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Are Energy Block Chain Currencies Affected by the Major US Energy Markets?

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ABSTRACT

While various economies have started to embark on a gradual shift towards renewable sources of energy, energy block chain based crypto currencies have emerged. The purpose of this study is to shed fresh light into whether an energy commodity price index (ENFX) and energy block chain based crypto price index (ENCX) can be used to predict movements in the energy commodity and energy crypto market. Using principal component analysis over daily data of crude oil, heating oil, natural gas, and energy based cryptos, the ENFX and ENCX indices are constructed, where ENFX (ENCX) represents 94% (88%) of variability in energy commodity (energy crypto) prices. Natural gas price movements were better explained by ENCX, and shared positive (negative) correlations with cryptos (crude oil and heating oil). Using a vector autoregressive model (VAR), while the 1-day lagged ENCX (ENFX) was significant in estimating current ENCX (ENFX) values, only the lagged ENCX was significant in estimating current ENFX values. Granger causality tests confirmed the two markets do not granger cause each other. One standard deviation shock in ENFX had a negative effect on ENCX, and one standard deviation shock in ENCX left ENFX unaffected. Both indices had 1 structural break on different dates. Overall findings suggest that while the ENFX and ENCX are good representative of commodity energy prices and energy block chain based cryptos respectively, the two markets are not robust determinants of each other.

Keywords: Energy Crypto Currencies, Energy Commodity, Vector Autoregressive, Impulse Response, Structural Break
JEL Classifications: Q02, Q41, Q42, Q47

1. INTRODUCTION

With daily volume well in excess of 1 billion dollars, the two most liquid crypto currencies as of 2018, Bitcoin (BTC) and Ethereum (ETH), have already penetrated the US futures markets by offering futures contracts to investors (Coindesk, 2018a). Ripple (XRP), one of the top 5 leading crypto currencies has also been witnessing some increase in futures trading volume since early 2018 (Coindesk, 2018b). To promote transparency, derivatives providers such as Chicago Mercantile Exchange (CME) group are already working on daily benchmarked dollar prices for cryptos like ETH (Coindesk, 2018c). While the banking industry is leading in terms of investments made in block chain technology, other industries such as retailing, healthcare, manufacturing and energy are poised for actions with implementations of block chain technologies. The global energy sector itself is currently worth over 2 trillion US dollars (Cryptoverze, 2018) with the International Data Corporation (IDC) forecasting strong, double digit growth in the energy sector during 2016–2021. The biggest benefits of adopting block chain technologies are in terms of time, cost and risk savings (IBM, 2017). For instance, countries such as Moldova, which imports more than 75% of its energy, will benefit from solar energy, through a crypto currency called solar coin. This would potentially reduce the reliance on imported fossil fuels such as natural gas and oil from Russia, with consumers also benefiting from lower prices (Tabary, 2018). Through the use of smart contracts and cryptocurrencies, nearly 15% of German firms have adopted block chain technologies in the nation's energy sector

(Witsch and Coester, 2018). Various start-ups in the energy sector have raised nearly $325 million in 2017 to implement block chain to energy related projects (Lacey, 2017). These projects range from facilitating peer to peer dealings without the need of a central utility or retailed based energy provider, to tracking low carbon impact energy production. While block chain aims to introduce decentralized energy trading in various energy sectors like the electric power sector, such sectors are mostly regulated in many countries. Nonetheless, policy makers have started to tap into regulatory guidelines to gradually allow for the implementation of block chain technologies.

Key to the rationale behind this study, there is a need to understand how the energy industry is changing and the role block chain is or would play. EIA (2018) forecasts the electric power sector to consume more energy than any other sectors, with renewable energy consumption growth being the fastest among other fuels. Natural gas consumption, is however, also expected to increase due to growth in the industrial sector, particularly for industrial heat and power, and liquefied natural gas produce. While natural gas production is expected to account for nearly 40% of U.S energy production by 2050, solar and wind power generation leads the growth among other renewables. Gradually, traditional centralized power plants run by fossil fuels are facing competition with distributed power generation like micro turbines and solar panels. With various climate conscious governments which are subsidizing clean energies, complemented with falling solar and wind power costs, renewable energy sources are expected to provide over ten per cent of global electricity supply over 2017–2022 (EIA, 2017). Despite the majority of renewable energies being deployable on large scale, solar energy is and has already been adopted on a smaller scale, where customers are managing their energy consumption through distributed energy resources. In 2016, firms have internationally spent nearly $50 billion in upgrading the existing digital electric power systems. Many established utilities in the electricity sector like E.ON in Germany have already embraced the potential benefits of block chain (Burger et al., 2016). In fact, utility related projects rank second in terms of the block chain ventures (Livingston et al., 2018). Enerchain, a utility based project using block chain, is expected to sell gas and electricity among 45 companies within Europe by the end of 2018 (Witsch and Coester, 2018).

With some of these firms are either involved in the wholesale production or distribution grids operations, the impact of these block chain related projects can be significant in the electricity market. For instance, 4New, an energy producer, has been the first company using waste to generate electricity to implement a block chain system (Keane, 2018). Other markets such as oil are also witnessing block chain related projects such as Toyota and Intel Hyper ledger, and Shell partnership with Energy Web Foundation (Gratzke et al., 2017). US retail giants like Walmart have recently been awarded a patent to develop an electric grid which will be powered by various crypto currencies (Alexandre, 2018). The block chained energy projects, being tokenized through energy crypto currencies, connect the customer or investor to renewable energy market, where the latter gradually disconnect dependence on non-renewable energy sources or fossil fuel markets. While there is big potential for time, cost and risk savings from the use of innovative systems, there are currently some issues with crypto currencies. For instance, in Canada, crypto miners have been consuming so much energy with their mining processes that the government had to stepped in and stop further requests of power from these entities (Meyer, 2018). To avoid potential rate increases of energy supply, in a decentralized environment where the price would be determined by the forces of demand and supply, governments like Australia and the UK have already signed on developing initial guidelines for applications related to energy related block chains (Metalitsa, 2018).

