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Technical Analysis, Energy Cryptos and Energy Equity Markets

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ABSTRACT

This paper principally assesses the use of technical trading strategies in forecasting both leading US energy equity prices and cryptos. Specifically, both Fibonacci and crossover strategies are integrated in a trading system. Both Sharpe and Sharpe per trade are used as performance measures, including benchmarking our model with the traditional buy-and-hold model. Leading market-capitalized weighted energy stocks from the S&P Composite 1500 Energy Index are used, with daily energy equity prices over the period 2017-2020. Findings suggest that the widely used Fibonacci tool tracks price movements of energy stocks better than for energy cryptocurrencies. Moreover, the technical analysis indicator tends to capture falling prices during bullish episodes better than rising prices during bearish ones. Although a Fibonacci coupled with a crossover strategy results in a superior model than the buy-and-hold, performance measures including Sharpe values were low, suggesting more factors such as macroeconomic variables can be included to enhance the model performance.

Keywords: Energy Markets, Technical Analysis, Trading Performance
JEL Classifications: Q47, G15, G17

1. INTRODUCTION

Energy policy, energy cryptocurrencies and renewable energies are key terms which are making the headlines internationally, especially in the US which has a market which has usually been coupled with GDP of the nation. In early 2016, the International Energy Agency (IEA) found that greenhouse gas emissions globally (GHG) did not change significantly in prior years despite GDP maintaining its growth at 3% per annum (IEA 2015, 2016). While this appears promising, towards controlling global temperature levels (Chemnick, 2016), this period also witnessed oil prices losing more than 67% of their value during 2014-2016. With prices still fluctuating around 45% of their 2011-2014 values, several oil-revenue dependent economies endured sizeable declines in economic growth. (World Bank, 2018).

These energy price volatilities resulted in economic activity disturbances which led several economies to adopt more adequate policies, which including diversifying away from oil revenue. This led to investors being further cautious when making investment decisions related to commodity and equity markets, which are led by oil price fluctuations. Although globalized markets lead to cross-market interdependence, such relationships are not straightforward. Gurrib (2019) finds that energy commodity price and energy block chain-based cryptocurrency price indices are not robust predictors in energy markets. In the same vein, while Gurrib and Kamalov (2019) report a change in the Sharpe for both natural gas and crude oil markets when comparing pre- and post- 2008 periods, Gurrib (2018a) finds that an energy futures index based on leading fossil fuels was unable to forecast leading stock market indices movements during the 2000 technology bubble. Similarly, Gupta et al. (2017) find that volatility in futures markets increase over time and are not unavoidably linked to volatility in other markets. Gurrib et al. (2021) study the impact of COVID-19 on oil price volatility on the Italian market and find a significant but temporary effect of the short selling ban.

Energy markets are also developing with EIA (2018) predicting the electric power sector to consume more energy than any other sectors, with renewable energy consumption growth being the fastest. Consumption of natural gas is also expected to swell due to industrial sector growth. While natural gas is projected to account for nearly forty percent of US energy production by 2050, wind and solar power generation leads the growth among other renewables. Increasingly, fossil fueled power plants are facing competition with distributed power generation. More governments, being conscious on climate change, are subsidizing cleaner energies. Renewable energy sources are expected to provide over 10% of global electricity supply over 2017-2022 due to falling solar and wind power costs of production (EIA, 2018).

Although there is evidence of the success of different trading models across markets such as cryptocurrencies, currencies markets, equity and bond markets (Nadaraja and Chu (2017); Shynkevich (2016, 2012); and Neely et al. (2014)), uncertainty results in tougher decisions for the investor or trader harder, especially when deciding among technical analysis and fundamental analysis tools. Seminal work on the effectiveness of technical analysis can be traced back to Fama (1970) and Ball (1978) where the first study supports the efficient market hypothesis that current market prices reflect all available information, such that reliance on such information would be unprofitable or result in a positive return that is accompanied by an unacceptable risk level. The second study found market timing-based strategies result in negative returns, after adjusting for transaction costs. Park and Irwin (2010), who support that technical analysis trading rules were not profitable for U.S. based futures markets, supported findings of Fama and Ball. Comparatively, Pruitt and White (1988) find their technical based system, which includes variables such as volume, RSI and moving average, to outperform the market after adjusting for transactions costs. In the same line of thought, Menkhoff (2010) finds most fund managers in five countries use technical analysis. In support of technical trading, Szakmary, Shen and Sharma (2010) find profitable trend following strategies in commodity futures markets and Tsaih et al. (1998) find their trading-based system to outperform a traditional buy and hold model in the S&P500 stock index futures market. Wong et al. (2003) find the use of RSI and moving average to yield significant positive returns in the Singapore Stock Exchange. Neely et al. (2009) find that both market conditions and profitability, upon using technical analysis techniques, evolves with time. This is supported by Gurrib (2018b) who looks at the performance of the Average Directional Index as a market timing tool for the most actively traded US based currency pairs and finds weekly trading horizons to be more profitable than monthly ones. Beyaz et al. (2018) analyze companies using both technical analysis and fundamental tools and find differences in the performance using either analytical tools were less pronounced for energy stocks, and combining both techniques improved forecasts of stock prices performance. Loginov et al. (2015) compare the use of Fibonacci retracements with moving averages and pivot points and report Fibonacci retracements to yield better results in the foreign currency markets. To our knowledge, we are the first study to analyze whether Fibonacci retracement complemented with a price crossover strategy can result in superior trade performance.

Our main contribution is centered on the analysis of leading energy stocks using technical analysis. Findings allow us to shed some light into whether there are some cohesions in the performance of energy companies, using tools like Fibonacci retracements and price crossovers. This paper contributes further to existing literature by comparing results from a Fibonacci retracement with crossover trading system with a buy-and-hold model and help in answering whether Fibonacci retracements as a technical analysis tool is a reliable indicator. Both the Sharpe and Sharpe per trade are included as performance measures to inform us if energy equity prices are better predicted by applying technical analysis or buy and hold strategies. Policy implications are laid out in terms of whether disruptions in commodity prices affect the profit potentials of techniques used by traders or more specifically speculators in energy financial trading.

The rest of the paper provides some literature review on the performance measure used, some descriptive statistics on the data, the methodology applied to set the trading system, research findings, before ending with some conclusive remarks.

2. LITERATURE REVIEW

Literature on the use of technical analysis in well-established. Smith et al. (2016) report that twenty percent of hedge funds used technical analysis; Gencay (1999) report profits in foreign currency markets with Olson (2004) adding further that risk adjusted trading rule profits decline over time; Brock et al. (1992) support that technical trading provided significant forecasting, over a 90-year period, for the Dow Jones Industrial Average (DJIA); Psaradellis et al. (2019) apply over 7000 trading rules and find only interim market inefficiencies in the crude oil futures market. The latter study is also backed by proponents of the adaptive market hypothesis like Lo (2017) and Urquhart et al. (2015) who support that investors and markets adapt, such that technical trading rules lose their predictive power over time. In the same vein, Fafula and Drelczuk (2015) use Ichimoku trends and find buying recent winners is ineffective.

Financialization of crude oil increased the interest for professional crude oil futures traders (Zhang, 2017; Creti and Nguyen, 2015). Although there is scarce evidence regarding energy stocks and technical analysis, the relationship between energy futures markets and technical analysis acts as a crucial point to understand relationships between technical analysis and energy stocks. Marshall et al (2008b) use 7000 rules on major commodity futures and find only few profitable strategies, after adjusting for data snooping. Comparatively, Szakmary et al (2010) and Narayan et al. (2013) confirm positive returns for commodity futures markets upon using moving averages. Narayan et al. (2014) find significant profits with momentum-based trading strategies in commodity futures. While Narayan et al. (2013) find that commodity futures, including oil, can predict commodity spot returns, Gurrib (2018a) supports that an energy futures index is not a reliable predictor of major stock market indices, suggesting other factors like uncertainty can drive price volatility.

More recently, Czudaj (2019) analyses crude oil futures prices and finds that the reaction to uncertainty varies significantly across different frequencies. While high frequencies have a very brief reaction to uncertainty, lower frequencies display a more persistent reaction to uncertainty shocks. Moreover, Marshall et al. (2008a) find investors to rely more on technical analysis for short term forecasting and also provide more emphasis to technical indicators using intraday trading horizons. To validate the use of the Fibonacci retracement tool to generate returns, our study further contributes to the literature by comparing the results of the tool with a naïve strategy, and further tap into whether combining the Fibonacci retracement with a price cross over strategy improves the occurrence of profitable trades.

Prices of financial products increase, decrease, pause for consolidation, seldom retrace, before continuing to trend upwards. The performance of the S&P500 market index is a good example showing two major global crises in 2000 and 2008, before resuming its uptrend move over the 1990 to 2020 period. Many practitioners believe that these retracements can be laudably predicted by various Fibonacci series arguments (Posamentier and Lehmann, 2007). The use of Fibonacci can be found in automated trading systems such as harmonic trading, which uses Fibonacci numbers and specific harmonic price patterns to define high probable reversals. Such patterns are identified, and positions are taken assuming that the past with replicate itself. Hurst (1973) reports that the periods of neighboring waves in price movements have the tendency to be related by a small whole number, explained by Fibonacci retracement levels. While harmonic price patterns, which are based on the Elliott wave theory (Elliott, 1935), and Fibonacci are conceptually similar, both assuming correction of prices at some point, the Fibonacci tool requires specific retracement levels which are aligned to the Fibonacci golden ratio or conjugate golden ratio. While the coverage of Fibonacci in the literature review is abundant (Bhattacharya and Kumar, 2006), the use of Fibonacci tool in the energy sector is rather scare.

Otake and Fallou (2013) analyze the use of the Fibonacci ratios in the African regional stock change and report its usefulness in predicting retracements, Lahutta (2016) finds similar effectiveness on Warsaw stock exchange. Gartley (1935) introduces the Gartley pattern where he posits that any retracement pattern must first be initiated with a 61.8% retracement (the conjugate golden ratio) and finds it to be one of the most profitable strategies for the stock market.

