidence of a causal relationship between the US and European crude oil prices. These results show bilateral relationships, interconnectedness and spillover effects among these markets.

Figure-5: Rényi Transfer Entropy with different values of q from the DCOILWTICO to DCOILBRENTEU
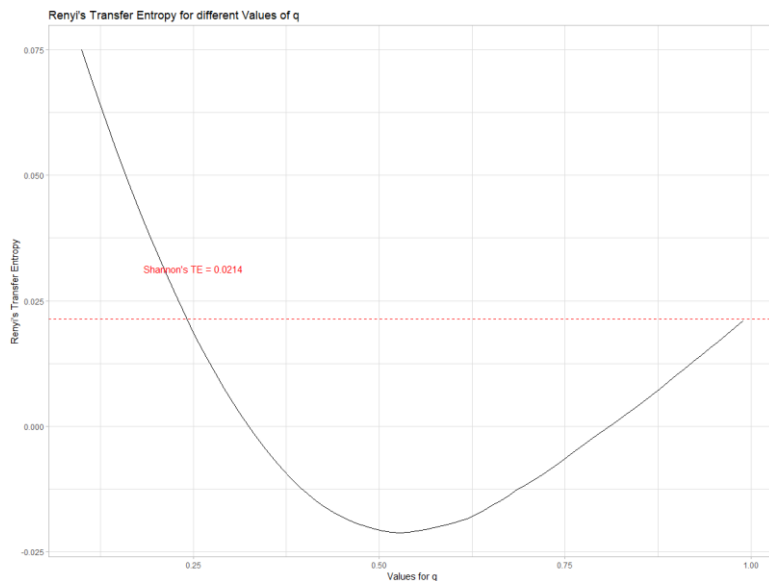
The highest transfer value is at the initial quantile. The lowest value for transfer is in the median quantile. Finally, it converges into Shannon's TE at quantile (q = 1). This implies that the transfer entropy between the US and European crude oil markets follows a quadratic curve. This bell shape indicates that the informational shock on either the US or the European crude oil index will result in a higher risk exposure on the other oil market.

Why do we perform the causal relationship analysis between the US and European crude oil markets? We would like to deeply investigate the multidimensional effects among these markets to explain the mechanism for transferring entropy. By illustrating the network of causal relationships from these results, we illustrate what we achieve by employing '*Transfer Entropy*'.

Figure 6: The Causal Relationship Network between the US and European Crude Oil and Cryptocurrency Markets
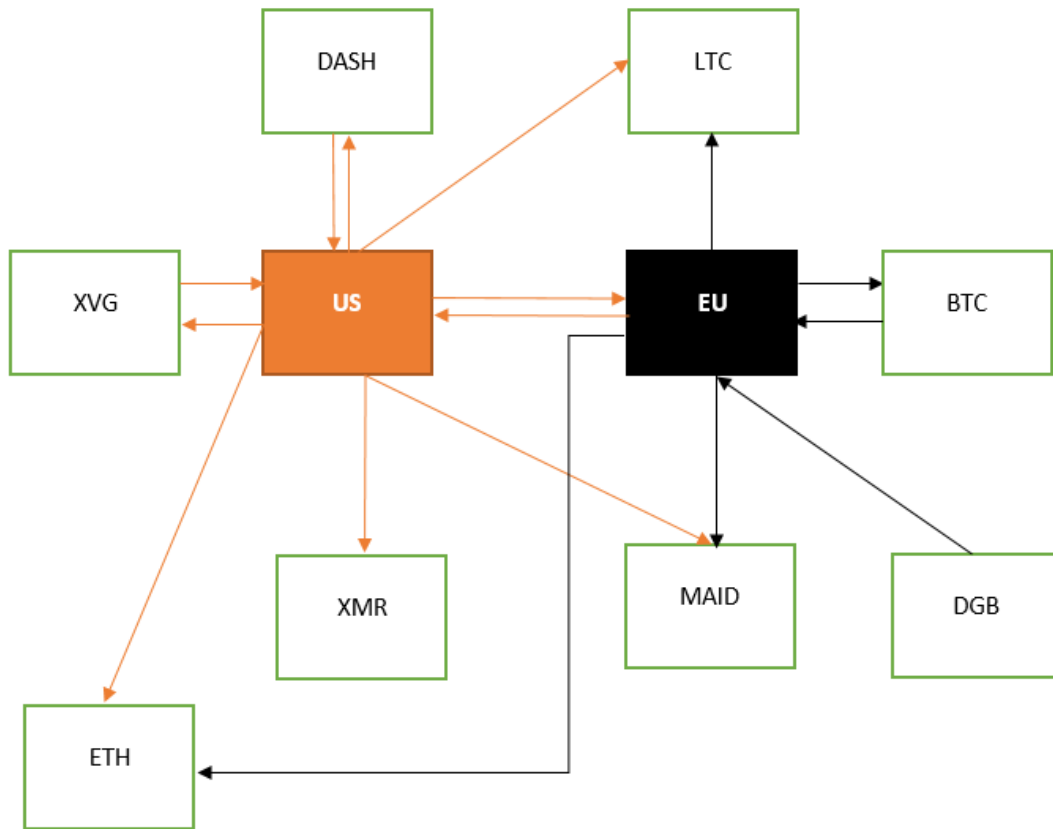
Note: Three coins have bilateral relationships whereas the remaining coins have a unilateral relationship to a specific crude oil market. The interconnectedness between US and European crude oil markets is one of the key factors enhancing causal relationships among the cryptocurrencies.