Based on the above, with fossil fuel becoming relatively less consumed as we move towards a more decentralized, cleaner, cheaper, and block chain backed technology, it is important to assess if leading fossil fuels such as heating oil, crude oil and natural gas prices are impacted by the leading energy crypto currencies or vice versa. These energy markets are specifically of importance since US is the number one consumer and producer of crude oil and natural gas. Heating oil is added as another fossil fuel, where the three shared strong correlations among their total reportable positions as reported by Gurrib (2018a). The relationship between these leading energy markets and energy crypto currency prices is yet to be done. A principal component analysis (PCA) framework is used in this study to create an index representing the leading energy futures markets and an index representing the energy cryptos. A vector autoregressive (VAR) model is used to analyze any potential relationship between the energy crypto prices and the leading fossil fuel prices. Impulse responses and structural breaks tests are added to boost the quality of the study. The rest of the paper provides some literature reviews, data, research methodology, and the research findings. Some conclusive remarks follow.

2. LITERATURE REVIEW

With oil prices having lost more than two-thirds of their value during the 2014–2016 period, and with prices still roaming around forty percent of their 2011–2014 values, various oil-revenue dependent economies suffered noticeable declines in investment, consumption and economic growth (World Bank, 2018). Volatilities in oil prices leading to volatility in economic activity led various economies to implement more adequate fiscal and monetary policies, as well as reforms to reduce reliance on oil. Part of these reforms include energy subsidies. For instance, the International Energy Agency (IEA) estimated subsidies to fossil fuel consumption, globally, to have dropped by $50 billion to $260 billion (IEA, 2017). Oil and gas subsidies alone represented nearly $150 billion and represented 11% and 22% of global oil and gas consumption. However, while various countries including the G7's have pledged to remove inefficient fossil fuel subsidies which promotes wasteful consumption, the latter spent at least $100 billion on fossil fuels subsidization during 2016 (Chen, 2018). More importantly, part of the drop in fossil fuels subsidies was also due to the drop in international energy prices since 2014.

The need to understand the relationship between demand and supply characteristics across markets is critical since the main object of the study is to assess whether energy crypto currencies share any significant relationship with fossil fuel energy prices. While not focusing exclusively on commodity energy markets and energy block chain based crypto currencies, He et al. (2016) provides a good overview of the currency characteristics of bitcoin and commodities, after summarizing the findings of Redish (1993), Calomiris (1988) and Bordo (1981). In terms of economic demand factors, both the crypto currency and commodity markets can be used as a store of value, although the former is prone particularly to exchange rate risk and the latter to commodity price risk. Both can be used as a medium of exchange, although the crypto currency is still new to the global market place. While commodities have intrinsic values and can be used as units of account, cryptos have neither of these two features. In terms of the supply factors affecting both markets, both of them are decentralized in nature. The source of supply is private under cryptos, and both public and private under commodity markets. The cost of production is relatively high with cryptos due to the amount of electricity required in crypto mining, and also high in the commodity markets which require mining. For commodity energy markets, as discussed earlier, the cost is trending downwards due to cheaper energy renewables, while Yermack (2013) supports that the volatility in cryptos is usually much higher than most currency pairs.

Gurrib (2018b) looked at whether structural changes in leading crypto currencies prices were due to major macroeconomic news announcements in the US, UK and Europe, and found major news releases did not take place during specific structural break dates during the end of 2017. Similarly, while Gurrib and Kamalov (2017) reported a change in the return per unit of risk in both the natural gas and crude oil markets when comparing the pre and post 2008 crisis, Gurrib (2018a) found that an energy futures index based on leading fossil fuels like natural gas, crude oil and heating oil, was unable to predict leading stock market indices movements during the 2000 bubble. Aggarwal (1988) reported that volatility in futures markets increased over time and are not unescapably linked to volatility in other financial markets. Dwyer (2014) found that average monthly volatility in crypto currencies such as Bitcoin (BTC) was higher than gold and numerous currencies. Chuen, Guo and Wang (2018) examined the dynamic co-movement between a market based crypto index (CRIX) and traditional assets, and found low correlations with commodities like gold. While Elendner et al. (2016) analyzed the top ten cryptos based on their market value and found them to be weakly correlated, Trimborn and Härdle (2016) found the CRIX to be more representative of the market than Bitcoin (BTC). While some of these studies attempt to explore the crypto and external world in areas like news announcements, stock markets, energy futures markets, and crypto currency prices, they lacked in some key areas respectfully. For instance, Gurrib (2018b) study took into account only news which were release without other news being simultaneously released on the same day. This limits the scope of the findings in that whenever more than one news is released from different categories (say interest rates and unemployment), it's not used in the data sample. Although Gurrib (2018a) proposed an energy index based on leading fossil fuels to predict stock market movements, the author did not benchmark the model against individual commodity prices such as crude oil or natural gas. Studies like Elendner et al. (2016) and Trimborn and Härdle (2016) either looked only at the top 10 cryptos or whole market index, such that generalization for key sectors like energy within the crypto markets are not made. While Chuen, Guo and Wang (2018) found the CRIX, in an efficient frontier setup, to yield the highest return and risk, compared to oil which had the lowest return with a proportionally high risk level, the study did not benchmark the use of individual crypto currencies as opposed to the CRIX index in their portfolio analysis. More importantly, none of the studies mentioned looked specifically at the relationship fossil energy prices and specific crypto currencies based on energy related block chain projects.