Lui and Mole (1998), after surveying Hong Kong foreign dealers, find that technical analysis is considered slightly more useful in forecasting trends than fundamental analysis, but significantly more useful in predicting turning points. More importantly, moving average (MA) and/or other trend-following systems are the most useful technical technique. Such tools are used widely because people adjust less by staying close to their anchors (here being the investment tools they used repeatedly) as proposed in Epley and Gilovich (2006), who confirm that adjustment to other techniques is indeed an effortful operation. While existing literature about the success of trend following systems is abundant, Hayes (2000) provide a good review of pioneer systems like the Dow Theory, which upon which today's Dow Jones Industrial Average is based.

The existence of technical analysis-based systems related to the moving average can be traced back to Tintner (1935) and Cowles (1933). Perhaps the most cited long-term measurement of trend among technical analysts is the 200-day MA. Spiegel (2013), using a percentage price oscillator approach with 1% up and down variation, testing the long run MA on the Dow Jones Industrial Average (DJIA) over the 1886-2006 period, and finds the market timing strategy to outperform a buy-and-hold strategy. Similar results were held for the Nasdaq Composite Index. Overall, the use of the MA technique resulted in annual excess return of 4% (adjusted for transaction costs) with 25% less volatility, when comparing the market timing and buy and hold strategies. Using a similar approach, Faber (2007) tested a 10-month MA for the S&P500 market index over the 1901-2012 period and finds the market timing strategy to outperform a buy-and-hold of the index in terms of risk and return performance measures. The use of the MA strategy had fewer instances of both large gains and large losses, with correspondingly higher occurrences of small gains and losses. Basically, the technical analysis tool signaled when an investor should be long a riskier asset class (equity) with upside potentials, and when to be out and sitting in cash (lower risk asset class). Alternatively stated, the MA strategy avoids the far-left tail of big losses while sacrificing the far-right tail of big gains.

The speed of the systems and the number of signals generated in crossover strategies depend on the length of the moving averages. Shorter moving average systems will be faster, generate more signals and be more prone for early entry. However, they will also generate more false signals than systems with longer moving averages. Gurrib (2016) proposes an optimized moving average strategy over the SPDR S&P500 exchange traded fund and finds the market timing strategy to outperform the buy-and-hold strategy over the 1993-2014 period.

To measure the performance of portfolios based on market timing techniques, performance measures such as Sharpe, M^2, Treynor, and Jensen's alpha are usually reported. In line with the development of performance measures, asset-pricing models were developed to explore which aspect of a portfolio should lead to lower or higher expected returns. For instance, the capital asset pricing model (CAPM) proposed by Sharpe (1964) suggests that relying on such a model assumes the portfolio is exposed to market risk. While Jensen's alpha (Jensen, 1968) is based on the difference between actual returns and expected return, it does not control firm specific risk which could be important for investors (Fama, 1972). Equally, Treynor's ratio proposed by Treynor (1965) looks only at the excess return per unit of systematic risk, similar to Jensen's alpha (Aragon and Ferson, 2006). The Sharpe ratio introduced in Sharpe (1966) captures excess return per unit of risk, where excess return is the difference between return and a risk-free rate, where the three-month US Treasury bill rate is used as a proxy.

3. DATA

Leading ten energy stocks are selected from the S&P Composite 1500 Energy Index, which tracks the performance of U.S. energy companies. Launched on December 31, 2005, the index has eighty-nine constituents with a maximum market capitalization value of $314,624 million and mean capitalization value of $14,677 million, as of 31st July 2019. The top ten stocks were selected based on their relative index weight to the index, and are specified in Table 1 as follows:

It is vital to note that the S&P Composite 1500 Energy index has been more volatile than the S&P500 market index and the S&P GSCI Natural Gas Index which provides investors with a benchmark of the natural gas market. The three market indices' performance can be observed in Figure 1. As noticed from late 2008, the natural gas market and crude oil market (represented by the S&P 1500 Energy index) decoupled, where on one hand, the demand for oil to produce electricity has plunged tremendously, 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, and 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 associated gas growth on natural gas prices (Mchich, 2018). Post 2008, the S&P 500 had a relatively good performance relatively to the S&P 1500 composite energy index. The volatility observed in the S&P Composite 1500 Energy Index makes the Fibonacci retracement tool, a conceivable indicator to be adopted, due to the assumption that volatility encompasses retracements and expansions. To allow for the current, as of January 2020, top ten energy stocks in the S&P Composite 1500 Energy Index to be analyzed, the period under study is set as 21st November 2017-17th January 2020. The annualized risk-free rate of 1.20% is based on the three-month US Treasury bill rate, which ranged from a minimum of 1.25% to 2.43% from November 2017-January 2020. The rate is sourced from the St Louis Federal Reserve (FRED) database. Energy stock prices are obtained from Factset, and energy crypto data sourced from Coinmarketcap.com

Table 1: Asset specification details

Company	Trading symbol	Sector	Industry	Sub industry
Exxon Mobil	XOM	Energy	Oil, Gas and Consumable Fuels	Oil and Gas Exploration and Production
Chevron Corp	CVX		Oil, Gas and Consumable Fuels	Integrated Oil and Gas
ConocoPhillips	COP		Oil, Gas and Consumable Fuels	Oil and Gas Exploration and Production
Schlumberger Ltd	SLB		Energy Equipment and Services	Oil and Gas Equipment and Services
EOG Resources	EOG		Oil, Gas and Consumable Fuels	Oil and Gas Exploration and Production
Occidental Petroleum	OXY		Oil, Gas and Consumable Fuels	Oil and Gas Exploration and Production
Marathon Petroleum Corp	MPC		Oil, Gas and Consumable Fuels	Oil and Gas Refining and Marketing
Phillips 66	PSX		Oil, Gas and Consumable Fuels	Oil and Gas Refining and Marketing
Anadarko Petroleum Corp	APC		Oil, Gas and Consumable Fuels	Oil and Gas Exploration and Production
Kinder Morgan Inc	KMI		Oil, Gas and Consumable Fuels	Oil and Gas Storage and Transportation

Source: Factset, S&P500 Dow Jones Indices

4. RESEARCH METHODOLOGY

4.1. Fibonacci Retracements

Fibonacci numbers form a sequence of integers which can be found in various entities ranging from nature (e.g. birth rates of rabbits) to mathematics (e.g. the Pascal triangle (Livio, 2008)). The *n*th Fibonacci number is structured as follows:

$$\theta_n=1, \text{ for } n=0,1$$

$$\theta_n=\theta_{n-1}+\theta_{n-2}, \text{ for } n\geq 2 \quad (1)$$

The Fibonacci recursive relationship model is based on the use of successive numbers from the Fibonacci series. Dividing both sides of equation (1) by θ_{n-1}, the following form is gathered:

$$\frac{\theta_n}{\theta_{n-1}}=1+\frac{\theta_{n-2}}{\theta_{n-1}} \quad (2)$$

As $n\rightarrow\infty, \frac{\theta_n}{\theta_{n-1}}\approx\frac{\theta_{n-1}}{\theta_{n-2}}$. Substituting $\frac{\theta_n}{\theta_{n-1}}$ as α, equation (2) is reduced to:

$$\lim_{n\rightarrow\infty} \pm=1+\frac{1}{\pm} \quad (3)$$

Solving for α from equation (3) for infinitely large values of *n*, the limiting value of the Fibonacci ratio can be found by solving for the roots of the polynomial $\alpha^2-\alpha-1$. The larger of two roots forms what is dubbed as the golden ratio value of 1.618, while the lower value of roots forms the golden ratio conjugate valued at 0.618. The relationship between the golden ratio value and the golden ratio conjugate value is that the golden ratio value is the reciprocal of the golden ratio conjugate value. Although not detailed further here for brevity, some important properties are (i) the golden ratio is equal to its own reciprocal plus 1 (continued fractions), (ii) the golden ratio is equal to its own square root plus 1 (nested radicals), most importantly, (iii) the golden ratio $\frac{\theta_n}{\theta_{n-1}}$ approaches the value of 1.618 as *n* increases, and (iv) the reciprocal of the golden ratio, i.e. $\frac{\theta_{n-1}}{\theta_n}$ approaches the value of 0.618 as *n* increases. Schneider (2016) provides a detailed overview of the different propositions underlying the Fibonacci sequence. The golden ratio and its variants has been applied in many ways in technical analysis, namely Fibonacci arcs, fans and projections. Due to the scope of this study, we focus predominantly on Fibonacci retracements. As reported in Schneider (2014), variations to the conjugate golden ratio lead to Fibonacci retracement levels, set as 23.6%, 38.2%, 61.8% and 78.6%, as are formulated as follows:

Figure 1: Performance of S&P 1500 Energy, S&P500, and natural gas

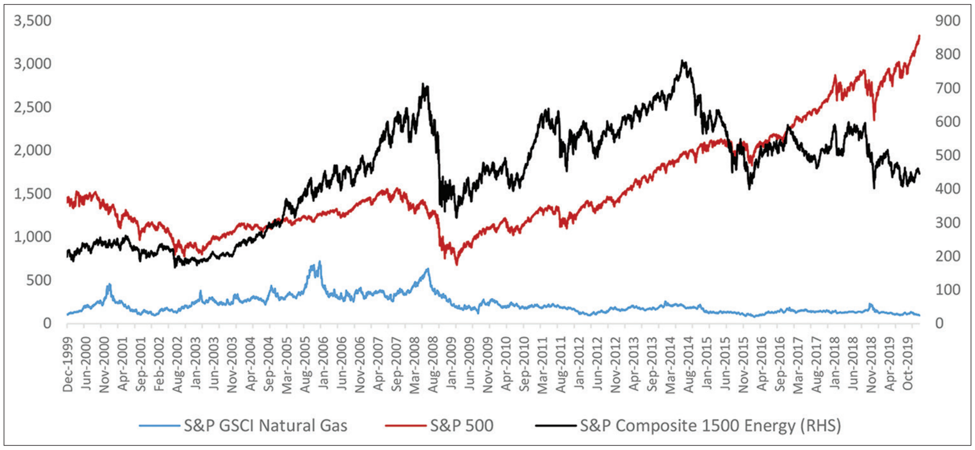


Figure 1 shows the performance of the S&P 500 market index, S&P Composite1500 Energy index and the S&P GSCI Natural gas, which is displayed on the right-hand side vertical axis. The data ranges from December 1999 to July 2019. Source: Factset, S&P500 Dow Jones Indices

