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Article

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Can the Leading US Energy Stock Prices be Predicted using the Ichimoku Cloud?

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ABSTRACT

The aim of this study is to investigate if Ichimoku Cloud can serve as a technical analysis indicator to improve stock price prediction for leading US energy companies. The methodology centers on the application of the Ichimoku Cloud as a trading system. The daily stock prices of the top ten constituents of the S&P Composite 1500 Energy Index - spanning the period from 12th April, 2012 to 31st July, 2019 - were sourced for experimentation. The performance of the Ichimoku Cloud is measured using both the Sharpe and Sortino ratios to adjust for total and downside risks. The analysis is split into pre and post oil crisis to account for the drop in energy stock prices during the July 2014 - December 2015. The model is also benchmarked against the naïve buy-and-hold strategy. The capacity of the Ichimoku indicator to provide signals during strengthening trends is analyzed. Despite the drop in energy stock prices, number of trades continued to increase along with profit opportunities. The PSX stock ranked first, with the highest Sharpe ratio, Sortino ratio, and Sharpe per number of trade. As expected, a number of buying signals occurred during strengthening bullish periods. Surprisingly, various sell signals also occurred during similar strengthening bullish trends. Most of the buy and sell signals under the Ichimoku indicator occurred outside of strengthening of bullish or bearish trends. The overall findings suggest that speculators can benefit from the use of the Ichimoku Cloud in analyzing energy stock price movements. In addition, it has the potential to reduce susceptibility to changes in energy prices. Last, the strength of the trend in place needs to be captured as it served as an additional layer of information which can improve the decision making process of the trader.

Keywords: Energy Stocks, Price Forecasts, Ichimoku Cloud, Trading Performance
JEL Classifications: Q40, G15, G17

1. INTRODUCTION

Energy markets have been grabbing global headlines with terms such as decoupling, decarbonization and energy policy. It has been particularly the case in the US where the energy market has traditionally been coupled with GDP growth. In 2016, the International Energy Agency (IEA) found that despite GDP growth of 3% per year the world greenhouse gas emissions (GHG) remained flat in 2014 and 2015 (IEA 2015, 2016). The decoupling of the GHG and global growth was seen as an encouraging revelation setting the path towards achieving the agreed objective of increasing the global mean surface temperature to less than two degrees Celsius above preindustrial levels (UNFCCC, 2016; Chemnick, 2016). However, during the same 2014- 2016 period, oil prices lost more than two-thirds of their value. With prices continuing to roam around 40-50% of their 2011-2014 values various oil-revenue dependent economies have suffered a substantial drop in consumption, economic growth, and investments (World Bank, 2018). Fluctuations in oil price resulted in volatile economic activity that led various economies to adopt more stringent fiscal and monetary policies, including reforms to reduce reliance on oil. This also meant that investors have become more prudent in making investment decisions related to commodities and equities led by the crude oil market.

Globalization has increased cross market interdependence. However, such linkages are not straightforward, especially with the advent of new alternative assets. For instance, Gurrib (2019) found that an energy commodity price index and energy block chain-based cryptocurrency price index are not robust forecasters in the energy commodity and energy cryptocurrency markets. Similarly, while Gurrib and Kamalov (2019) 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 index movements during the 2000 bubble. Furthermore, Gupta et al. (2017) reported that volatility in futures markets increased over time and is not unavoidably linked to volatility in other financial markets.

The energy market dynamics are evolving. The EIA (2018) forecasted 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 anticipated to surge due to growth in the industrial sector, particularly for industrial heat and power, and liquefied natural gas production. Natural gas production is expected to account for nearly 40% of the US energy production by 2050. Wind and solar power generation lead 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 subsidies for clean energy from climate conscious governments and 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, 2018).

Various trading strategies have shown evidence of success in traditional markets including cryptocurrencies, currencies markets, bond and equity markets (Nadaraja and Chu, 2017; Neely et al., 2014; Shynkevich, 2012; Shynkevich, 2016). However, uncertainty in financial markets complicates the choice between fundamental analysis and/or technical analysis techniques for investors and traders. In their seminal work, Malkiel and Fama (1970) and Ball (1978) asserted the efficient market hypothesis which states the current market prices reflect all available information and reliance on such information would be unprofitable or result in a positive return that is accompanied by an unacceptable risk level. The studies found that market timing-based strategies result in negative returns after adjusting for transaction costs. Park and Irwin (2010) supported findings of Fama and Ball that technical analysis trading rules were not profitable for U.S. based futures markets. In comparison, Pruitt and White (1988) found their technical based system, which includes variables such as volume, RSI and moving average, outperform the market after adjusting for transactions costs. In the same line of thought, Menkhoff (2010) found most fund managers in five countries use technical analysis. In support of technical trading, Szakmary et al. (2010) found trend following strategies to be profitable in commodity futures markets and Tsaih et al. (1998) found their trading based system to outperform the traditional buy and hold strategy in the S&P500 stock index futures market. Wong et al. (2003) found the use of RSI and moving average to yield significant positive returns in the Singapore Stock Exchange. Neely et al. (2009) found that both market conditions and profitability change over time when applying technical analysis techniques. This is in line with Gurrib (2018b) who looked into the performance of the Average Directional Index as a market timing tool for the most actively traded US based currency pairs and found weekly trading horizons to be more profitable than monthly ones. Beyaz et al. (2018) analysed various companies using both fundamental and technical analysis and found differences in the performance using either analytical tools were less pronounced for energy stocks and combining both techniques improved forecasts of stock prices performance. More recently, Kamalov (2020) was able to apply machine learning techniques to achieve market beating performance in predicting significant swings in stock price. Although there exists a plethora of research on technical analysis, few authors have applied the Ichimoku Cloud in their studies. There is a lack of focus on the market under study and the use of trend based rules in the application of the Ichimoku Cloud.