IV.V. What We have Learned from Transfer Entropy

We report empirical evidence on *'Transferring entropy'* process from the US and European crude oil markets to the cryptocurrency markets. We identify what particular types of coins are senders or receivers in the transmission process. Our analysis reveals that 8 of the 14 cryptocurrencies (over 50%) have a strong connection with crude oil returns. We also find that the European crude oil market seems to be a sender whereas the US crude oil market is likely to be a receiver. This conclusion is mainly based on the bilateral relationships of the Transfer Entropy process, as it is difficult to explain how many different cryptocurrencies have casual relationships with US and European crude oil markets. Nevertheless, our findings do indicate which coins have a directional impact and the exact relationships with crude oil markets. Applying an econophysics approach such as *Transferring Entropy* is one of the new methodological contributions in establishing the relationships between the crude oil and cryptocurrency markets.

There are already some oil-based cryptocurrencies in the exchange markets (such as Petro for Venezuela or Neft-coin for Russia). Hence, understanding the transfer entropy process is important to explain how the co-movements of these financial assets (crude oil and cryptocurrencies) work. For instance, the shocks in crude oil markets might cause a decline in oil-based coin and depreciate the oil-cryptocurrencies issued by the government. This could be considered a contagion effect on the linked markets.

Consistent with the findings of Guesmi et al. (2018) and Symitsi and Chalvatzis (2019), our results are crucial to investigate pairs of cryptocurrencies. We also argue that it is important to study the shocks from the US and European crude oil markets, as a number of countries have indicated their intention to develop their own cryptocurrencies (using the fundamental platform of Bitcoin, Ethereum and Litecoin). Examples of these new cryptocurrencies include Bilur Energy (UK), OilCoin and PetroDollar in the USA.

It is possible to draw the conclusion that ETH is the receiver from two markets. White et al. (2020) also consider that many investors consider ETH as record transactions. In addition, ETH should be known as the oil-based characteristics to run the operations of many other cryptocurrencies. Finally, it is evident that there is no bilateral relationship between ETH and the crude oil markets. Our paper, therefore, contributes to the evidence on contagion networks as well as the precise directions from the US-European oil to cryptocurrency markets. As expected, the fundamental cryptocurrencies (such as Bitcoin, Ethereum and Litcoin) have a strong relationship with the crude oil markets. Our paper is therefore a contribution to the embryonic literature on the linkage between cryptocurrency and crude oil markets.

IV.VI. Robustness check

In order to make our results robust and consistent, we employ another methodology, namely frequency connectedness, as proposed by Baruník and Kocenda (2019), to capture the interconnectedness as well as the spillover effect for significant Transfer Entropy values in Table 4 and Table 5. However, this method is based on balanced data; thus, we have the sub-sample from 2016 to 2019 for our variables. Two main conclusions can be drawn from the robustness check. First, our directional frequency interconnectedness is different from zero, which indicates the presence of a causal relationship in this sub-sample using a different methodology. Second, we also see from time to time increases in the connectedness among our variables.[7]

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[7] The results are available upon request.

V. Conclusion and Policy Implications

Fintech, smart contracts, and blockchain, cryptocurrencies are becoming one of the alternative investments. Researchers and policymakers are interested in understanding the determinants of their pricing mechanisms. Treating cryptocurrencies as another kind of monetary currency, we can observe the influence of crude oil markets on them. Cryptocurrencies are currently used as a source of innovation within the financial system, to integrate the methods of settling individual/corporate/government payments, and to anonymously transfer monetary funds. Our paper investigates the transmission channel measured by informational flows from the US and European crude oil markets to 14 different cryptocurrencies.