Limits Retracement levels

$$\begin{pmatrix} \lim\limits_{n\to\infty} \dfrac{\theta_n}{\theta_{n+3}} & \lim\limits_{n\to\infty} \dfrac{\theta_n}{\theta_{n+2}} \\ \lim\limits_{n\to\infty} \dfrac{\theta_n}{\theta_{n+1}} & \lim\limits_{n\to\infty} \sqrt{\dfrac{\theta_n}{\theta_{n+1}}} \end{pmatrix} = \begin{pmatrix} 23.6\% & 38.2\% \\ 61.8\% & 78.6\% \end{pmatrix} \quad (4)$$

Nowakowski and Borowski (2005) provide in depth details about further retracements and expansion levels, all coming from variations in the conjugate golden ratio. As outlined in Kumar (2014), these levels are imposed onto a stock price chart, after a swing high and a swing low is identified over a specific time period. Another common retracement level used is 50%, which is in line with the Gann theory (see Gann, 1927, 1949) where prices are expected to normally retract by 50%. A swing high (low) occurs when the high (low) price reached is higher (lower) than a given number of highs (lows) positioned around it. When a swing high event is followed by a swing low event, the Fibonacci retracements levels can be used to act as support at the different levels, with the time period set between the two events. Similarly, when a swing low event is followed by a swing high event, the retracement levels can be used to act as resistance, with the time period set between the two events. The different corresponding stock and crypto prices relative to each retracement level are calculated as follows:

$$\text{Swing low price } + \begin{pmatrix} 23.6\% \\ 38.2\% \\ 50\% \\ 61.8\% \\ 78.6\% \end{pmatrix} |\Delta| \quad (5)$$

$$\text{Swing high price } - \begin{pmatrix} 23.6\% \\ 38.2\% \\ 50\% \\ 61.8\% \\ 78.6\% \end{pmatrix} |\Delta| \quad (6)$$

, where Δ is the absolute difference between the swing high price and swing low price. Initially, we take those swing prices to be where trends change direction. While equation (5) applies for support levels, equation (6) is applicable for resistance levels.

4.2. Price Crossover Strategy

In line with Gurrib (2016) who put together an optimized moving average strategy and Murphy (1999) who introduce double crossovers, a price crossover strategy is pursued. As with all moving averages, the general length of the moving average defines the timeframe for the system. A system using a 10-day Simple Moving Average (SMA) and 26-day SMA would be usually classified as short-term. Similarly, a trading rule using a 100-day SMA or 200-day SMA would be classified more as a medium-term or long-term strategy. A bullish price crossover occurs when the spot price crosses above the longer moving average and is referred as a golden cross. Conversely, a bearish crossover occurs when the spot price crosses below the longer moving average and is referred as a dead cross. For the scope of this study, a 50-day moving average is used. The price cross over trading strategy is set as follows:

$$\begin{pmatrix} \delta_{t-1} < SMA_{t-1}, \delta_t > SMA_t \\ \delta_{t-1} > SMA_{t-1}, \delta_t < SMA_t \end{pmatrix} \to \begin{pmatrix} Golden\,cross \\ Dead\,cross \end{pmatrix} \to \begin{pmatrix} Buying\ signal \\ Selling\ signal \end{pmatrix} \quad (7)$$

4.3. Setting up the Trading Strategy

Before testing whether Fibonacci retracements work in energy markets, it is crucial to find out whether there is in an uptrend or downtrend in motion. While different ways can be used tools to determine the existence of an up or downtrend, for the purpose of this study, we calculate the slope of a linear regression based on the daily closing prices. We chose a minimum of 50 days to allow the regression to capture enough movements in the energy prices, while not giving too many unreliable up or downtrends. An area of future research could consider validating the slopes over different regression periods.

5. RESEARCH FINDINGS

5.1. Descriptive Statistics

Figure 2 shows the daily closing stock prices for the select energy companies. 543 daily observations are obtained for each stock. As expected, their prices behaved mostly in the same fashion over the period November 2017 to January 2020. Correlation values ranged from -0.69 to 0.95 among the energy stocks. When excluding KMI, the correlation values ranged from 0.2 to 0.95. With values ranging from a minimum of $14.71 for KMI to a maximum of $133 for CVX, the average stock prices ranged also from a minimum of $18.53 for KMI to a maximum of $119.90 for CVX. While KMI had the smallest risk value with a standard deviation of $1.74, EOG had the highest risk with values of $16.65. Although half of energy stocks were negatively skewed with the remaining half (COP, SLB, MPC, PSX, VLO) exhibiting positive skew, the skewness values, all negative skewness values ranged between −0.5 and 0.5, suggesting fair symmetrical distributions. With the exception of CVX which had a kurtosis value of nearly zero, remaining energy stocks had platykurtic distributions with negative kurtosis values ranging from −0.56 for MPC to −1.52 for SLB. Although not reported here, correlation values among the energy cryptos were significantly positive, ranging from 0.79 to 0.94. The average prices ranged from $0.0189 for TSL to $0.3090 for GRID. Similarly, standard deviations were the smallest (highest) for TSL (GRID). Distributions of energy crypto prices were positively skewed and also were leptokurtic.

5.2. Trends in Energy Equity and Crypto Markets

Panel A of Figure 3 displays the relationship between different energy equity prices and their respective trends, and Panel B captures the relationship between different energy crypto prices with their trends. The gray areas represent periods with uptrends. White spaces in between represent downtrends. As observed from Panel A, the trends in the energy equity prices tend to be mostly in line with the ongoing prices. More importantly, trends tend to follow the same direction in most energy equity markets. For instance, between April 2018 and June 2018, all equity prices witnessed, on average, increases in an uptrend period. It is important to note that each slope is based on a 50-day period calculation. Comparatively, for the energy cryptos, the prices did not witness uptrends compared to energy stock prices. Other periods were also used in the slope value estimations, but results did not improve. The lack of uptrends can be explained due to the presence of more frequent downtrend in the energy crypto markets since late December 2017/ early January 2018, when crypto prices fell dramatically from their prior highs. While for energy stocks, uptrends and downtrend are easily noticeable, for energy cryptos, a downtrend scenario is assumed from December 2017 or early January, depending on the highs of each cryptocurrency around that time.

5.3. Fibonacci Retracements

In line with equations (5) and (6), the Fibonacci retracements are applied onto the energy stocks and energy crypto prices over the period November 2017 to January 2020. The swing high and swing low prices were initially taken as the prices where new uptrends/ downtrends would occur. However, this resulted in retracements ranges not capturing most of the price movements in the next trend in place. For example, Figure 4 shows how KMI retracement levels were not broad enough.

Consequently, equations (5) and (6) were updated where swing high (low) prices represent the highest (lowest) prices within a specific period, where prices are either trending upwards or downwards. For instance, if the previous period had an uptrend, the difference between the highest and lowest prices are selected during that uptrend. Figure 5 Panels A and B captures how the energy stock and energy crypto prices behave around the Fibonacci retracements levels. As observed in Figure 5, the Fibonacci tool tends to capture price movements of energy stocks relatively better than energy cryptos. Despite the higher volatility found in cryptos relative to energy stocks, the energy cryptos, like most major cryptos such as Bitcoin, Ethereum and Ripple, witnessed their highest peaks during Nov-Dec 2017, followed by a gradual fall subsequently. Comparatively, energy stocks fluctuated within more defined price ranges over the period

Figure 2: Leading US energy stocks (Nov 2017-Jan 2020)

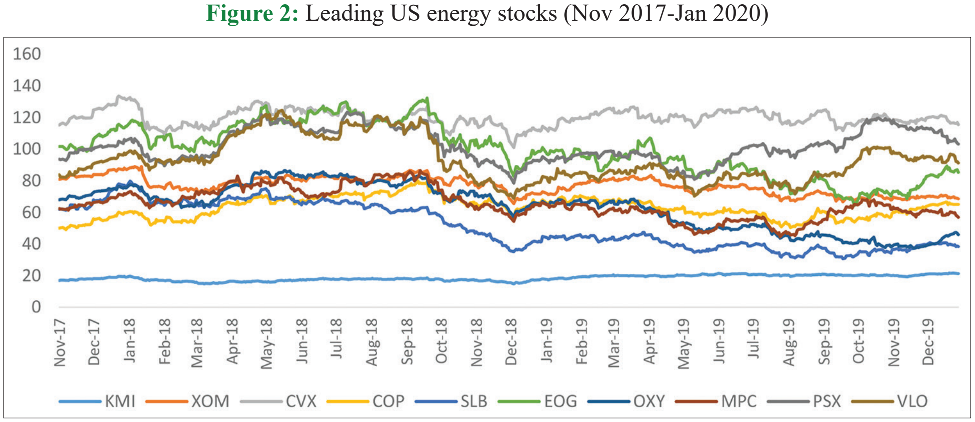


Figure 2 shows the daily stock prices, at close, for the ten energy companies, which are all listed as leading constituents under the S&P1500 Composite 1500 Energy index. The companies (trading symbols) include Exxon Mobil (XOM), Chevron Corp (CVX), ConocoPhillips (COP), Schlumberger Ltd (SLB), EOG Resources (EOG), Occidental Petroleum (OXY), Marathon Petroleum Corp (MPC), Phillips 66 (PSX), Valero Energy Corp (VLO) and Kinder Morgan Inc (KMI). Source: Factset, S&P500 Dow Jones Indices.