For the purpose of this study, we tap into the performance of the Ichimoku Cloud as a trading model and compare the results with the naïve buy and hold strategy. While there exist studies that have applied the Ichimoku Cloud to Japanese and US equities (Lim et al., 2016) and Polish equities (Fafuła and Drelczuk, 2015), this is the first study to look into the use of Ichimoku Cloud as a trading strategy for the leading US energy stocks. Our analysis of the leading energy stocks is the first to provide insights into whether there are shared characteristics there are commonalities in the performance of energy-based companies, using tools like the Ichimoku Cloud. This paper contributes to the existing literature by comparing the results from the Ichimoku Cloud trading strategy with a buy and hold strategy. It helps to determine if the Ichimoku Cloud is a more reliable technical analysis tool. The performance of the Ichimoku Cloud is measured using both the Sharpe and Sortino performance measures and compared with the traditional buy-and-hold strategy. Our approach provides guidance to the differences in predicting energy equity prices using technical analysis and naïve buy and hold strategies. The use of both the Sharpe and Sortino measures allows the possibility of capturing both the total and downside risks of trading energy stocks with the help of the technical analysis tool. Last, but not least, we look at the ability of the technical indicator to provide trading signals, by complementing the analysis with the existence of trends and the strength of the trend in place. The policy implications of disruptions in commodity prices with respect to profit potentials are presented. The analysis is of importance to traders and speculators in energy markets. Our paper is structured as follows. We provide a review of existing literature on performance measures used in our study. Next, the descriptive statistics for the data in the study is presented. Then we provide the methodology applied to set the trading system together with the research findings. We end the paper with a number of conclusive remarks.

2. LITERATURE REVIEW

An extensive amount of literature exists when it comes to the success or failure of technical analysis in financial markets. For instance, Smith et al. (2016) reported that 20% of hedge funds used technical analysis; Gencay (1999) reported profits in foreign exchange markets with Olson (2004) adding further that risk adjusted trading rule profits declined 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) applied over 7000 trading rules and found 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.

While there is a vast literature regarding the use of technical analysis in various markets such as foreign currencies, technical trading applications regarding the energy market has been covered relatively more in recent decades due to the financialization of crude oil, which made it a product of interest for professional crude oil futures traders (Zhang, 2017; Creti and Nguyen, 2015). While there is scarce literature regarding energy stocks and technical analysis, the relationship between technical analysis and energy futures market serves as a reference point for potential relationships between technical analysis and energy equities. Marshall et al. (2008b) applied 7000 rules on major commodity futures and found only some strategies were profitable, after adjusting for data snooping. Comparatively, Szakmary et al. (2010) reported moving average strategies resulted in positive returns for most commodity futures markets. Narayan et al. (2014) applied momentum-based trading strategies in commodity futures, ranked the commodities, and took long positions in the top performing commodities and short positions in the worst performing ones, a strategy which led to significant profit opportunities. Similarly, Narayan et al. (2013) found that simple moving average breaks-based trading strategies reliably produce statistically significant returns in oil and gold markets. While the same authors found that commodity futures, including oil, can predict commodity spot returns, Gurrib (2018a) supported that an energy futures index based on crude oil and heating oil is not a reliable predictor of major stock market indices, particularly, due structural breaks like the 2000 technology bubble. This is also supported by Aggarwal (1988) who found not only an increase in volatility following the introduction of futures markets, but also an increase in volatility over time, suggesting futures markets is not necessarily linked to volatility in other markets. This suggests other factors like uncertainty shocks can drive volatility as well in markets.

Recently, using technical analysis as proxies for momentum trading, Czudaj (2019) analyzed crude oil futures prices and found that the reaction to uncertainty varies significantly across different frequencies. While high frequencies witness a very brief reaction to uncertainty, lower frequencies displayed a more persistent reaction to uncertainty shocks. Further, Marshall et al. (2008a) found investors to rely more on technical analysis for short term forecasting and also provide more emphasis to technical indicators for intraday horizons compared to yearly based ones. As part of validating the use of the Ichimoku Cloud system to generate returns, our study further contributes to the literature by comparing the results of the Ichimoku model using daily.

To measure the performance of portfolios based on market timing techniques, performance measures such as Sharpe, M^2, Treynor, and Jensen's alpha are used in the investment industry. 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 in the short term (Fama, 1972). Equally, Treynor's ratio proposed by Treynor (1965) looks only at the excess return per unit of systematic risk, which is similar to Jensen's alpha as discussed in Aragon and Ferson (2006). The Sharpe ratio introduced in Sharpe (1966) captures excess return per unit of total risk, where excess return is the difference between return and a risk-free rate, where the 3-month US Treasury bill rate is used as a proxy.

While various applications exist regarding the use of Sharpe (Gurrib, 2016; Aragon and Ferson, 2006 for a review), the Sharpe ratio does not differentiate between downside and upside risk. This is particularly important since various financial markets tend to display non-normal distributions. For instance, Leland (1999) suggests the need to look into higher moments of distributions to capture investors' utility functions. For positively (negatively) skewed distributions, a portfolio would have a higher (lower) mean than for a normally distributed function, resulting in a relatively lower (higher) risk and higher (lower) excess return per unit of total risk. To tackle the issues related to the Sharpe performance measure and distributions, Sortino and Van der Meer (1991) introduced the Sortino ratio which compared to the Sharpe measure, looks at downside risk, where downside risk relates to returns falling below a defined target rate. Harry Markowitz, the founder of Modern Portfolio Theory, also discussed the importance of downside risk in his seminal Markowitz (1959) paper, despite using standard deviation in his portfolio theory model. Various studies used the Sortino, including Sortino (1994), Ziemba (2003), and Chaudhry and Johnson (2008) where the latter found the Sortino ratio to be superior to the Sharpe when distribution of excess returns are skewed.

2.1. Data

To carry out the objective of our study, we employ the top ten stocks from S&P Composite 1500 Energy Index. The selected stocks provide a good representation of the performance of publicly listed energy companies that are members of the Global Industry Classification Standard (GICS). 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 at 31st July 2019. The top ten stocks were selected based on their relative index weight. The summary of the data is presented in Table 1.

