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Trading Momentum in the U.S. Crude Oil Futures Market

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ABSTRACT

This paper investigates if the Rate of Change (ROC), as a popular measure of momentum, can serve as a reliable technical analysis indicator to improve stock price prediction for U.S. West Texas Intermediate (WTI) crude oil futures market. The methodology centers on the application of the ROC and/or Moving Average (MA) price crossover/cross under strategies as a trading system. End of month futures prices of West Texas Intermediate (WTI) crude oil prices are collected for the period May 28th, 2004-April 30th, 2024. The performance of the trading system is measured using both the Sharpe and Sortino ratios, thereby adjusting for total and downside risks. The model is also benchmarked against the naïve buy-and-hold strategy. Overall findings suggest a ROC based on 14-month periods outperform other momentum-based indicators, including when combined with price-crossover moving average strategies, and the naïve buy-and-hold strategy. After adjusting for the negative returns, the downside risk or semi-deviation amounted to 8.5%, and a Sortino value of 4.58. The Sortino value is however biased due to the 295% return witnessed in 2009. Findings have some vital policy implications for regulatory bodies and traders in the WTI crude oil energy futures market.

Keywords: Energy, Crude Oil, Futures Markets, Rate of Change, Technical Analysis, Performance
JEL Classifications: Q40, G13, G15

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.

Contu et al. (2021) mixed views on energy sources support that energy markets 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 (Nadarajah 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 investigated 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) analyzed various companies using both fundamental and technical analysis and found differences in the performance using either analytical tool was less pronounced for energy stocks and combining both techniques improved forecasts of stock prices performance. More recently, Kamalov et al. (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 momentum strategies within a trading system in their studies. There is a lack of focus on the market under study and the use of momentum rules in the application of the ROC indicator.

For this study, we tap into the performance of the ROC as a trading model and compare the results with the naïve buy and hold strategy. While there exist studies that have applied the ROC, this is the first study to investigate the use of ROC as a trading strategy for the WTI US energy futures market. Our analysis of the leading energy stocks is the first to provide insights into whether this technical analysis tool is useful in energy derivatives markets. This paper contributes to the existing literature by comparing the results from the ROC trading strategy with a buy and hold strategy. It helps to determine if the ROC is a more reliable technical analysis tool. The performance of the ROC 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 rest our case with some conclusive remarks.

2. LITERATURE REVIEW

2.1. Factors Affecting Crude Oil Futures Market

Oil is an important raw material for industrial manufacturing and a nonrenewable source of fossil fuels. World oil consumption was over 98 million barrels in 2017 (BP, 2019). The oil markets often respond to changing expectations of future supply and demand. Changes in oil supply and prices can significantly affect the world's macro-economy. The crude oil price has been observed to fluctuate since the first oil crisis in the 1970s and continued to do so more frequently and violently (BP, 2019). As more commercial participants are joining the crude oil futures market, improvements have been made to enhance price discovery, risk mitigation and speculation standardization within the crude oil futures markets. Oil prices can be adjusted according to supply and demand under the influences of fundamental, political, and financial factors. A review of these factors is given below:

2.1.1. Supply and demand

The price of a commodity is highly influenced by Supply and demand factors which determine the price of a commodity. When crude oil demand increases, the supply might not be flexible enough in the short term to control the surge of demand (Sokhanvar et al., 2023). The increase in crude oil prices in 2007-2008 proved this as there was insufficient production capacity to meet the strong demand, initiating a decrease in oil prices elasticity. The recent shale revolution in the United States has allowed the country to reduce the dependence on imported crude oil, moreover, profound effect has been created to the global oil market (Bataa and Park, 2017; Kupabado and Kaehler, 2024). However, market driven remains to be the core factor and the importance of traditional oil producers and still play dominant roles in the global oil market (Ansari, 2017).

2.1.2. Macroeconomic shocks

Strong successful economy will increase the consumption of the oil and create stability in the short-run oil production. On the contrary, recession can negatively affect oil consumption and oil market (Takahashi, 2023). Global economy expansion is one of the major contributing factors that influences oil prices (Chen et al., 2023; Wang and Sun, 2017; Monge and Cristóbal, 2021). Guo et al., 2022 proved that since the mid-1980s, the major factor in oil price fluctuations was macroeconomic shock, but financial shocks and oil supply have had a substantial impact in the early 2000s, especially the impacts of financial shocks are more significant since the mid-2000s.

2.1.3. Economic uncertainty

A significant economic uncertainty could happen due to change in oil prices, and this might be reflected in economic policies and regulations. Consequently, economic uncertainty provides feedback to impact oil prices (Kang et al., 2017; Sheng et al., 2020). The producers of the oil will amend the production to match with the demand and reduce oil supply elasticity, thus oil pricing will be affected (Dokas et al., 2023). Accordingly, the impacts of economic policy uncertainty and equity market uncertainty on oil prices together present strong consistent impacts of economic uncertainty on oil prices (Dokas et al., 2023; Wang and Sun, 2017; Wei et al., 2017).