Figure 3: Leading US Energy Stocks prices and Trends (Nov 2017-Jan 2020)

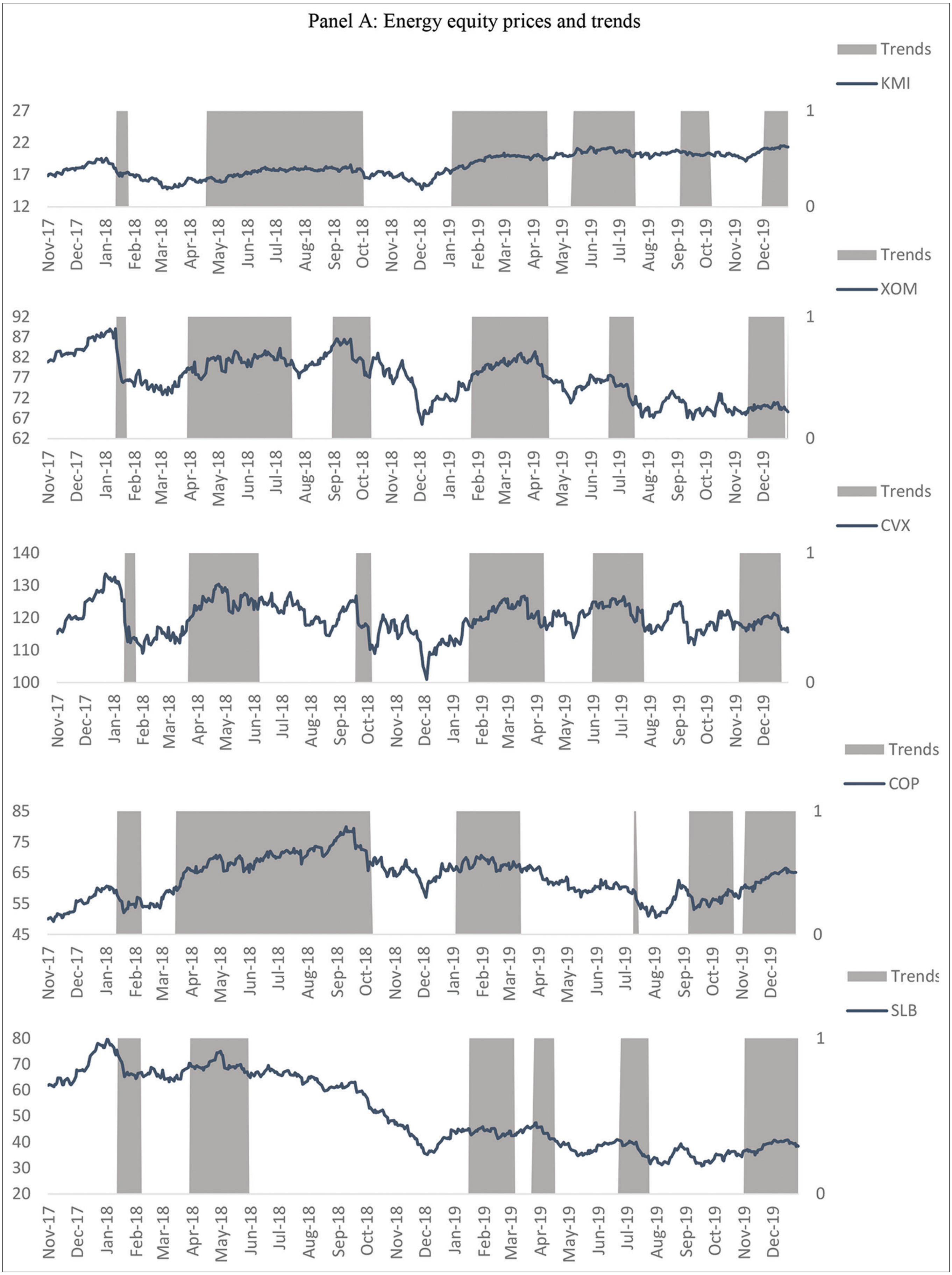


Figure 3: *(Continued)*

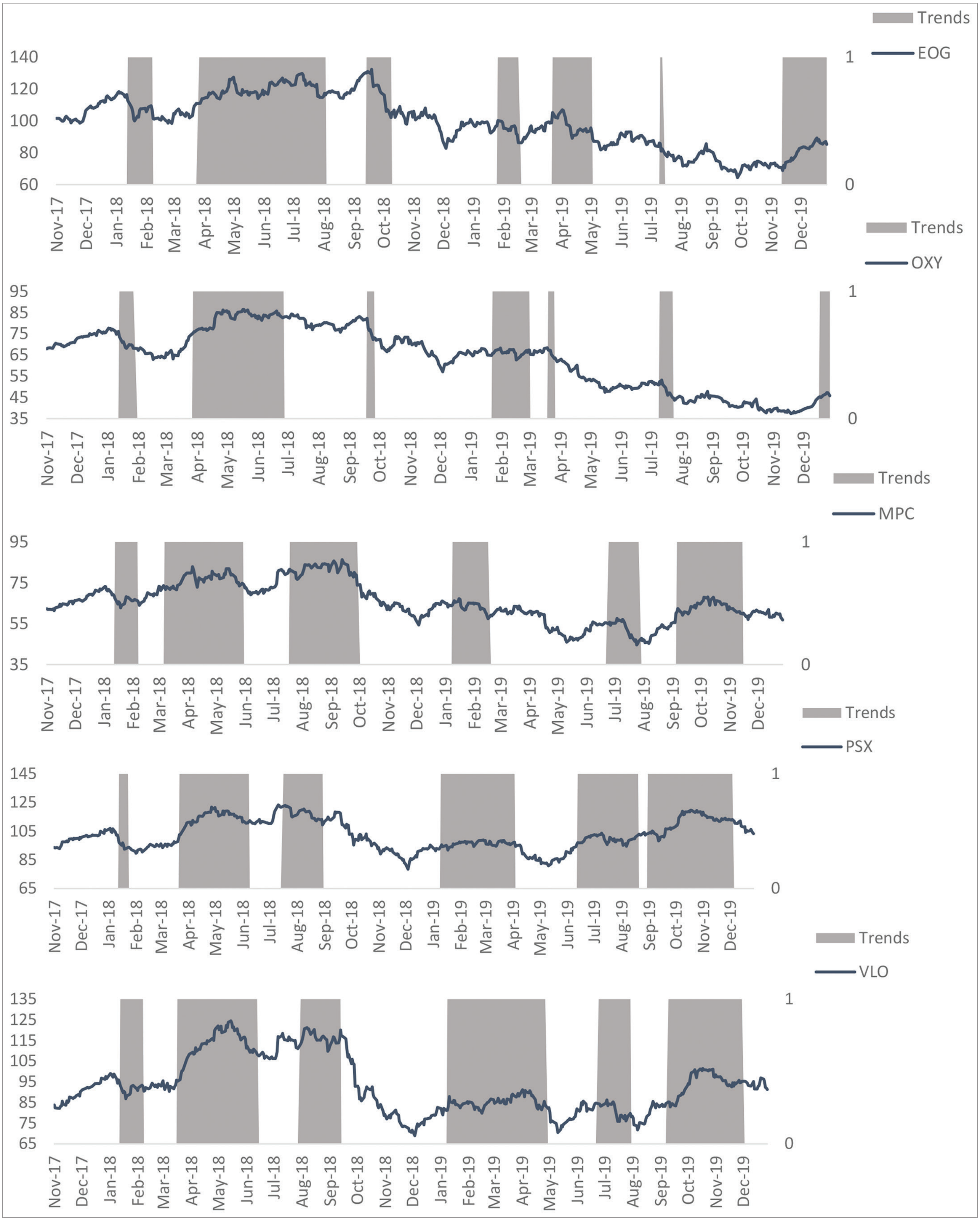
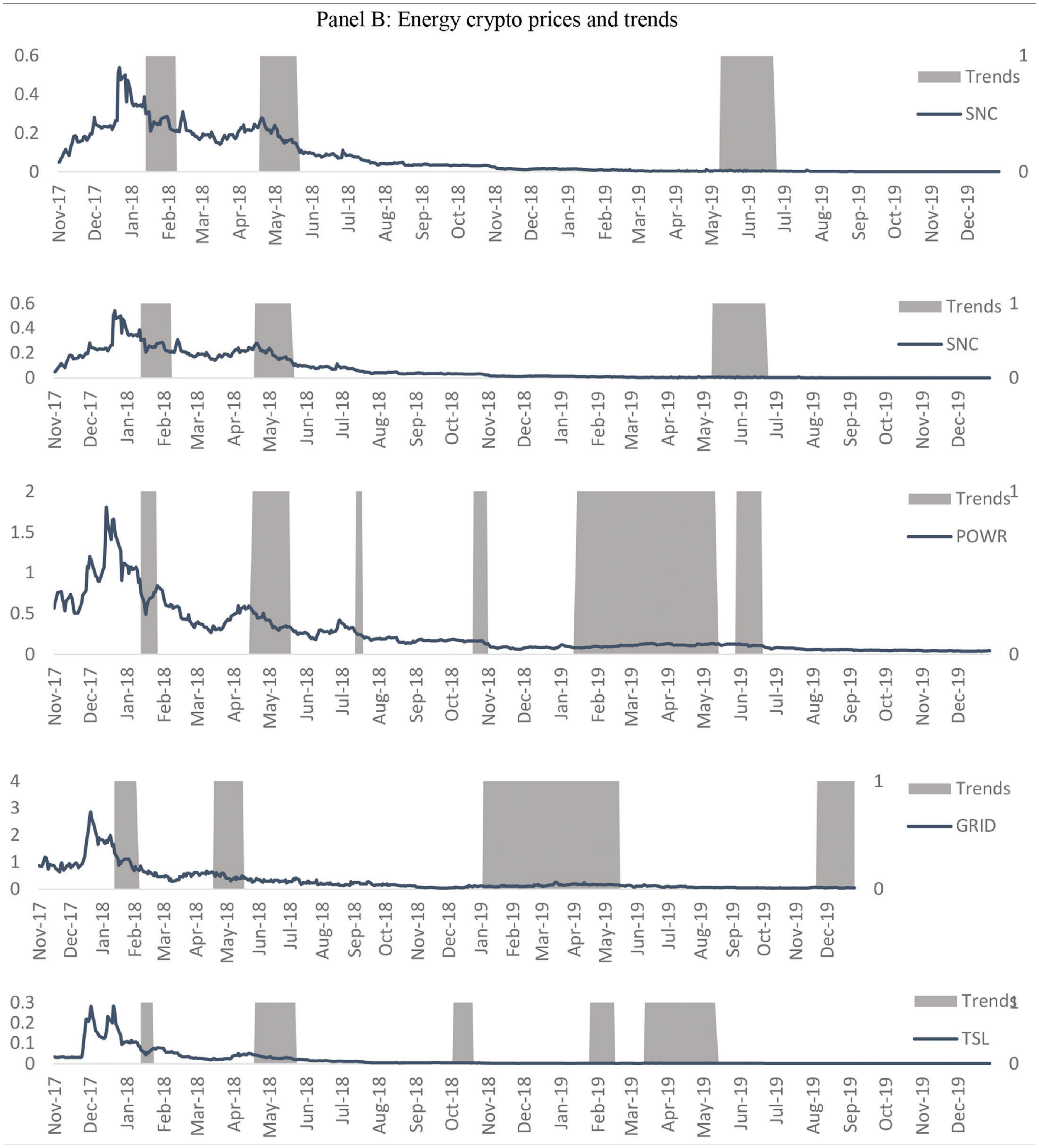


Figure 3: *(Continued)*



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Nov 2017- January 2020, which allowed tools such as Fibonacci retracements to capture price movements better. Noticeably, all the energy stocks priced trended mostly in the same fashion, with an uptrend noticed for all stocks around April/May 2018.