It is important to note that the S&P Composite 1500 Energy index has been relatively volatile compared to the general S&P500 market index and the S&P GSCI Natural Gas Index. The performance of the three market indices can be observed in Figure 1. We observe that the natural gas market and crude oil market (represented by the S&P 1500 Energy index) decoupled

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

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

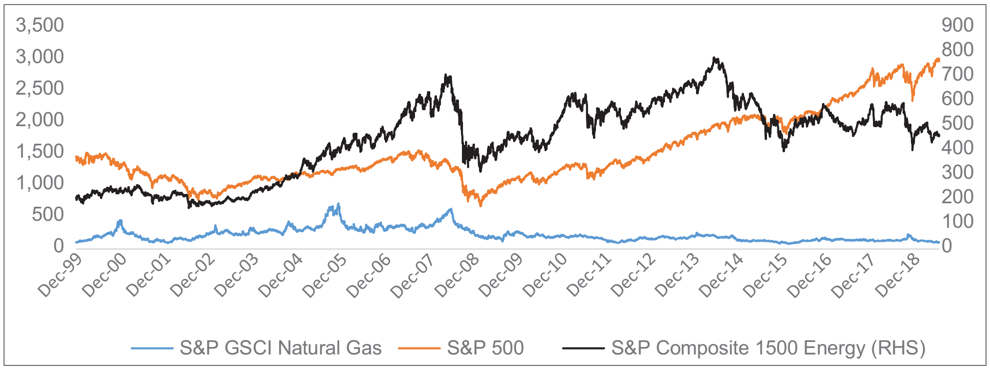

Figure 1 shows the performance of the S&P 500 market index, S&P Composite1500 Energy index and the S&P GSCI natural gas, which is displayed on the right-hand side vertical axis. The data ranges from December 1999 to July 2019. Source: Factset, S&P500 Dow Jones Indices

starting from late 2008. The demand for oil to produce electricity has plunged tremendously due to retirement of aged petroleum assets, lower natural gas prices, more efficient gas fired turbines, and more consciousness on the environmental impact of the relatively high sulfur content of oil. Despite the growth in natural gas production in the US, which is a leading producer in the world, strong supply from shale players such as Marcellus/Utica have reduced the effect of the associated gas growth on natural gas prices (Mchich, 2018). Beginning in 2009 the S&P 500 general index had a relatively better performance compared to the S&P 1500 Composite Energy Index. The volatility observed in the S&P Composite 1500 Energy Index makes the Ichimoku Cloud a good candidate to be used as a technical indicator as it is based on the moving average convergence divergence (MACD) indicator. To achieve more robust results our analysis of the top ten energy stocks in the S&P Composite 1500 Energy Index spans the period of 12th April 2012 to 31st July 2019. The annualized risk-free rate of 1.20% is based on the 3-month US Treasury bill rate, which ranged from a minimum of 0.02% to 2.4% from April 2012 to July 2019. The risk-free rate is sourced from the St Louis Federal Reserve (FRED) database. Energy stock prices are obtained from Factset.

3. RESEARCH METHODOLOGY

The Ichimoku Cloud can be traced back to Goichi Hosoda, a journalist using the pseudonym Ichimoku Sanjin who combined moving averages with candlestick charts with aim of improving the robustness of his technical analysis. In 1996, Hidenobu Sasaki revised Goichi's model and published Ichimoku Kinko Studies. Sasaki's work forms the current framework underlying the Cloud chart analysis. Voted the best technical analysis book in the Nikkei newspaper for nine years consecutively, this method is still considered as one of the most popular approaches to technical analysis financial tools used in Japan and globally. The Ichimoku Cloud primarily consists of five components, namely the conversion line (*Tenkan-sen*), the base line (*Kijun-sen*), the leading Span A (*Senkou Span A*), leading Span B (*Senkou Span B*), and the lagging span (*Chikou Span*). The five components are decomposed as follows:

$$Tenkan-sen\left(Conversion\,line\right)=\frac{9\;period\;High+9\;period\;Low}{2} \tag{1}$$

$$Kijun-sen\;(Base\,line)=\frac{26\;period\;High+26\;period\;Low}{2} \tag{2}$$

$$Senkou\;Span\;A\left(leading\;span\;A\right)=\frac{Conversion\,line+Base\,line}{2} \tag{3}$$

$$Senkou\;Span\;B\left(leading\;span\;B\right)=\frac{52\;period\;High+52\;period\;Low}{2} \tag{4}$$

$$Chikou\;Span\left(lagging\;span\right)=Closing\;price\;plotted\;26\,days\,in\,the\,past \tag{5}$$

The Tenkan Sen is the moving average of the highest high and the lowest low over the last 9 trading days, and is used primarily to measure the short-term momentum. It is interpreted in the same manner as a short-term moving average. A steeply angled Tenkan Sen indicates a sharp recent price change or strong momentum, while a flatter angled Tenkan Sen indicates low or no momentum. The Kijun Sen is the moving average of the highest high and the lowest low over the last 26 trading days. Similar to the Tenkan Sen, the Kijun Sen is used primarily to measure stock's momentum. However, because of its longer time period it is a more reliable trend indicator. A flatter Kijun Sen indicates a range bound price, while an inclined line indicates a trend with the angle of the line showing the momentum of the trend. The Senkou Span A, also known as the 1st leading line, is the moving average of the Tenkan Sen and Kijun Sen and is plotted 26 trading days ahead. It is predominantly used in combination with the Senkou Span B to form the Ichimoku Cloud. Together they indicate probable future support and resistance levels. As price tends to respect prior support and resistance levels, time-shifting this line forward gives a visual representation of how the price on a date relates to support and resistance from 26 trading days prior. The Senkou Span B is the moving average of the highest high and the lowest low over the last 52 trading days and is plotted 26 trading days ahead. As the most extended long-term representation of equilibrium in the Ichimoku trading system, it is used in combination with the Senkou Span A to indicate probable future support and resistance levels. As price tends to respect prior support and resistance levels, time-shifting this line forward gives a visual representation of how the price on a date relates to support and resistance from 52 trading days prior.