We found that over half of this sample of 14 cryptocurrencies are interconnected with the crude oil market (BTC (bilateral), LTC, ETH, XMR, DGB, DASH (bilateral), XVG (bilateral) and MAID). The US crude oil market is a receiver of informational flows from cryptocurrencies whereas the European crude oil is the sender in the transmission process. The features of these cryptocurrencies can be used to integrate them into a smart contract and create new coins for gasoline and crude oil trading.

Our results have important implications for investors and policymakers. *First*, by exploring the relationship between crude oil indices and crypto returns, investors may choose independent coins (XEM, DOGE, VTC, XLM, USDT, XRP) for their portfolios for diversification or hedging. In particular, investors can use these coins for hedging the movement of US or European crude oil movements, as their return is quite different from that of the oil indices. In other words, these coins can be added to portfolios which already contain a selection of crude oil indices. Many cryptocurrencies use digital platforms and, as a result, the trading mechanism and hedging process are likely to cost-effective and less time-consuming.

Second, for policymakers who intend to use the fundamental platform to establish petrol-coins, these findings will be very useful in understanding the dynamics and pricing mechanism of both assets. Understanding these directional movements, governments will be able to value their petrol coins and avoid the market risk or individual effects from these coins. Taking into consideration these risk factors, it is necessary for a country to use Bitcoin or Ethereum as its next-generation digital platform to build its own petrol coins, because the informational effects originating from these coins are strong.

Third, our paper adds to the theoretical literature on the economic valuation of cryptocurrencies, which is an emerging area of research in the energy literature. We apply valuation

models used in *Physics* and contribute to the empirical evidence in establishing the transmission mechanisms of the economic value of crude oil and digital currency. Our findings thus add to the cryptocurrency puzzle and we identify alternative avenues of investments in this relatively underdeveloped area of research.

Fourth, the time transfer calculated in our analysis supports the evidence in the literature that the cryptocurrency market is inefficient, which gives arbitrage opportunities to investors. However, it is advisable to consider the time discrepancy in implementing the most appropriate strategies for investors. Furthermore, US policymakers can also consider the implications of European shocks to make timely decisions to restrict or minimize the spillover effects.

However, our findings are subject to limitations. Our paper could not match the automatically measured information flows from crude oil markets to cryptocurrencies. With the development of machine learning and deep learning, we can overcome this gap by using reinforcement learning with different approaches to solving this puzzle. We, however, leave this to future studies. Furthermore, our study only focuses on two of the biggest crude oil types such as WTI and BRENT while there is a potential avenue for examining the relationship between crude oil markets and cryptocurrencies in the developing economies.

We do identify avenues for future research. As cryptocurrency is an emerging line of research and we are observing inefficiency in the trading process, it will be interesting to investigate investors' choices to use one cryptocurrency rather than another. Understanding this may not be possible using traditional economics and finance models, and hence we suggest a behavioural economic perspective in understanding investors' preferences in these complex new digital markets.