Similarly, around January 2019, all energy stocks witnessed price increases.

While Fibonacci retracement levels tend to capture energy stock prices relatively well compared to energy crypto prices, it is worthwhile to analyze the existence of price violations during an uptrend or downtrend. Figure 6 displays the price violations which occurred against the five retracement levels. While Fibonacci retracement levels tend to capture energy stock prices relatively well compared to energy crypto prices, it is worthwhile to analyze the existence of price violations during an uptrend or downtrend. While, during an uptrend, the least number of price violations took place for energy cryptos (SNC and TSL with no price violations), the highest number of support violations was found for KMI with 48 violations at different support levels. This was followed with XOM and MPC with 29 and 27 support violations respectively. Relatively, the number of price violations during a downtrend was higher than during uptrends. In fact, for the ten energy stocks, there were more violations during downtrends compared to uptrends for seven of the stocks, except for KMI, MPC and VLO. This was also found for energy cryptos, with price violations of the retracement levels for all cryptos, during periods of downtrends. More importantly, it was found that, during uptrends, the highest number of violations occurred at the 61.8% retracement level, compared with more violations occurring at the 23.6% level during downtrends. This suggests that, while the Fibonacci retracement tool captured most of the down movements in energy equity and crypto prices during an uptrend, price increases during downtrends were not captured. Noticeably too, constituents which had relatively more price violations at a particular retracement level, tend to have price violations at other retracement levels. This raises a critical question is whether violations during an uptrend, say at 61.8%, is followed by violations at the prior retracement levels of 50%.

Figure 4: KMI retracement levels

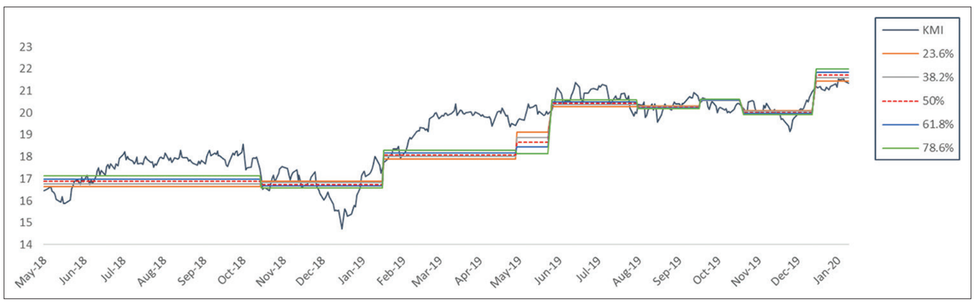


Figure 4 shows the daily stock prices, at close, for Kinder Morgan Inc (KMI). The 23.6%, 38.2%, 50%, 61.8%, and 78.6% Fibonacci retracement levels are applied to KMI prices from November 2017 to January 2020. Swing high and swing low prices are taken as the prices at the start of the current and previous trends. Source: Factset and S&P500 Dow Jones Indices.

Figure 5: Energy stocks, energy cryptos and fibonacci retracements

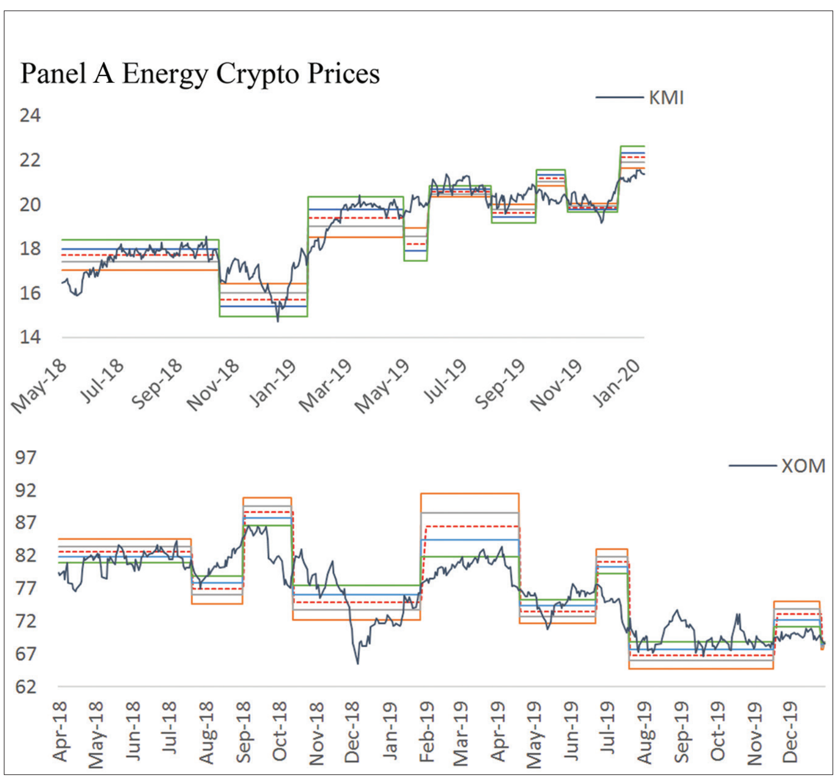


Figure 5: *(Continued)*

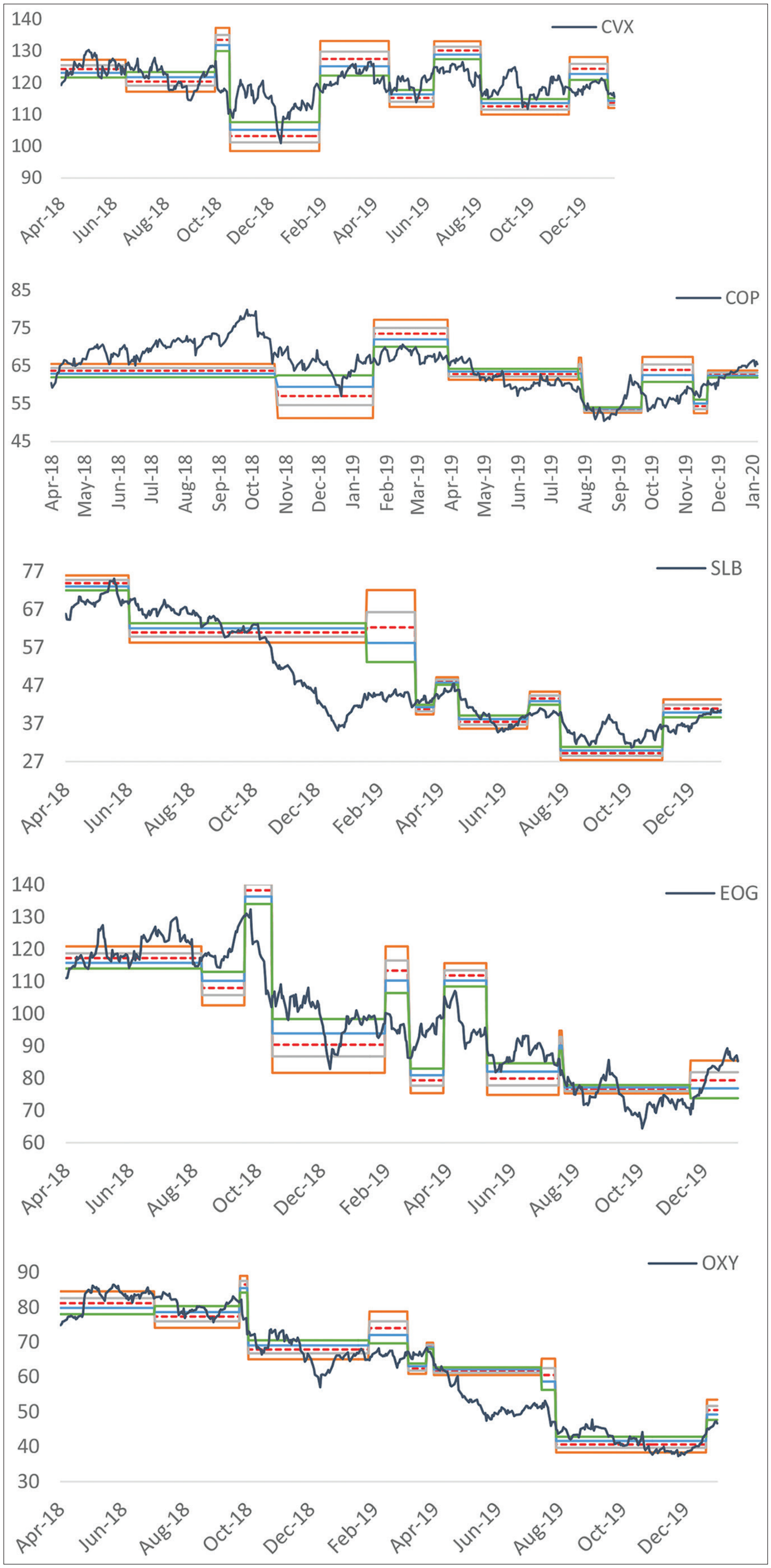
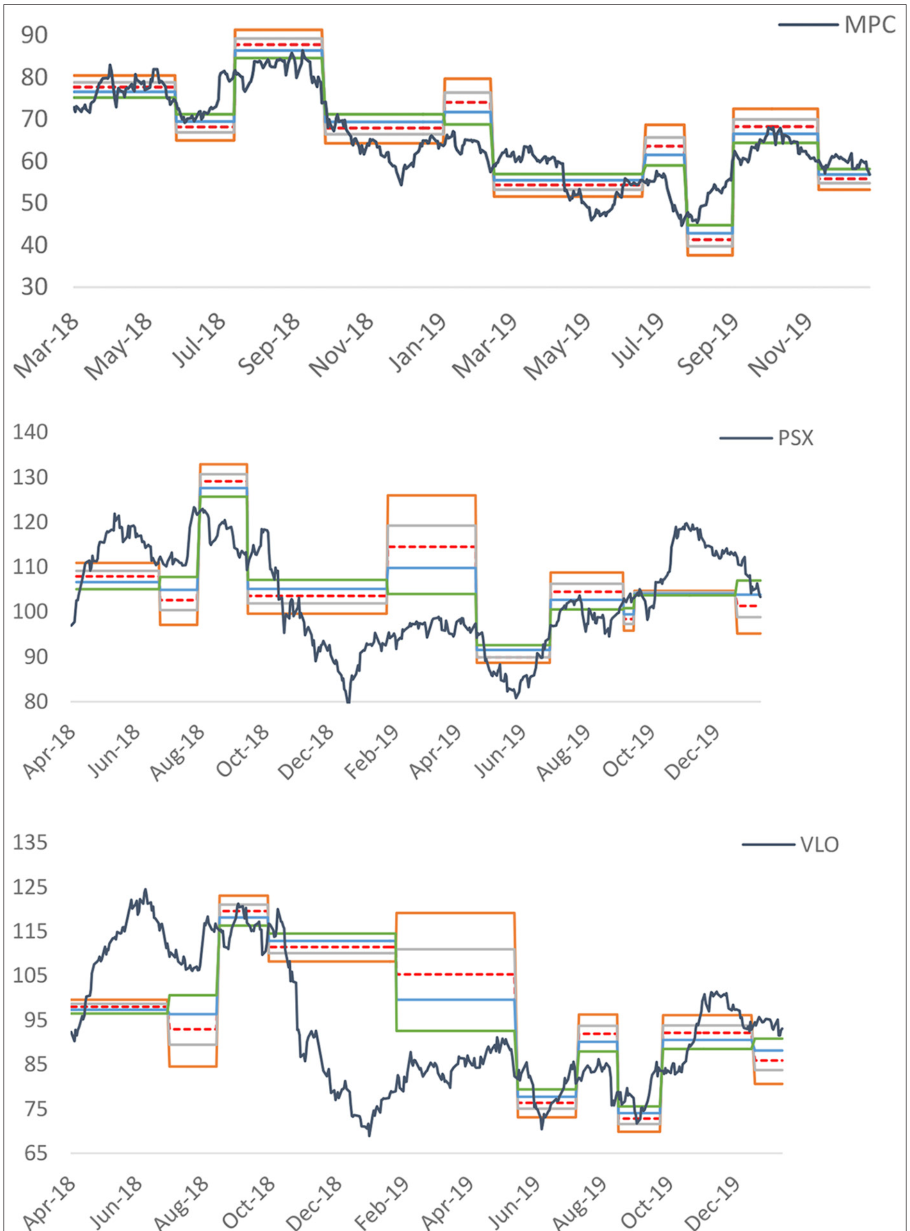