The Kumo (Japanese term for cloud), is used to indicate probable future support and resistance levels. The top and the bottom of the Kumo indicate the first level and the second levels of support respectively when the price is above the Kumo. Similarly, the bottom and the top of the Kumo indicate the first and second level of resistance when the price is below the Kumo. A price above the Kumo indicates a bullish trend and a price below indicates a bearish one, while price within the Kumo indicates a potentially trend-less or range-bound situation. The thickness of the Kumo shows the level of historical volatility, as well as the strength of support or resistance. A thicker Kumo shows a greater the level of historical volatility and support or resistance, and vice-versa. Last but not least, the Chikou Span, also known as the lagging line, is the closing price plotted 26 trading days behind, i.e. into the past, thereby providing a view of how the price compares to that 26 days ago. While there are many potential strategies which can be formed using the Ichimoku Cloud system, for the purpose of this study, in line with Lim, Yanyali and Savidge (2016), the buying and selling trading signals are set as follows:

Long-only strategy: Open a long position when the Chikou line crosses the top of the Cloud from below.

Close the long position when the Chikou line crosses the bottom of the Cloud.

Short-only strategy: Open a short position when the Chikou line crosses the bottom of the Cloud from above.

Close the short position when the Chikou line crosses the top of the Cloud.

We allow both long-only and short-only strategies to be implemented to increase potential trading and return opportunities. Short positions is allowed to precede long positions and vice versa. For the purpose of this study, we do not differentiate between a green and a red Cloud, which happens when the Senkou Span A is above the Senkou Span B, and vice versa. Nonetheless, we provide further insights in the trading strategy, by providing useful information whether the trend is bullish or bearish, and also whether it is strengthening. A long position being opened during a bullish trend which is strengthening allows for potentially better profit results. Similarly, a short position being opened during a bearish trend which is strengthening allows for potentially higher profits. A bullish trend which is strengthening, is assumed to be in place when the price is above the Cloud, where the current leading Span A is above current leading Span B, and the current period leading Span A value is greater than its previous leading Span A value. Similarly, a bearish trend which is strengthening, is assumed to be in place when the price is below the Cloud, where the current leading Span B is above current leading Span A, and the current period leading Span B value is greater than its previous leading Span B value. Whilst the trend can change from bullish to bearish, and vice versa, while a position is kept open, buying and selling signals can only take place when the Chikou crosses over and crosses under leading Spans respectively. Whenever the Chikou is within the Ichimoku Cloud, no trading signal happens to avoid false signals. Further, positions are closed whenever a long position is followed by a short position, and vice versa. Due to the study being constrained to a time period ranging from 2012 to 2019, all positions would be closed at the end of period, i.e. 31st July 2019. This allows the results under the daily Ichimoku model to be compared with the buy-and-hold strategy.

As far as the performance measures are concerned, the Sharpe and the Sortino risk-adjusted values are calculated. While the Sharpe ratio is the excess return per unit of total risk, and assumes both upside and downside risk, the Sortino ratio assumes only downside risk. In line with Sortino and Van der Meer (1991), the Sortino ratio is calculated as follows:

$$Sortino\,ratio = \frac{\overline{R_A} - MAR_A}{\sigma_A^d} \tag{6}$$

where $\sigma_A^d = \sqrt{\frac{\sum (R_A - MAR_A)^2}{n}}$ and represents the target downside deviation. $\overline{R_A}$ represents the average return generated from buying and selling the energy stocks, n is the number of returns, and MAR_A represents the minimum acceptable return. If $(R_A\text{-}MAR_A)>0$, the resulting value is substituted to zero, otherwise, the value is set as $R_A\text{-}MAR_A$. This ensures that the model captures only downside risk. For the purpose of this study, the minimum acceptable return is set as the risk-free rate.

4. RESEARCH FINDINGS

4.1. Descriptive Statistics

Figure 2 shows the daily closing stock prices for the top energy constituents of the S&P1500 Composite Energy index. A total of 1837 daily observations were captured for each stock. As expected, for the most part the prices behaved in the same fashion over the period April 2012 to July 2019. Although not reported here, the correlation values among the energy stocks ranged from 0.29 to 0.91. The values ranged from the minimum of $12 for KMI to the maximum of $135 for CVX. The average stock prices ranged from the minimum of $27 for KMI to the maximum of $112 for CVX. The XOM stock had the smallest total risk value with the standard deviation of $7.20. Both PSX and EOG shared the highest total risk with values of nearly $18.5 respectively. Half of the energy stocks were positively skewed with the remaining half (PSX, OXY, EOG, SLB and SLB) exhibiting negative skew. The skewness values, with the exception of CVX which had a negative skew of −0.8, all ranged between −0.5 and 0.5. It suggests fairly symmetrical distributions. The XOM, KMI, APC, OXY, EOG and COP stocks had platykurtic distributions with negative kurtosis values ranging from −0.23 for XOM to −1.63 for KMI. The MPC stock with the kurtosis value of nearly zero was an exception. The PSX, SLB and CVX stocks were the only three stocks with more weights in the tails, relative to rest of the distributions.

4.2. Ichimoku Cloud

Figure 3 shows the Ichimoku Cloud for the leading energy stocks of the S&P Composite 1500 Energy Index over the period 1st August 2012-25th June 2019. The Cloud is made of the Leading Span A and Leading B as boundaries. The Leading Span A is based on the average of the conversion line and the base line. The Leading Span B is an average of the 52 period High and 52 period Low prices. Both leading spans are plotted 26 periods ahead. The conversion line (base line) is an average of 9 (26) High and Low. The Chikou is the current stock price, plotted 26 days ago. While traditionally, green Cloud are usually pictured when the leading span A is above leading span B, and red Cloud are drawn when the leading span B is above leading span A, we do not distinguish from the two colours in our trading strategy. As laid out in the methodology part, a long only strategy is pursued when the Chikou span crosses the top of the Cloud from below, with the long position being closed when the Chikou crosses the bottom of the Cloud. Similarly, for a short only strategy, a short position is opened when the Chikou crosses the bottom of the Cloud from above, with the short position being closed when the Chikou line crosses the top of the Cloud.