This study bridges the gap in the existing literature on various grounds. First, it is the first, to test whether the leading fossil fuel prices are related with the energy crypto currency prices. It is expected that when crude oil and heating oil prices rise, this would allow, ceteris paribus, renewable energy based crypto prices to go up, by acting as substitutes, and vice versa. It would also shed further light as to whether natural gas price movements is better explained by an index based on fossil fuels like crude oil and heating oil, or one based on energy block chain cryptos, the rationale being that both natural gas and block chain technologies are expected to be used even more in the future, as we move away gradually from crude oil and adopt more decentralized systems. Since 2008, crude oil and natural gas prices have decoupled based on demand and supply factors. On one hand, the demand for oil to produce electricity has dropped massively, due to aged petroleum assets being gradually retired, lower natural gas prices, more efficient gas fired turbines and more consciousness on the environmental impact of the relatively high sulfur content of oil. On the other hand, despite growth in associated gas in US, where US is the world leader in natural gas production, strong supply from shale players like Marcellus/Utica has reduced the effect of associate gas growth on natural gas prices (Mchich, 2018).

Second, an index for the energy based crypto currencies is proposed for the first time in literature. Similar to the S&P 500 market index which informs how the top 500 companies in the US are performing relative to their market capitalizations, the proposed index would allow investors to better understand the performance of leading energy based cryptos. This would also help regulatory bodies, by providing further insights into whether the energy crypto currency market is affected by energy commodity prices like crude oil and natural gas, or vice versa. A VAR model is adopted to test the relationship between an energy prices index based on leading fossil fuels and an energy index based on energy crypto currencies. Third, this study sheds some light in terms of the response of energy currency prices to shocks in leading fossil fuels' prices, and vice versa. This allows some inference as to whether such shocks, have short or long term effects across the commodity and crypto currency markets. Lastly, but not least, the energy crypto currency index is tested for structural breaks. This provides some guidance on the relationship between structural breaks in the fossil fuel markets and crypto currency markets.

3. DATA

For the purpose of this study, energy spot prices are collected from the Federal Reserve Economic Database (FRED) which sources the data from the U.S. Energy Information Administration (EIA). The energy markets selected are the West Texas Intermediate (WTI) Crude Oil, European Brent Crude Oil, Henry Hub Natural Gas and No. 2 Heating Oil (New York Harbor). The energy crypto currencies selected are SunContract (SNC), Power Ledger (POWR), Energo Labs (TSL) and Energy Coin (ENRG). While there are other energy based cryptos like 4NEW, KWHCoin, Energi and Energi Mine, they were disregarded since they were first released only between June and August 2018. The daily data sample is set from 21st November 2017 to 10th September 2018. While the Chicago Mercantile Exchange (CME) allows electronic trading of energy contracts from Sunday to Friday, and pit trading is from Monday to Friday, the crypto market does not close its trading hours. Due to the relatively small sample size, to avoid loss of quality in the data analysis, all missing days with no trades from the commodity markets are filled with previous closing prices. The crypto currencies closing prices are collected from Coin Market Cap.

4. RESEARCH METHODOLOGY

A critical part of this study is related to the construction of the energy commodity index and energy block chain based crypto index. For brevity, Gurrib (2018a) provides a good overview of the use of PCA to construct an energy index based on the leading energy futures markets. The benefit of PCA is that it allows the transformation of correlated variables like crude oil and heating oil into uncorrelated series dubbed principal components. While all principal components are uncorrelated, the first principal component is linear and captures the highest data variability. Due to the volatility inherent in the energy commodity and crypto markets, the principal component values are demeaned and normalized by their respective standard deviations. This standardization process is also observed in Cardarelli et al. (2011) and Nelson & Perli (2007). The energy commodity index is constructed using the crude oil, heating oil and natural gas spot prices, after ensuring they are strongly correlated. Similarly, the energy block chain based crypto index is constructed using energy crypto prices (SNC, POWR, TSL and ENRG).

Once the indices are constructed, the methodology then centers on first adopting a VAR model using the indices. A VAR model allows the possibility to capture any linear dependence among various time series, without necessitating theoretical knowledge on the forces linking the different endogenous variables, compared to other models like simultaneous equations. Once the model is specified, stationarity testing is performed using the Augmented Dickey Fuller (ADF) test. To remove redundant lags in the model, lags are optimized by minimizing various information selection criteria. Conventional diagnostic testing is performed to check for normality (Jarque-Bera normality test), serial correlation (Durbin Watson autocorrelation test) and heteroscedasticity in errors. The paper then moves to analyze shocks within the VAR system, by looking at the effect of 1 standard deviation change in the error terms of one index over the other. In line with Sims (1980) who strongly supported the use of unrestricted models, a VAR model framework is adopted in our study. The model is specified as follows:

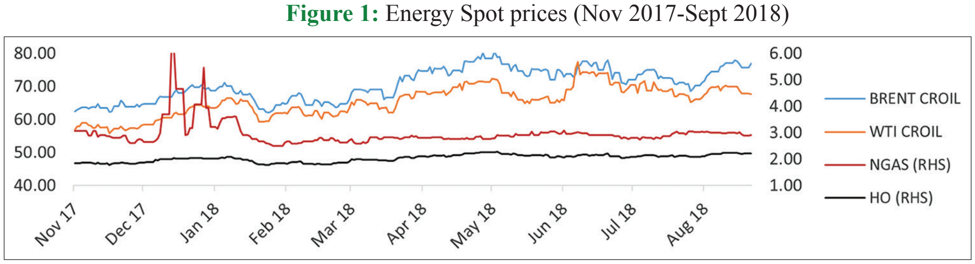
$$\begin{bmatrix} ENFX_t \\ ENCX_t \end{bmatrix} = \begin{bmatrix} \acute{a}_1 \\ \acute{a}_2 \end{bmatrix} + \begin{bmatrix} ENFX_{t-1} \\ ENCX_{t-1} \end{bmatrix} \begin{bmatrix} \pi^1_{11}\pi^1_{12} \\ \pi^1_{21}\pi^1_{22} \end{bmatrix} + \ldots +$$
$$\begin{bmatrix} ENFX_{t-n} \\ ENCX_{t-n} \end{bmatrix} \begin{bmatrix} \pi^n_{11} & \cdots & \pi^n_{1x} \\ \pi^n_{x1} & \cdots & \pi^n_{xn} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (1)$$

Where $ENFX_t$ and $ENCX_t$ represent the energy commodity based index and the energy block chain based cryptos. α_1 and α_2 represent the intercepts in equation (1). $ENFX_{t-1}$ and $ENCX_{t-1}$ are 1 day lagged index values. Each dependent variable is a function of its own lagged variables, in addition to other lagged dependent variables, thereby allowing for only endogenous variables in the system. For example, $ENFX_{t-n}$ is the energy commodity based index lagged by n days. n is the number of lags after optimizing the lag structure. π's represent the coefficients of the independent variables. ε_{1t} and ε_{2t} are the error terms of the equations in the model. To avoid the possibility of spurious regressions, the ADF stationarity test is carried out, with the minimum Akaike Information Criteria (AIC) value selected to determine the number of lags as per Akaike (1973). This is in line with Trimborn and Härdle (2016) who recommended AIC when constructing the CRIX, compared to other information criteria like Schwarz Information Criteria (SIC) and Hannan-Quinn (HQ) since it uses the most information available by relying on likelihood.

5. RESEARCH FINDINGS

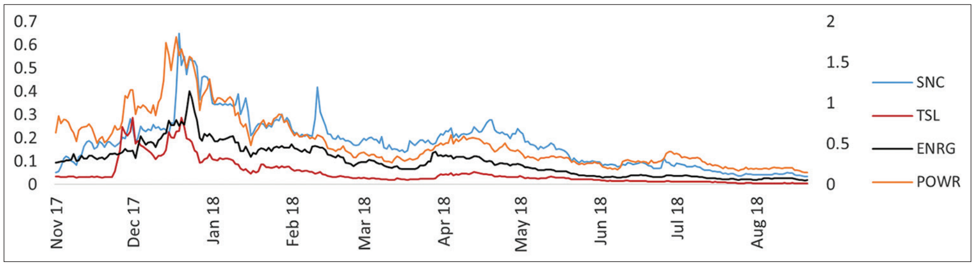
Descriptive statistics - While Figure 1 displays spot prices of crude oil (Brent and WTI), natural gas and heating oil during the period

Figure 1: Energy Spot prices (Nov 2017-Sept 2018)



BRENT CROIL and WTI CROIL represent the European crude oil and west Texas intermediate crude oil daily spot prices, in US dollars per barrel. NGAS represents the Henry Hub Natural Gas daily spot prices, in US dollars per million BTU. HO represents the No. 2 Heating Oil daily spot prices (New York harbor), in US dollars per gallon. NGAS and HO are displayed on the secondary vertical axis. Prices are sourced from the U.S. Energy Information Administration

Figure 2: Energy Cryptos prices (Nov 2017- Sept 2018)



SunContract (SNC), Power Ledger (POWR), Energo Labs (TSL) and Energy Coin (ENRG) represent four cryptos with block chain technologies in the energy sector. The daily closing prices are displayed over the period Nov 2017-September 2018. POWR prices are displayed on the secondary vertical axis. All prices are sourced from Coin Market Cap