Figure 5: *(Continued)*



Panel B Energy Crypto Prices

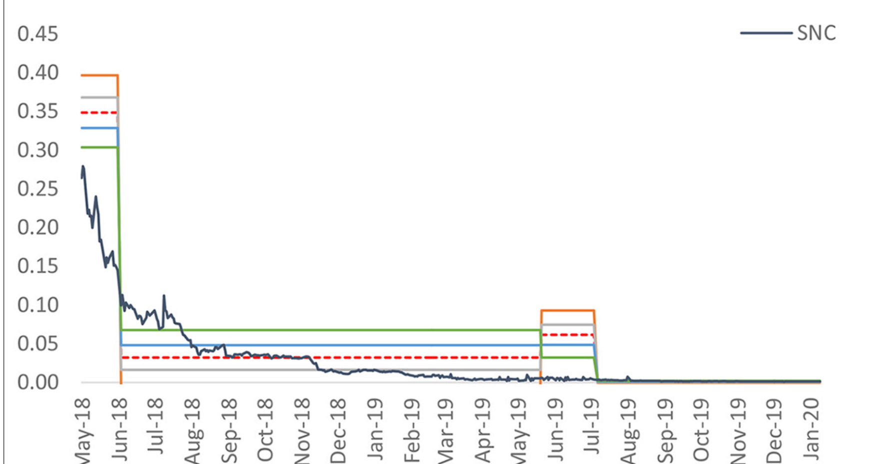
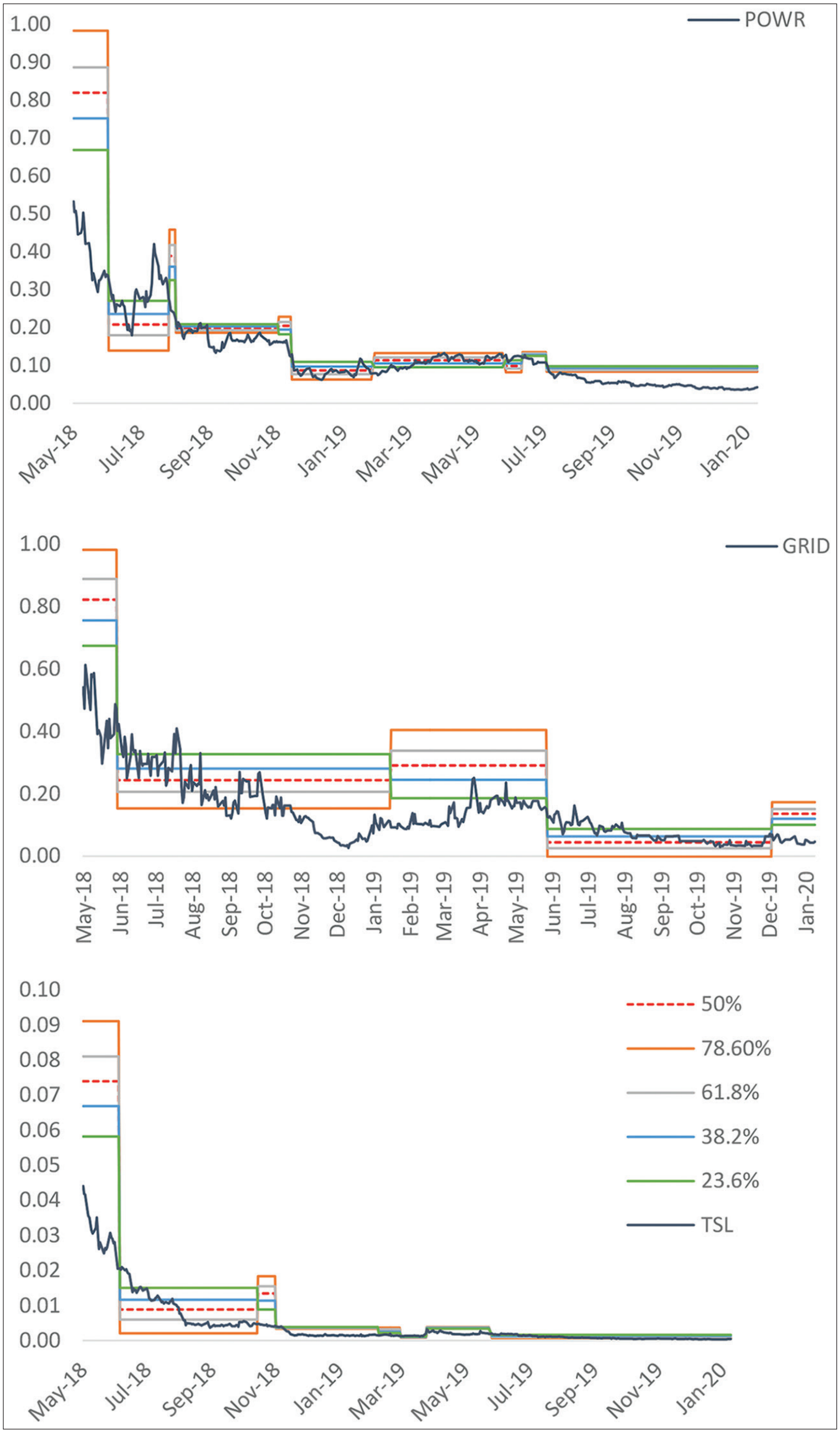
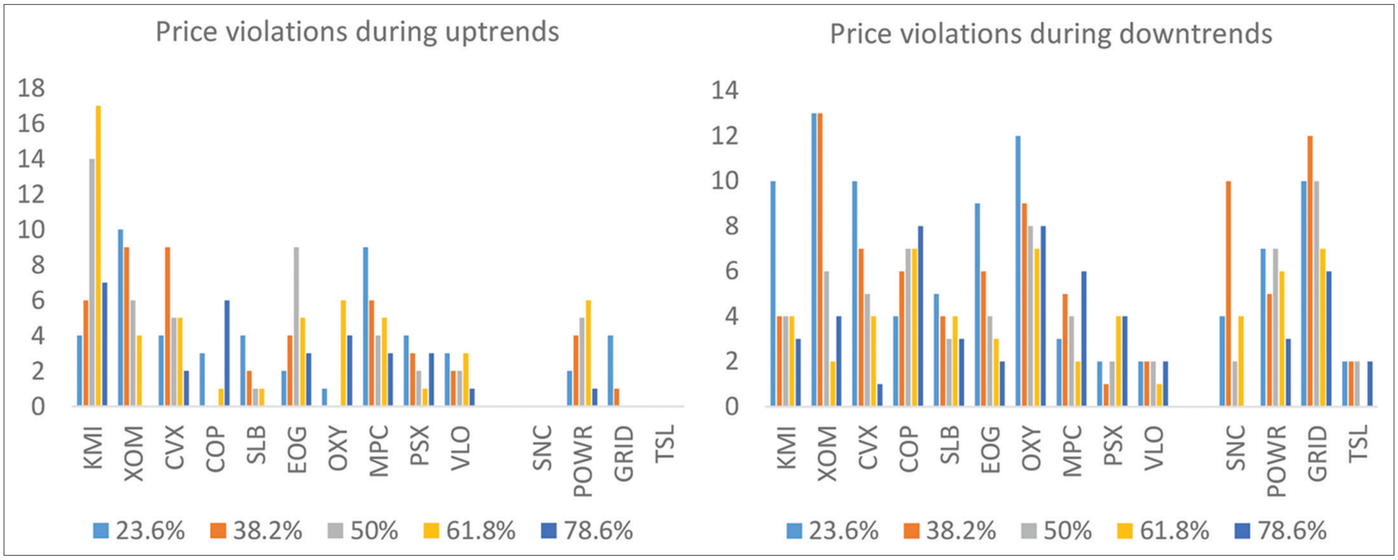


Figure 5: *(Continued)*



Panel A (B) represents the 23.6%, 38.2%, 50%, 61.8% and 78.6% Fibonacci retracement levels for the leading US energy stock (crypto) prices over the period November 2017-January 2020.