As observed in Figure 3, the Chikou spans for all energy stocks experienced significant drop in values except for PSX, around the period of June 2014 to December 2015. Although not reported here, correlation values among the ten stocks for the period June 2014 to December 2015 were calculated. These were very high and positive, ranging from 0.6 to 0.98, except for MPC and PSX, which showed low or negative correlations with the other energy stocks. The drop in the oil prices can be attributed to various reasons. For instance, major players in emerging markets like China, Russia and India, all experienced slowdown in their respective growth rates, which led to relatively subdued demand for oil compared to pre 2008 global financial crisis. Further, developed nations like US extended their effort in the extraction of oil using methods like fracking into shale formations areas such as North Dakota. Similarly, Canada pursued its extraction of Alberta's oil, which represents the world's third largest reserve. With lower imports from these nations, this resulted in lower demand for oil. Saudi Arabia, the largest oil reserve gatekeeper, and other OPEC members also kept production levels stable, rather than curbing production levels which usually had the effect of increasing prices due to a lack of supply.

4.3. Trading Signals

Recall that Figure 3 depicts the Chikou spans crossing over and under the Ichimoku Cloud. In line with the figure, the buy and sell signals are compiled. In Figure 4, the trading signals for the top US energy stocks of the S&P Composite 1500 Energy index over the period 1st August 2012-25th June 2019 are presented. Both the buy and sell signals are captured, together with the trading prices of the ten energy stocks. To avoid more than one buy or sell position held at one single point in time, buying (selling) signals in instances where a long (short) already exists are disregarded. Although not shown here, there were only rare occasions where the

Figure 2: Leading US energy stocks (April 2012-July 2019)

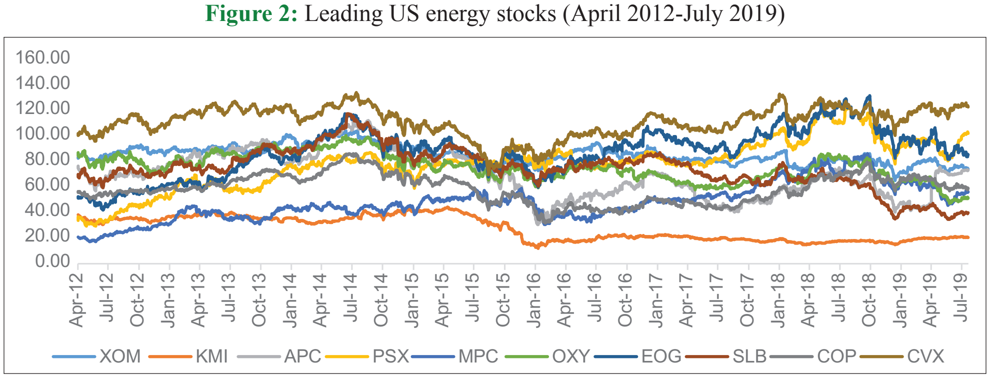

Figure 2 shows the daily stock prices, at close, for ten energy companies. The companies are all listed as the leading constituents of the S&P1500 Composite 1500 Energy index. The companies (trading symbols) include Exxon Mobil (XOM), Chevron Corp (CVX), ConocoPhillips (COP), Schlumberger Ltd (SLB),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