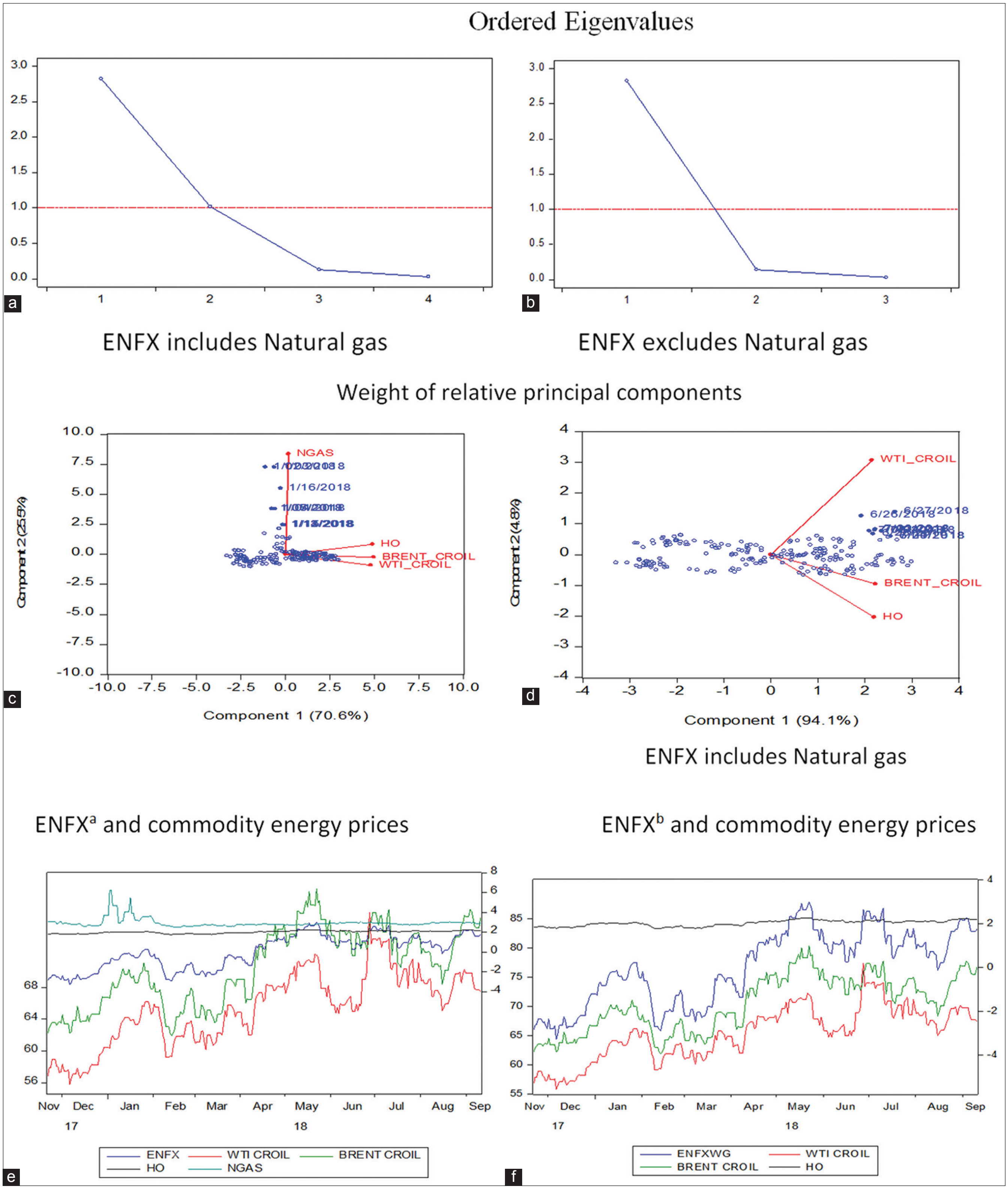
November 2017-September 2018, Figure 2 shows the performance of four energy based cryptos. As observed in Figures 1 and 2, the energy spot markets tend to move together, and the energy based cryptos tend to behave similarly, despite trading on different scales. At this stage, some noise is graphically noticeable around December 2017-January 2018 and April-May 2018 in both the commodity and crypto energy markets. In line with Figure 1, commodity prices were strongly positively correlated with each other, except for natural gas which shared very low correlations with the other energy commodity prices. In line with Figure 2, the energy cryptos were strongly positively correlated with each other, with correlations ranging between 0.72 and 0.9. Crude oil prices were and the energy cryptos were negatively correlated ranging from −0.31 to −0.52. This is consistent with Chen (2018) who found the crypto index CRIX to have low correlations with commodity like gold. While heating oil also shared a negative correlation with the cryptos ranging from −0.3 to −0.46, natural gas and the energy cryptos prices were positively correlated ranging from 0.28 to 0.53. POWR had the highest correlation value. The relatively positive correlation of natural gas with energy cryptos is in line with EIA (2018), where natural gas is in line to become 40% of U.S. total energy production by 2050, with consumption increasing in the industrial sector. The negative correlation between natural gas and crude oil can be explained by the events under the period of study, i.e., Nov 2017-Sept 2018. On one hand, in November 2017, OPEC and non-OPEC oil producers agreed to extend oil output cuts till the end of 2018, which led to an increase in the oil price. On the other hand, following the cold Winter 2018 in the US which led to higher prices during December 2017-January 2018, natural gas production hit new highs later in March which reduced the prices.

The crude oil market had the highest risk with standard deviation of 4.82 for Brent and 4.57 for WTI. This was followed by natural gas with 0.46. Heating oil had the lowest risk of 0.13. Comparatively, most of the energy cryptos had lower risk levels of 0.05 (TSL), 0.07 (ENRG) and 0.11 (SNC). The only exception was for POWR with a standard deviation of 0.34. While crude oil and heating oil were fairly skewed, all energy cryptos exhibited positive skewness. Natural gas had the highest positive skew of 4.19. All energy cryptos including natural gas had leptokurtic distributions, compared to crude oil and heating oil being platykurtic with negative excess kurtosis. All the distributions were not normally distributed with the Jarque-Bera test statistic reporting probabilities being close or equal to 0, with the exception of the WTI which was significant only at 1% level. The third and fourth moment of the distributions suggest that the energy cryptos and natural gas prices tend to behave in a similar fashion, while crude oil and heating oil tend to move together as energy commodities.