Figure 6: Price violations



Similarly, during a downtrend, are price violations, say at the 38.2% level, followed by the 23.6% retracement level price violation.

We looked up to three days backwards, to capture whether price violations at a specific retracement level, was preceded by another price violation at a different retracement level. We analyzed more than 1 day back in time to allow the energy stock and energy crypto prices to fluctuate and potentially cross retracement levels. For example, there was a price violation during an uptrend or downtrend, say at the 50% retracement level (1 day, 2 days, and 3 days back) followed by a price violation at the 38.2% level. The analysis is decomposed into both up trending and down trending periods, for both stocks and cryptos. Table 2 reports the existence of price violations, where a current price violation at a specific retracement level was preceded by another price violation at the prior descending or ascending retracement level. While violations at the 23.6%, 38.2%, 50% and 61.8% levels are analyzed, violations at 78.6% is not, since this is the upper boundary of our Fibonacci retracement levels, and we are assuming prices could not have broken a higher retracement level 1, 2 or 3 days back, when it has currently broken the 78.6% level. Most price violations which took place, say at time *t*, were preceded by price violations at the next higher retracement level at time *t-1*. This was more noticeable during downtrends, where retracement levels were broken more frequently 1 day before, including the current retracement break. There were fourteen instances where a 23.6% retracement level was broken for energy stocks, which were preceded by a 38.2% retracement 1 day prior to the 23.6% retracement break. Energy cryptos did not seem to witness consecutive violations in retracement levels, whether during an uptrend or downtrend. The highest number of consecutive price violations for energy cryptos occurred during downtrends, with only four instances of retracement breaks occurring consecutively one and two days, at the 50% and 61.8% levels.

As we moved from one day, to two and three days' prior, less consecutive retracement breaks took place, suggesting most retracement levels were broken consecutively within a 1-day period. Interestingly too, most of the price violations for energy stocks, which were accompanied by a prior price violation one day, two days or three days before, took place at the higher retracement levels of 50% and 61.8%. This suggests that price violations tend to occur more frequently when the 61.8% and 50% are broken, with 78.6% and 61.8% preceding such price violations during a short period of time. Alternatively stated, the number of consecutive price violations which took place at the 23.6% and 38.2% retracement levels were relatively lower compared to the 61.8% and 50% levels. During an uptrend, prices are expected to rise, such that price violations would tend to occur after the rises took place. This explains why the 50% and 61.8% retracement levels tend to be broken more consecutively, compared to other lower retracement levels. Similarly, during downtrends, prices are expected to fall, such that price violations would tend to occur after the prices fall. The only exception to this was during downtrends, where most of the price violations took place consecutively at the lower retracement levels of 23.6% and 38.2% respectively.

Based on the above findings where retracements tend to witness lesser price violations at lower retracement levels, a trading strategy is put together to test the use of Fibonacci retracement levels onto energy stock and crypto prices. During an uptrend, a long position is pursued when the price crossovers the 23.6% retracement level, with the position closed out when the 61.8% retracement level is crossed under. Similarly, during a downtrend, a short position is pursued when the price crosses under the 23.6% level with a subsequent long position after the 61.8% level is crossed over. This is summarized as follows:

Position	Uptrend	Downtrend
Long	$Price_{t-1}$<23.6% retracement<$Price_t$	$Price_{t-1}$<61.8% retracement<$Price_t$
Short	$Price_t$<61.8% retracement<$Price_{t-1}$	$Price_t$<23.6% retracement<$Price_{t-1}$

Assuming that a transaction is based on the purchase or sale of one stock, and that long or short energy stocks can be transacted

Table 2: Behavior of price violations

	1 day prior to current break							
	Uptrend				Downtrend			
	0.0%	0.0%	0%	0.0%	0.0%	0.0%	0%	0.0%
Energy stocks								
KMI	0	0	2	3	3	0	1	0
XOM	0	2	1	0	4	2	0	1
CVX	1	0	1	1	3	4	0	0
COP	0	0	0	0	0	0	2	0
SLB	0	0	0	0	1	0	0	0
EOG	0	0	0	0	0	1	1	1
OXY	0	0	0	1	3	1	1	0
MPC	4	0	1	1	0	2	1	0
PSX	0	0	0	1	0	0	0	0
VLO	1	1	0	0	0	0	0	0
Cryptos								
SNC	0	0	0	0	0	0	0	0
POWR	0	0	0	0	0	1	2	0
GRID	0	0	0	0	0	1	2	0
TSL	0	0	0	0	0	0	0	0
	23.6%	38.2%	50%	61.8%	23.6%	38.2%	50%	61.8%
	2 days prior to current break							
	Uptrend				Downtrend			
	23.6%	38.2%	50%	61.8%	23.6%	38.2%	50%	61.8%
Energy stocks								
KMI	0	0	4	0	0	1	0	1
XOM	3	0	0	0	1	1	2	1
CVX	0	2	0	0	2	0	1	0
COP	0	0	0	0	0	1	0	1
SLB	0	1	0	0	0	0	1	1
EOG	0	2	1	0	1	1	0	1
OXY	0	0	0	0	0	3	2	0
MPC	0	0	0	1	0	0	0	0
PSX	1	0	0	0	1	0	0	1
VLO	0	0	1	0	1	0	1	0
Cryptos								
SNC	0	0	0	0	0	0	0	0
POWR	0	0	0	0	0	0	0	2
GRID	0	0	0	0	0	0	0	2
TSL	0	0	0	0	0	0	0	0
	23.6%	38.2%	50%	61.8%	23.6%	38.2%	50%	61.8%
	3 days prior to current break							
	Uptrend				Downtrend			
	23.6%	38.2%	50%	61.8%	23.6%	38.2%	50%	61.8%
Energy stocks								
KMI	0	0	1	1	0	0	0	1
XOM	0	1	1	0	2	0	0	0
CVX	0	0	2	1	0	0	0	1
COP	0	0	0	0	0	1	1	1
SLB	0	0	0	0	0	0	1	1
EOG	0	0	1	0	0	1	0	0
OXY	0	0	0	1	0	0	0	2
MPC	1	0	1	0	0	0	0	1
PSX	1	1	0	0	0	0	0	0
VLO	1	1	0	0	0	0	0	0
Cryptos								
SNC	0	0	0	0	0	0	0	0
POWR	0	0	0	1	0	0	0	1
GRID	0	0	0	1	0	0	0	1
TSL	0	0	0	0	0	0	0	0
	23.6%	38.2%	50%	61.8%	23.6%	38.2%	50%	61.8%

without restrictions, like a buy (sell) should be followed by a sell (buy), the total net profit or loss during periods of uptrends and downtrends is calculated. Due to the non-restrictive ability to buy and sell energy stocks, the total return is calculated as follows:

$$Total\ return = \frac{\sum_{u}^{s} price + \sum_{d}^{s} price + \varphi.n}{\sum_{u}^{l} price + \sum_{d}^{l} price + \theta.n} \quad (8)$$

, where $\sum_{u}^{s}$ *price* represents the sum of all prices where short positions were taken during an uptrend. Similarly, $\sum_{d}^{s}$ *price* represents the sum of all prices where short positions were taken during a downtrend. $\sum_{u}^{l}$ *price* and $\sum_{d}^{l}$ *price* represent the sum of all prices where long positions were taken during periods of uptrends and downtrends. ϕ represent the price at which open positions are closed at the end of the trading period, where open positions were net long prior to the close of all positions. In the same line of thought, θ represent the price at which open positions are closed at the end of the trading period, where open positions were net short prior to the close of all positions. *n* represents the number of open positions at the end of the trading period, just before they are offset with a close. Due to the approach taken to calculate return, average risk is proxied by using an average standard deviation of energy prices. All positions are closed at the end to allow for comparison with the buy and hold strategy. Buy and Hold returns are based on a buy on 28th November 2017 with a subsequent sale on the 17th January 2020.

During uptrends, energy stocks tend to display relatively more long positions with six of the ten stocks displaying net long positions. Only KMI EOG and OXY reported net short positions during uptrends.

Comparatively, during downtrends, eight of the energy stocks had net short positions, apart from COP and PSX. This suggests that energy stocks, during uptrends (downtrends) tend to attract more buys (sales), based on traders following a Fibonacci retracement strategy. Assuming that a transaction is based on the purchase or sale of one stock, and that long or short energy stocks can be transacted without restrictions, like a buy (sell) should be followed by a sell (buy), the total net profit or loss during periods of uptrends and downtrends is calculated. Apart from COP and PSX, all energy stocks reported positive total returns ranging from 4% for SLB to 289% for EOG. The negative performance for COP and PSX can be attributed to their negative gains, particularly during up trending periods where they reported $202.19 and $514.89 losses respectively. The average risk ranged from $9.20 for SLB to $27.42 for CVX.

Sharpe values were relatively low, with the highest value being 0.344 for KMI. This was consistent with the highest Sharpe per trade value of 0.0072 for the same energy stock. Compared to the Fibonacci based trading strategy, buy and hold returns reported negative returns for six of the energy stocks. The highest (lowest) return of nearly 30% (-40%) was found in COP (SLB). For the energy cryptos, the use of our Fibonacci based strategy resulted in every few trades. During uptrends, only GRID reported net long positions. POWR reported net short positions during up trending periods, with the other two energy cryptos showcasing no transactions. During periods of downtrends, all the four energy cryptos reported net short positions. All the cryptos had positive total returns except for GRID which reported a loss of 9%. Although TSL had a very high total return relative to all stocks and cryptos, this was largely due to the cryptos have only net short positions during downtrends. These open positions were all closed at the end of the trading horizon under study. The low amount and type of transactions (short or long) resulted in the abnormally high Sharpe value for TSL. Buy and hold returns were negative for all cryptos compared to superior performance found under the Fibonacci based strategy.