Figure 3: Ichimoku cloud

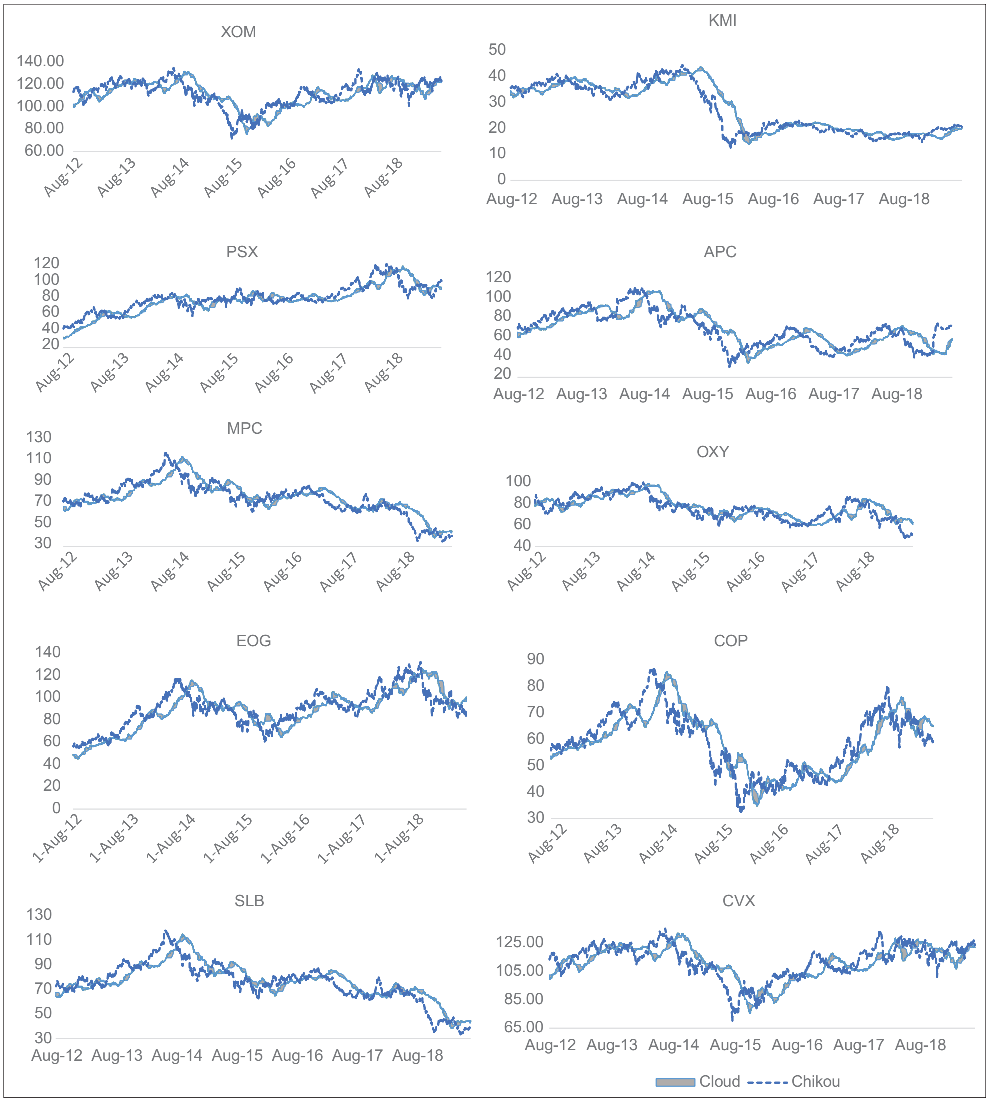

Figure 3 shows the Ichimoku Cloud for the leading energy stocks of the S&P Composite 1500 Energy Index over the period 1st August 2012-25th June 2019. The Cloud is made up of the Leading Span A and Leading B as boundaries. The Leading Span A is based on the average of the conversion line and base line. The Leading Span B is an average of the 52 period High and 52 period Low prices. Both leading spans are plotted 26 period ahead. The conversion line (base line) is an average of 9 (26) High and Low. The Chikou is the current stock price, plotted 26 days ago

Ichimoku Cloud system came up with long (short) positions where already a long (short) position was in place. This meant a long (short) position is always followed by a short (long) position and vice versa. As observed, all the stocks, to some extent, witnessed a drop in their stock prices around June 2014 till December 2015. As laid out previously, this is directly linked to the fall in oil prices which affected the attractiveness of energy companies as a lucrative sector within the equity asset class.

During the period of August 2012 to June 2019, there were 801 days with at least 1 long or short position. There were 347 days with only 1 buy signal per day, 80 days with 2 buys per day, 10 days with 3 buys per day, 3 days with 4 buys per day, and 1 instance of 5 buying signals. Similarly, for the selling signals, there were 382 days with no selling signals, 326 days with 1 selling signal, 69 days with 2 selling signals, 3 days with 4 selling signals, 2 days with 5 selling signals, and 1 day with 7 selling signals. A closer look at the behavior of buying and selling signals is warranted to provide light into whether the drop in the energy stock prices has resulted in a significant change in the buying and selling opportunities provided by the Ichimoku Cloud. Initially, the whole period under analysis is broken down into pre and post June 2014 window periods, to capture if the trading patterns have changed following the significant drop in oil prices around July 2014. While there were 212 days with at least one buying or selling signal for the period August 2012-June 2014, compared to 589 days with at least one buying or selling signal post June 2014, this can be explained by the relatively longer number of trading days available from July 2014 till June 2019. Noticeably, in both pre and post June 2014 periods, most of days had either one long or one short position. The highest number of long trades, on any single day post June 2014, was 5, and it occurred only on 25th June 2019, where all short positions had to be closed by forced long positions. Excluding those forced positions, there were 3 days