Figure 3 shows the scree plot of the ordered eigenvalues and the orthonormal loadings bi-plots of the principal components of commodity energy prices. Due to the relatively low correlation observed earlier between commodity energy prices and natural gas, the energy commodity index (ENFX) is constructed after analyzing the impact of the index on natural gas. The purpose of the index is to represent most of the variability in leading commodity energy prices. As observed and confirmed by the screen plots and loadings bi-plots in Figure 3, the ENFX without natural gas explains 94% of the variability among crude oil and heating oil, compared to 71% if natural gas is included in the index construction. An ENFX index based on natural gas as well as crude oil and heating oil, was found to be hardly correlated (0.03) with natural gas prices, while being strongly, positively correlated with WTI crude oil (0.95), Brent crude oil (0.98) and heating oil (0.97). When removed from the ENFX construction, the index was still strongly positively correlated with WTI crude oil (0.95), Brent (0.99), and heating oil (0.97). The relationship between natural gas and ENFX did not improve with a low correlation of 0.02. The commodity energy price index (ENFX) is more representative of variations in crude oil and heating oil prices as observed in the ENFX and commodity energy prices[b] graph.

Due to the positive correlations observed earlier between energy cryptos' and natural gas prices, complemented with the low significance of the natural gas component in the ENFX and other commodity energy prices, it is crucial to analyze if natural gas can be a potential candidate in the construction of the energy crypto index, on top of existing energy cryptos which already share positive relationships among themselves Figure 4 provides the results for the energy block chain based cryptos index (ENCX). For brevity, only the bi-plots of the 1st and 2nd principal components, and the relationship between the ENCX (with and without natural gas) and energy cryptos are provided below. As observed, the ENCX with exclusively energy crypto prices explains 88% of the variability among the energy cryptos, compared to 75% if ENCX takes into account natural gas during the construction process. While the later two graphs in Figure 4 show roughly the same ENCX, the correlation between energy cryptos and the energy crypto index, was still strong and positive, whether the ENCX

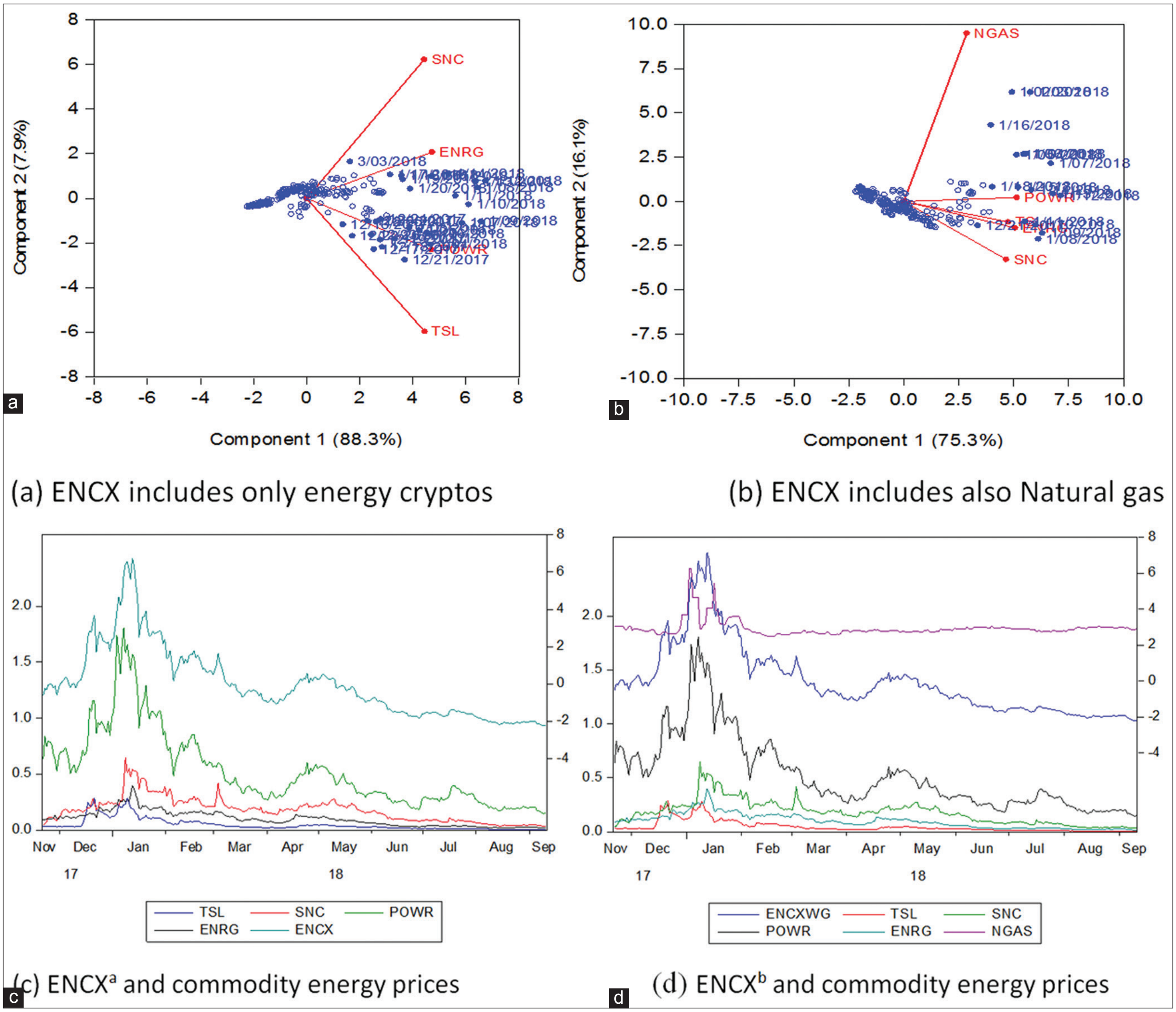
Figure 3: (a-f) Principal component analysis of the commodity energy price index (ENFX) ordered eigenvalues