While Table 3 shows the results of a trading strategy based solely on the use of Fibonacci retracements, it is interesting to test whether complementing the Fibonacci tool with a price crossover strategy results in a superior trading model for the energy commodities. Table 4 provides the findings on a Fibonacci retracement strategy complemented with price crossover rules. Due to the addition of price crossover rules to the existing model, fewer trading opportunities are expected. During uptrends, energy stocks tend to display relatively more short net positions with only XOM reporting one net long position. Similarly, to the model based only on Fibonacci retracements, only KMI, EOG, OXY and VLO reported net short positions during uptrends. Comparatively, during downtrends, five of the energy stocks had net short positions, except for EOG which reported a net short position. This suggests that energy stocks, during uptrends (downtrends) tend to attract more sales (buys), based on traders following a Fibonacci retracement strategy complemented with a price cross strategy. Assuming that a transaction is based on the purchase or sale of one stock, and that long or short energy stocks can be transacted without restrictions, like a buy (sell) should be followed by a sell (buy), the total net profit or loss during periods of uptrends and downtrends is calculated. Except for KMI, XOM, CVX and SLB, all energy stocks reported positive total returns ranging from 4% for COP to 34% and 35% for EOG and OXY respectively. While the negative performance for XOM can be attributed to loses during both up trending and down trending periods, the negative returns observed for KMI and CVX were due to closing the open positions at lower prices at the end of the trading horizon. The average risk ranged from $2.52 for KMI to $10.72 for EOG. Sharpe values were relatively low, with the highest value being 0.044 for OXY. This was consistent with the highest Sharpe per trade value of 0.0074 for the same energy stock. Compared to the Fibonacci based trading strategy and the buy and hold strategy, the model which complemented both the Fibonacci and price crossover strategy did not result in superior total returns. In fact, for SLB no transaction occurred due to the latter strategy.

The Sharpe and Sharpe per trade ratios barely increased and were mostly very low to attract investors' attention. For the energy cryptos, the use of our Fibonacci based strategy, complemented with the price crossover strategy resulted in even fewer or no trading signal. During uptrends, no energy cryptos reported net long positions. POWR and GRID reported net long positions during the downtrend periods, with SNC reporting a net short position. Only SNC reported a total return of 40%, which was based on closing the net short position at the end of the investment horizon. POWR and GRID both however reported negative returns of 64% and 67%, caused primarily by closing positions at lower

Table 3: Performance evaluation of fibonacci based strategy

Panel A: Energy Stocks										
	KMI	XOM	CVX	COP	SLB	EOG	OXY	MPC	PSX	VLO
Net positions (uptrend)	–11	6	0	4	3	–1	–5	4	6	3
Net positions (downtrend)	–5	–13	–5	2	–2	–8	–8	–4	0	–2
Total gain (uptrend)	216.20	–502.5	–121.9	–202.1	–124.57	511.06	493.47	–197.6	–514.8	–253.1
Total gain (downtrend)	100.84	922.17	586.88	–124.19	99.73	738.81	433.98	270.37	1.69	184.57
Total return	–5%	–4%	–7%	177%	4%	44%	–770%	12%	11%	4%
Average risk	5.22	20.44	27.42	12.60	9.20	22.30	16.44	15.46	19.37	17.62
Sharpe	–0.014	–0.003	–0.003	0.139	0.002	0.019	–0.470	0.006	0.004	0.001
Sharpe per trade	0.000	0.000	0.000	0.006	0.000	0.001	–0.012	0.000	0.000	0.000
Buy-and-hold returns	25.4%	–16.1%	–0.7%	29.8%	–38.4%	–14.6%	–33.5%	–8.6%	9.8%	9.6%

Panel B: Energy cryptos				
	SNC	POWR	GRID	TSL
Net positions (uptrend)	0	–3	4	0
Net positions (downtrend)	–2	–4	–5	–5
Total gain (uptrend)	0.00	0.37	–0.81	0.00
Total gain (downtrend)	0.01	0.90	0.64	0.04
Total return	10%	66%	–5%	1595%
Average risk	0.00	0.04	0.05	0.00
Sharpe	24.10	17.34	–1.45	16568.33
Sharpe per trade	2.01	0.54	–0.06	1656.83
Buy-and-hold returns	–0.986	–0.938	–0.960	–0.987

Table 3 Panel A reports the different performance evaluation results of investing in the top ten US energy stocks of the S&P Composite 1500 Energy index over the period November 2017 – January 2020. Panel B reports the results for four energy cryptos. Average returns and average risk are based on arithmetic averages. Sharpe values represent the excess return per unit of total risk. The US 3-month Treasury bill rate is used as a proxy for the risk free asset. Buy-and-hold returns represent the returns for opening a position at the start and closing the position at the end of the trading period. Fibonacci retracement based returns are calculated by closing any remaining open positions at the end of the period. Net positions is the number of short positions deducted from long positions

Table 4: Performance evaluation of fibonacci/price crossover strategy

Panel A: Energy stocks										
	KMI	XOM	CVX	COP	SLB	EOG	OXY	MPC	PSX	VLO
Net positions (uptrend)	–6	1	0	0	0	–1	–2	0	0	–2
Net positions (downtrend)	0	1	0	2	0	–1	1	1	1	0
Total gain (uptrend)	116.32	–81.38	–1.12	0.00	0.00	158.08	163.87	0.00	0.00	186.10
Total gain (downtrend)	0	–75.92	0.00	–125.00	0.00	96.86	–64.83	–54.21	–90.83	0.00
Total return	–9%	–13%	–1%	4%	-	34%	35%	5%	14%	2%
Average risk	2.52	6.33	10.21	5.32	0.00	10.72	7.40	3.81	6.66	7.75
Sharpe	–0.044	–0.023	–0.003	0.004	-	0.030	0.044	0.008	0.018	0.000
Sharpe per trade	–0.0037	–0.0058	–0.0014	0.0010	-	0.0051	0.0074	0.0039	0.0088	0.0000
Buy-and-hold returns	0.254	–0.161	–0.007	0.298	–0.38	–0.146	–0.335	–0.086	0.098	0.096

Panel B: Energy cryptos				
	SNC	POWR	GRID	TSL
Net positions (uptrend)	0	0	0	0
Net positions (downtrend)	–1	1	2	0
Total gain (uptrend)	0.00	0.00	0.00	0.00
Total gain (downtrend)	0.00	–0.12	–0.62	0.00
Total return	40%	–64%	–67%	-
Average risk	0.00	0.01	0.02	-
Sharpe	3273.55	–109.96	–29.63	-
Sharpe per trade	1636.77	–54.983	–4.939	-
Buy-and-hold returns	–0.986	–0.938	–0.960	–0.987

Table 4 Panel A reports the different performance evaluation results of investing in the top ten US energy stocks of the S&P Composite 1500 Energy index over the period November 2017 – January 2020, based on a Fibonacci retracement strategy which is complemented with a price crossover strategy. Panel B reports the results for four energy cryptos. Average returns and average risk are based on arithmetic averages. Sharpe values represent the excess return per unit of total risk. The US 3-month Treasury bill rate is used as a proxy for the risk-free asset. Buy-and-hold returns represent the returns for opening a position at the start and closing the position at the end of the trading period. Fibonacci retracement-based returns are calculated by closing any remaining open positions at the end of the period. Net positions is the number of short positions deducted from long positions. The price crossover strategy is based on a 50-day moving average

prices. The low amount and type of transactions (short or long) resulted in the abnormally high Sharpe value for energy cryptos. Buy and hold returns were negative for all cryptos compared to superior performance found under the Fibonacci based strategy. This suggests the use of the Fibonacci retracement tool complemented with the price crossover strategy is not warranted. This could be explained due to the significant down trending periods which took place since January 2018 which allowed for no positions during relatively small pockets of eventual uptrends. This results in performance measures as the Sharpe or Sharpe per trade less reliable, due to very few or zero transaction, when relying on the Fibonacci/Price crossover trading model.

6. CONCLUSION

Oil price fluctuations affect other commodities but also other alternative assets such as stocks and cryptocurrencies. With Middle East sanctions, Chinese trade wars, decoupling of energy commodities, crypto currencies, and COVID-19, energy policy makers such as the Commodity Futures Trading Commission (CFTC) are active. Falling energy stock prices during the July 2014 – December 2015, due to oil prices which dropped due to various abovementioned reasons provide a good focal point. The drop of energy crypto prices, post December 2017 was impactful for many investors. Among others, investors and traders use fundamental and technical analytical tools to gain profits through some set strategies. We emphasize on Fibonacci retracements and price crossovers, as a technical analysis trading system, which has not been documented sufficiently in the existing literature, when it comes to technical analysis application to energy equity and energy cryptos, and its performance compared to a buy and hold trading strategy. Our analysis investigates its performance during the 2017-2020 period over the leading energy stocks of the S&P 1500 Composite Energy Index, including leading energy cryptocurrencies.

Findings support that Fibonacci retracements track energy stock prices better than energy cryptos. This can be explained as energy stock prices generally fluctuate within a narrower range, allowing the technical analysis tool to capture the price movements better, compared to the energy cryptos where prices fluctuations are more pronounced. Violations in prices tend to occur more during downtrends compared to uptrends for both risky assets. Most of down price movements were captured during uptrends, with however price increases during downtrends not similarly captured. Although the use of technical indicator led to better profitable results compared to a buy and hold model, performance measure values were still low, even after including a price crossover to augment the model.

The findings provide some insights in financial policies, particularly related to market stability and speculative activities in energy markets. Regulatory bodies such as CFTC and SEC can benefit from our results where despite significant falls in energy commodity prices, traders in energy stocks manage to make profitable trades by using technical analysis. Drops in energy prices, although susceptible to lower profits for energy companies, do not necessarily result in losses for speculators who use technical analysis. On the other side of the coin, hedgers in energy markets can tap in the use of technical analysis into understanding where energy prices can go, especially in terms of price retracements. Future research can look into how events like COVID-19 affects the use of technical analysis in energy markets.

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