Figure 4: Trading signals in energy stocks

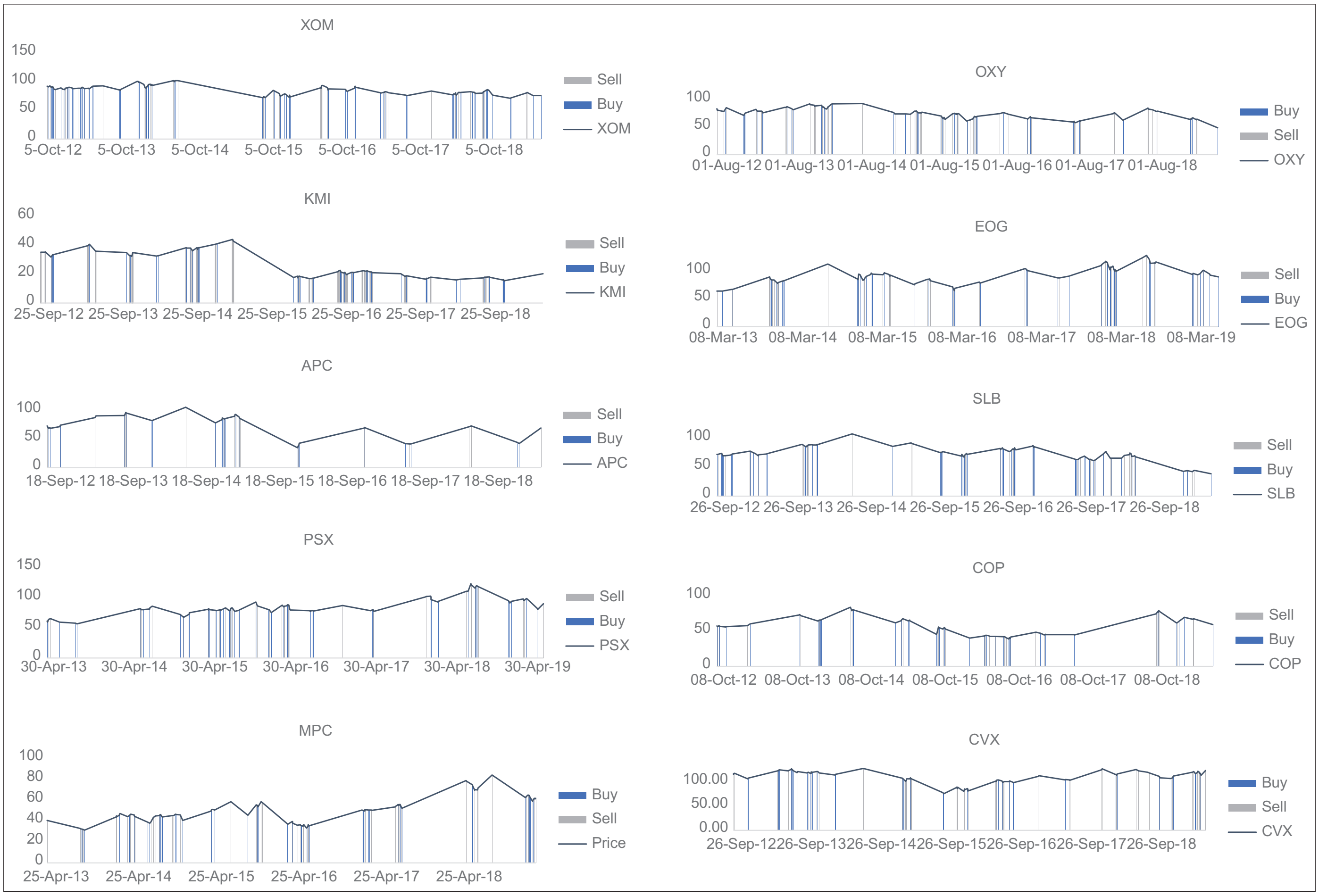

Figure 4 displays the trading signals for the top US energy stocks of the S&P Composite 1500 Energy index over the period of 1st August 2012- 25th June 2019. Both the buy and sell signals are captured, together with the trading prices of the energy stocks

where 4 buying signals took place. Regarding the selling signals, the highest number of selling trades on any single day took place on one day, i.e. 11th July 2018.

To avoid the bias of the pre and post June 2014 sample size that can affect the trading patterns we further break down the whole sample period into three distinct periods. These are January 2013-June 2014, July 2014-December 2015, and January 2015-June 2016. These groups allow us to better analyze if buying and selling patterns changed during the July 2014-December 2015 period, compared to other pre and post periods, each constructed over 15 months. The first observation is that there was still an increase in the number of trades which occurred through the July 2014- December 2015 period, despite a drop in oil prices which affected energy stocks prices. Compared to the January 2013-June 2014 period which had 162 trades, the July 2014-December 2015 period experienced 177 trades. This further increased to 202 during January 2015-June 2016. It is important to note that while there were more days with more than 4 and 5 selling trades each in the pre June 2014 period, compared to the July 2014-December 2015, there were only 2 days which witnessed 4 and 5 trades each respectively in the pre June 2014 era. Similarly, there were only 2 days during the June 2014-December 2015 period, with 4 buying trades each. This was also the case for the period January 2015-June 2016. The number of days with at least one buying or selling trade continued to increase over the three periods, suggesting that the drop in oil prices did not affect the trading signals from the Ichimoku Cloud indicator.

4.4. Performance Evaluation

The performance of the ten energy stocks based on the Ichimoku Cloud strategy are presented in Table 2. All stocks traded were for 1735 days with all positions closed on 25th June 2019. The XOM stock had the highest number of trades with 79 transactions, involving either a long followed by a short position, or a short position followed by a long one. While APC reported the smallest number of trades with 25 trades, the same stock also had the highest total return of 260%. The SLB stock had the smallest total return of 124%. The total return can be translated in an annualized return of 31% for APC compared to 19% for SLB. This also meant that APC had the highest average daily return of 10.4%, compared to the other stocks which had average returns ranging between 1.8% and 5%. A closer look at the average daily risk shows that APC also had the highest risk value of 34%, compared to XOM and CVX with 6% as average risk values. All the stocks had standard deviation values below 15%. In terms of the performance of each stock, the Sharpe values ranged from 0.30 to 0.53. SLB reported the smallest Sharpe value of 0.30, compared to PSX which shared

Table 2: Performance evaluation

	XOM	KMI	APC	PSX	MPC	OXY	EOG	SLB	COP	CVX
Trading days	1735	1735	1735	1735	1735	1735	1735	1735	1735	1735
Number of trades	79	49	25	45	56	64	49	64	38	56
Total return	145%	195%	260%	223%	204%	187%	240%	124%	199%	160%
Annualized return	21%	26%	31%	28%	26%	25%	29%	19%	26%	22%
Average return	1.8%	4.0%	10.4%	5.0%	3.6%	2.9%	4.9%	1.9%	5.2%	2.9%
Average risk	6%	11%	34%	9%	11%	8%	10%	7%	14%	6%
Sharpe	0.32	0.35	0.31	0.53	0.34	0.37	0.49	0.30	0.38	0.46
Sharpe per trade	0.0041	0.0071	0.0122	0.0118	0.0062	0.0058	0.0100	0.0046	0.0100	0.0083
Sortino	1.63	1.63	0.54	3.74	1.86	2.08	2.73	0.96	3.13	2.92
Buy-and-hold returns	−12%	−42%	2%	135%	120%	−41%	79%	−46%	8%	12%

Table 2 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 1st August 2012-25th June 2019. Average returns and average risk are based on arithmetic averages. Sharpe values represent the excess return per unit of total risk. Sortino values represent the excess return per unit of downside 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

the highest excess return per unit of total risk. In line with Gurrib and Elshareif (2016), who proposed to adjust the Sharpe ratio to the number of trades as a proxy to transaction costs, PSX reported the highest Sharpe per number of trade value of 0.0118, compared to XOM which had the lowest Sharpe value per number of trades, due to the relatively high number of trades. To assess the impact of only downside risk over the performance of each stock, the Sortino values were also calculated and reported. PSX had the highest Sortino value of 3.74, compared with APC with a value of 0.54. The highest Sharpe, Sharpe per number of trade, and Sortino values for PSX support that the stock was the top performer among the other nine energy stocks, upon applying the Ichimoku Cloud technical indicator. A comparison with a buy and hold strategy also support PSX's as the top ranked stocks among the selected, with a total return of 135%, followed by 120%. Reliance on the technical analysis indicator yielded superior returns for all the ten stocks. The buy and hold strategy also produced negative returns for XOM, KMI, OXY and SLB, thereby reducing its reliability compared to the Ichimoku Cloud.