ENFX represents the energy price index based on energy spot prices. BRENT CROIL and WTI CROIL represent the European Crude Oil and West Texas Intermediate Crude Oil daily spot prices, in US dollars per barrel. NGAS represents the Henry Hub Natural Gas daily spot prices, in US dollars per million BTU. HO represents the No. 2 Heating Oil daily spot prices (New York harbor), in US dollars per gallon. ENFXa represents the ENFX index based on crude oil, heating oil and natural gas. ENFXb represents the ENFX index based on crude oil and heating oil only

takes into account natural gas or not. An ENCX based purely on energy cryptos resulted in correlation values of 0.91 for both TSL and SNC, and 0.97 for both POWR and ENRG. An ENCX which includes also natural gas in its construction, had correlation values of 0.9 (TSL), 0.88 (SNC), 0.97 (POWR), 0.96 (ENRG), and 0.54 for natural gas. As expected, natural gas had a lower correlation

Figure 4: (a-d) Principal component analysis of the energy blockchain based crypto index (ENCX) weight of relative principal components



SunContract (SNC), Power Ledger (POWR), Energo Labs (TSL) and Energy Coin (ENRG) represent four cryptos with block chain technologies in the energy sector. The daily closing prices are displayed over the period Nov 2017-Sept 2018. ENCXa represents the ENCX index based on energy crypto prices only. ENCXb is based on energy crypto prices and natural gas

value (0.43) when using an energy crypto index based purely on energy crypto prices. Natural gas price movements are better explained by the energy crypto index than the energy commodity price index, which had correlation values of 0.02–0.03 relative to natural gas prices.

To ensure stationarity in the commodity energy price index (ENFX) and energy block chain based crypto price index (ENCX), the Augmented Dickey Fuller (ADF) stationarity test is carried out. Using both an intercept only, and an intercept with trend, both ENFX and ENCX were stationary after 1st order differencing, at 5% significance level. Due to the downward trend observed in the ENCX, caused primarily by dropping crypto currency prices, the ADF-GLS stationarity test is also adopted to de-trend the series (Elliott et al., 1996). ENCX was confirmed to be stationary after 1st order differencing. To optimize the lag structure in the VAR model, different information criteria models are compared including Akaike's Final Prediction Error (FPE), Akaike Information Criteria (AIC), Schwarz-Bayesian Information Criteria (BIC) and Hannan-Quinn (HQ) criteria. Lütkepohl (2005) provides a good comparison of these estimators. All the four information criterion unanimously point to an optimal lag order of one. The output from the VAR model is illustrated in Table 1 and equations (2) and (3). As observed in table 1, the 1-day lag value of ENFX (ENCX) was significant in estimating the current value of ENFX (ENCX). However, while the 1-day lag value of ENFX was significant in estimating current ENCX values, the 1-day value of ENCX, with a probability value of 0.855, was not significant in estimating current ENFX values. A 1% increase in the previous day ENFX index value is expected to change the current ENFX (ENCX) index value by 0.982% (−0.024%), while a 1% increase in the previous day ENCX index value is expected to change the current ENCX index value by 0.979%. Intercepts in both VAR equations were not significant at 5% level. Durbin-Watson statistics were close to two, suggesting no autocorrelation in the models. The removal of the insignificant 1-day ENCX coefficient in determining current ENFX values did not significantly affect the Durbin-Watson value. R-squared values stood at 0.9715 and 0.9726 in equations where ENFX and ENCX were dependent variables. Due to the relatively small impact of the lagged ENFX over ENCX, a Granger causality test is carried out. There was 16% probability that ENFX does not Granger cause ENCX, and 53% probability that ENCX does not granger cause ENFX. The latter result confirms the high p-value of 0.855 from Table 1 that the 1-day energy crypto index lagged values are not significant in estimating the current commodity energy price index value.

$$ENFX_t=0.016+20.982ENFX_{t-1}-0.002ENCX_{t-1} \quad (2)$$

$$ENCXt=-0.006+0.979ENCX_{t-1}-0.024ENFX_{t-1} \quad (3)$$

Before proceeding further, it is worth carrying out some diagnostic tests on the VAR model residuals. Extremely low probability values of the Jarque-Bera statistic point to the rejection that the residuals in the VAR model are normal. Lagrange Multiplier (LM) serial correlation test support the Durbin-Watson statistics, that the residuals are not serially correlated. Lastly, but not least, the Breusch-Pagan-Godfrey heteroscedasticity test supports residuals were homoscedastic at 5% level in equation (2), where ENFX was the dependent variable, but shows the presence of heteroscedasticity in the residuals in equation (3), where ENCX was the dependent variable. Although not reported here, this could be explained by the volatility observed in the ENCX residuals (equation 3) around the month of January 2018.

The last section of this study looks at the impulse response and stability diagnostic tests of the VAR model. The impulse response is important in that it helps to understand how the energy crypto index (ENCX) and the commodity energy price index (ENFX) respond to a shock to each other's variable. Figure 5 displays the response of ENCX to 1 standard deviation shock in ENFX and the response of ENFX to one standard deviation shock in ENCX. 95% confidence intervals are represented by the red dotted lines. As observed, ENFX had a small positive effect on the ENCX in the 1st day following 1 standard deviation shock to ENFX. Over the remaining 9 days, ENCX however dropped in a continuous fashion. This is in line with Table 1 which found the 1 day lag of ENFX to be significant in estimating ENCX. Conversely, a shock in the energy crypto index did not have a noticeable effect on ENFX in the first 10 days. This is in line with the earlier findings of Table 1 that the 1 day lagged ENCX was not a significant factor towards estimating the commodity energy price index.