Appendix Robustness check

Appendix A.1. WTI Crude oil robustness check

Causality	Full sample	Frequency-connectedness
DCOILWTICO → LTC	0.0117* [0.0028]	0.74
DCOILWTICO → ETH	0.0268*** [0.0043]	0.01
DCOILWTICO → DASH	0.0171** [0.0032]	1.15
DASH → DCOILWTICO	0.0140* [0.0033]	0.01
DCOILWTICO → XMR	0.0136* [0.0032]	0.66
DCOILWTICO → XVG	0.0132* [0.0033]	13.83
XVG → DCOILWTICO	0.0184** [0.0035]	7.50
DCOILWTICO → MAID	0.0107* [0.0031]	2.68
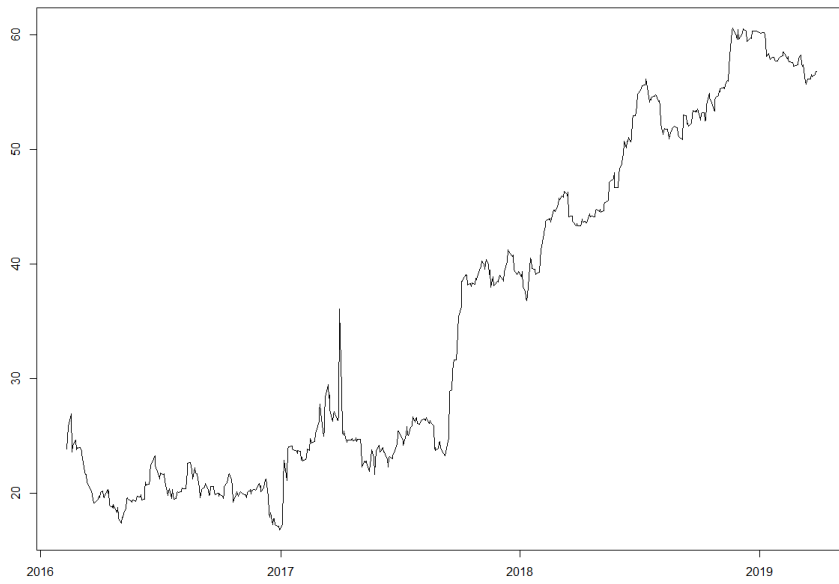
(a) WTI oil
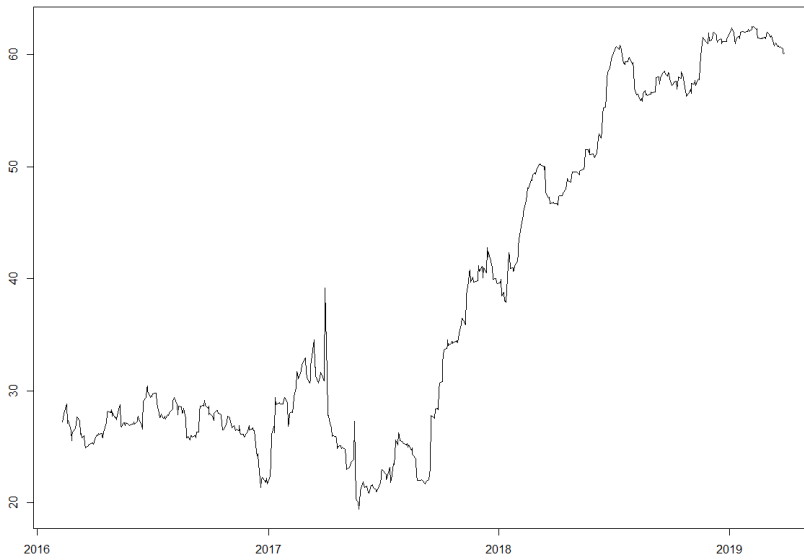
(b) BRENT oil

Figure A.1. The connectedness between cryptocurrency and crude oil markets

Appendix A.2. BRENT crude oil

Causality	Renyi Transfer Entropy	Frequency-connectedness
DCOILBRENTEU → BTC	0.0113* [0.0025]	0.01
BTC → DCOILBRENTEU	0.0106* [0.0026]	0.11
DCOILBRENTEU → LTC	0.0116* [0.0028]	0.09
DCOILBRENTEU → ETH	0.0177** [0.0041]	0.16
DCOILBRENTEU → XMR	0.0128* [0.0032]	0.11
DGB → DCOILBRENTEU	0.0152** [0.0031]	0.02
DCOILBRENTEU → MAID	0.0120* [0.0032]	0.02

Appendix A.3.

Information on the variable's full name

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)	Circulating Supply (unit)	Date of issue
BTC	Bitcoin	174,918,379,274	18,236,475	01st May 2013
LTC	Litecoin	4,769,521,120	64,159,150	01st May 2013
ETH	Ethereum	28,589,119,108	109,844,644	8th Aug 2015
XEM	NEM	21,240,638	8,999,999,999	3rd Apr 2015
DASH	Dash	938,226,050	9,344,247	15th Feb 2014
DOGE	Dogecoin	315,532,005	123,461,542,248	19th Dec 2013
XMR	Monero	1,398,868,850	17,458,076	21st May 2014
VTC	Vertcoin	16,413,384	53,593,747	20th Jan 2014
XVG	Verge	69,366,673	16,187,838,743	26th Oct 2014
DGB	DigiByte	84,789,677	12,859,912,607	07th Feb 2014
XLM	Stellar	1,370,120,659	20,205,010,713	05th Aug 2014
USDT	Tether	4,653,741,622	4,642,367,414	07th March 2015
MAID	MaidSafeCoin	43,986,645	452,552,412	28th Apr 2014
XRP	Ripple	11,642,567,056	43,749,413,421	07th Aug 2013

Note: Our database is updated to 25th February 2020 and retreived from coinmarketcap.com

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