4.5. Ichimoku and Trends

Our analysis so far has followed the traditional Ichimoku Cloud components such as the leading span A, leading span B and the Chikou span. The application of the Ichimoku Cloud resulted in significantly stronger reported returns compared to a naïve buy and hold strategy model. As an added bonus, the Ichimoku Cloud encompasses the existence of trends in the study. A long position is created if there is a buy signal from the Ichimoku Cloud, and a close position is created if there is a sell signal from the same indicator. More importantly, the strength of the trend in place needs to be captured, as it serves as an additional layer of information which can improve the decision making process of the trader. For instance, it is more appropriate to enter a long position, if there is a buy signal from the Ichimoku Cloud, which is backed by a strengthening bullish period. Likewise, it is more appropriate to enter a short position, if there is a selling signal from the Ichimoku Cloud which is supported by a strengthening bearish period. A buy or sell signal from the technical analysis indicator during a period where the trend is weakening can result in increased uncertainties including potential trend reversals and reduced profit opportunities. For the purpose of this study, a bullish trend or a bearish trend which is strengthening can occur when the following conditions are met:

$$\text{Strengthening trend} = \begin{cases} \text{Bullish trend}_t,\ \text{Price}_t > \text{Senkou Span } A_t, \\ \quad \text{Senkou Span } A_t > \text{Senkou Span } A_{t-1} \\ \quad \text{Senkou Span } A_t > \text{Senkou Span } B_t \\ \text{Bearish trend}_t,\ \text{Price}_t < \text{Senkou Span } A_t, \\ \quad \text{Senkou Span } B_t > \text{Senkou Span } B_{t-1} \\ \quad \text{Senkou Span } B_t > \text{Senkou Span } A_t \end{cases} \tag{7}$$

where $Price_t$, $Senkou\ Span\ A_t$ and $Senkou\ Span\ B_t$ represent the current price, current leading Span A and current leading Span B values. $Senkou\ Span\ B_{t-1}$ and $Senkou\ Span\ A_{t-1}$ represent the leading Spans B and A one period before. There were 43 instances where buy signals occurred during a period which was bullish and strengthening. The XOM and EOG stocks had the relatively highest number of buy signals (6) compared with KMI which witnessed only one such trade. There were only 5 long trades which took place when the trend was bearish and strengthening with XOM, MPC and EOG bearing those. Although it was expected that sell signals would likely to occur in a bearish trend which is strengthening only 5 trades by XOM, KMI, OXY and SLB witnessed such a possibility. In comparison, there were 106 selling trades which happened when the trend was bullish and strengthening. Several stocks experienced those sell signals, namely CVX (16), XOM (15), COP and PSX (13), MPC and SLB (12). The APC and OXY stock had the lowest number of sell trades during a strengthening bullish period. If the strength of the trend is considered, these findings suggest that the technical analysis indicator provides buy signals during periods of strengthening bullish trends, as is expected by most traders. You buy in a bullish state which is gaining momentum. However, surprisingly, for sell signals this is not the case. The Ichimoku Cloud technical indicator provided more sell signals during a strengthening bullish trend compared to sales which would be expected to occur during a bearish trend which is strengthening. Only a fraction of the buy and sell signals took place during a bullish or bearish trend which is strengthening. It could be the result of the trend is bullish or bearish but weakening. The weakening trends are out of the scope of the present study and were not investigated.

5. CONCLUSION

Energy commodities such as crude oil and natural gas affect not only other commodities but also a range of alternative assets such as equities. The challenges of decoupling energy commodities, increased competitiveness of renewables, and other critical factors affecting demand and supply of crude oil have kept energy policy makers rigorously at work. Macroeconomic activity, economic sanctions, and technology have also affected energy markets. The drop in energy stock prices during the July 2014-December 2015 period caused by the corresponding drop in oil prices provide a good reference point. Investors and traders often use fundamental and technical analytical tools in an attempt to gain profits through a set of strategies. This paper focuses on the Ichimoku Cloud as a technical analysis tool. It has not been documented sufficiently in the existing literature. Our analysis looks at its performance during 2012-2019 for the ten leading stocks of the S&P 1500 Composite Energy Index.

The indicator provided at least 800 days with a minimum of one long or short position over a possible 1735 trading days. To better understand the effects of the drop in energy prices on the buying and selling opportunities the entire sample was divided into three distinct periods around the July 2014 – December 2015 price drops. We note that the number of trades increased despite the fall in oil and energy stock prices. The Ichimoku Cloud indicator was able to provide profits during the period where energy stock prices declined. In terms of performance, all stocks had total risk values below 15% with Sharpe ranging from 0.3 to 0.53. While APC had the highest total return of 260% with the lowest number of trades, PSX ranked best in terms of the Sharpe, Sharpe per number of trade, and Sortino. The Ichimoku Cloud indicator performed better than the buy and hold strategy, where the latter produced negative returns for four energy stocks. Buying (selling) during a strengthening bullish (bearish) is commonly advocated as rational decisions. As expected, our indicator produced a number of buying signals during a bullish period. But it was surprising to observe sell signals produced by the indicator during a bearish trend. However, the majority of buy and sell signals occurred outside the strengthening trends.

The policy implications concern mainly the role of speculators in financial markets and, more specifically, energy equity and commodity markets. Our findings indicate that the use of the Ichimoku Cloud can provide a profitable trading strategy even during periods of significant drop in oil price. Our insights help regulatory bodies like the Securities Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) better understand the profitability of energy traders during the declining markets. While the issue whether speculators are price destabilizers is beyond the scope of this study, our findings do suggest that the drop in oil price is passed on from commodity markets to energy stocks. As a result, oil companies are affected through lower stock prices. However, the losses for speculators who are skilled in the use of technical analysis indicators such as the Ichimoku Cloud are mitigated. In other words, financialization provided some benefits to commodity speculators who have access to energy stocks. Future research with alternative trading frequencies - both a higher (say intraday trading) and lower (say weekly) frequency - is warranted. Furthermore, future analysis can accommodate buying and selling opportunities during weakening trends in addition to strengthening ones.

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