Although some volatility spikes are noticeable in the ENCX residuals around January 2018, it is critical to statistically check for potential multiple breakpoint points. Using Bai-Perron breakpoint test, only 1 breakpoint date for ENCX (equation 3) was captured on the 13th January 2018. The Chow break test was applied and the low probability value of the F statistic supports a breakpoint on that date. This was also confirmed in Figure 6 where the cumulative sum of squares increased significantly in early January. For the commodity energy price index (ENFX) of equation (2), the same procedure was applied and the Bai-Perron test, Chow test and cumulative sum of squares point to a structural break on the 9th of April 2018. The different break dates reaffirm that the energy commodity and the energy block chain based crypto currencies are not witnessing the same shocks over the selected time period. For instance, the break in the energy commodity price index is due mostly to news related to crude oil inventories news release.

6. CONCLUSION

With a relatively thin literature on crypto currencies and commodity markets, and an even thinner or non-existent one on energy block chain based cryptos and traditional fossil fuels, this paper proposes two indices using PCA. While the commodity energy price index (ENFX) captured more than 90% of variation in crude oil and heating oil prices, the energy block chain based energy crypto price index (ENCX) captured nearly 90% of variation in the energy cryptos and natural gas. This was explained

Table 1: VAR model

Dependent variable	Independent variables	Coefficient	t-statistic	Probability	Durbin-Watson
ENFX	ENFX (lagged by 1 day)	0.982	90.060	0.000	1.821
	ENCX (lagged by one day)	−0.002	−0.183	0.855	
ENCX	ENFX (lagged by 1 day)	−0.024	−1.954	0.051	1.945
	ENCX (lagged by one day)	0.979	91.185	0.000	

ENFX represents the commodity energy price index. ENCX represents the energy block chain crypto price index. ENFX includes crude oil (WTI and Brent) and heating oil as constituents. ENCX includes energy crypto prices and natural gas as constituents of the index. Numbers in italic are significant at 5% level

Figure 5: (a and b) Response of ENFX and ENCX to 1 standard deviation shock

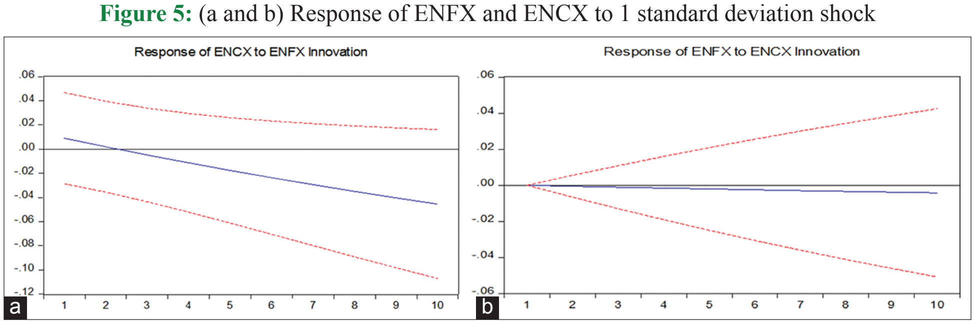
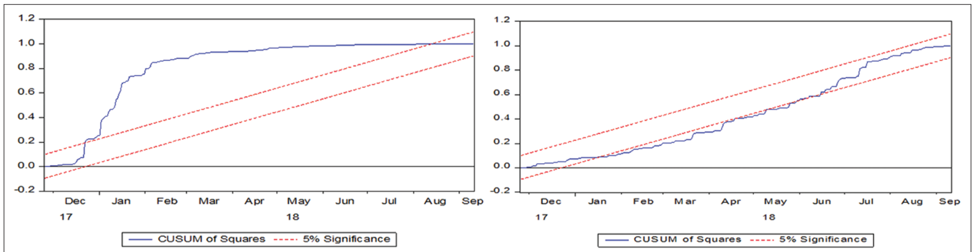


Figure 6: Recursive estimates



(a) ENCX (b) ENFX

by the decoupling between natural gas and crude oil as observed by the negative correlation of natural gas with crude oil and heating oil, and the positive correlation between energy cryptos and natural gas. Using a VAR model, 1 day lagged value of ENFX (ENCX) had a significant positive effect in estimating the current ENFX (ENCX) value. While 1 day lagged values of ENFX had a small negative, yet statistically significant in estimating current ENCX values, 1 day lagged values of ENCX were not significant in estimating current ENFX values. A granger causality test confirms both ENFX and ENCX are not significantly granger causing each other. An 1 standard deviation shock in ENFX caused ENCX to increase over 1 day and then drop over the next ten 10 days, while ENFX did not respond to a shock in ENCX.

Lastly, but not least, different structural breaks dates observed for each of the index suggests the two markets are not affected by the same events. This study shed light into energy block chain based cryptos and their relationships with energy commodity markets where various governments are moving towards cheaper, cleaner sources of energy. The weak relationship between the two energy markets provides policy makers some guidance into what matters most for future crypto currency regulation. With natural gas and energy cryptos being prone to be a significant part of the commodity industry and block chain industry, and with the gradual shift away from crude oil, a future research avenue could tap into analyzing how US and the rest of the world can benefit from natural gas being priced in a decentralized way using block chain technology.

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