2.1.4. Political factors

There is a huge geographical inequality between oil supply and consumption countries, and this makes oil a politically sensitive commodity, and any changes in political factors in oil-producing regions might have a significant impact on oil prices (Miao et al., 2017; Zhang et al., 2023). It worth to mention as an example that Political risks in OPEC countries have a significant positive impact on oil prices, and their impact is only less than that of oil demand shocks (Dokas et al., 2023; Chen et al., 2023). Song et al. (2022) argued that war and political tensions and instability among oil-producing countries and their neighbouring countries might lead to increase crude oil prices sharply, but their study could not confirm a definitive impact. In general, it is a challenge to determine the political risk factors impact on oil prices because most studies are mainly qualitative.

2.1.5. Financial factors-speculation

The oil futures markets improve the price discovery and risk aversion functions, and the associated financial properties (Shao and Hua, 2022). Since 1991, the US Commodity Futures Trading Commission (CFTC) has given financial companies the same rights to purchase unlimited quantities of crude oil futures (Cifarelli and Paladino, 2010). Due to the increase in investment funds the oil price, has increased which initiated concerns on the impact of speculation on oil price fluctuations. The market was in line with the law of supply and demand, rather than contrived by speculators. Chu et al. (2023) noted that financial markets have a significant impact on oil prices. Sokhanvar and Bouri (2023) proposed that the liquidity increase in the BRIC countries (Brazil, Russian, India and China) created a significant rise in real oil prices, global oil production, and global real aggregate oil demand, which, consequently, has had a substantial influence on oil prices. Zhang et al. (2023) studied the influencing factors for predicting crude oil prices and found that financial factors have greater impact than supply and speculation. The collapse of oil prices in mid-2014 was attributed to the combined effects of demand, commodity markets, and financial factors. As the international crude oil market is mainly settled in US dollars, the influence of the US dollar exchange rate on crude oil prices has also become a research topic.

2.1.6. Bubbles

The bubble is defined as severe fluctuations in oil prices, where traditional theory cannot explain. Understanding the mechanism of oil price bubbles helps to more understanding of the causes of oil price volatility (Chen et al., 2023). The root causes of the oil price bubble originally stalk from two aspects: (a) Majority of economic activities are depending on crude oil as source of energy, and (b) crude oil will eventually be depleted in the future. These two reasons make the crude oil market very sensitive to various information, in which investors in the crude oil futures market are always ready to use various information to make profits (Chang, 2024). Some studies verified evidence of speculative bubbles in oil price dynamics and examined the impact of bubbles on oil price (Chang, 2024; Chen et al., 2023).

2.2. Relationship between Crude Oil Futures and Spot Markets

Relationship between futures and spot prices has been explored extensively in literature. Currently, the main focusing is on the leading-lag relationship and price discovery. Guiding relationship of spot prices initially empirically has been tested and analyzed by Garbade and Silber (1983), where they established a dynamic analysis model reflecting the relationship (Garbade and Silber, 1983). Currently, the association between futures and spot research almost cover all financial derivatives markets, including index futures (Li and Kim, 2023) and energy futures (Zeng et al., 2021). Considering financial instruments diversification, oil futures are broadly used in the risk hedging mechanism to control the risks of spot oil transactions. The price fluctuations directly spread to the spot market once the oil futures market price changes. As an example prior to 2018, many research have been pursued on the spillover effects between the Chinese crude oil spot market and the international crude oil futures market, finding that global financial markets such as crude oil show a trend of global integration (Mohti et al., 2019) and that there are also significant spillover effects between Chinese crude oil spot and WTI crude oil futures (Mohti et al., 2019). A study of the relationship between fuel oil futures and other energy financial derivatives also finds that the correlation between Chinese fuel oil spot, fuel oil futures, and energy equity markets is weaker than that of the US market, and the strength of the correlation has weakened after the financial crisis (Ji et al., 2021).

2.3. Momentum Indicators and ROC

To increase analysis efficiency, several advanced indicators have been developed by technical analysts in the past few years. Although there are hundreds of indicators and more are added daily, this study will discuss one of the most used. The rate of change (ROC), a momentum indicator. ROC is a momentum indicator that refers to the speed of the movement of the price (Karasu and Altan, 2022). It is usually used to compare the most recent closing price to the previous closing price. The movement of this indicator has been used by the practitioners to identify whether the price is in a certain trend, either in an upward or downward trend. One of the most important momentum indicators is ROC, because it looks at the speed at which a variable change over a specific period. Practically, practitioners monitor the speed at which one variable change relative to another. Moreover, ROC can clarify the momentum behind the movement of the price; it quantifies the change in the percentage. For most parts, current price and ROC should move together. When the current price and ROC diverge, the technician looks to ROC for a clearer indication of the underlying trend. For momentum, the Rate of Change (ROC) indicator simply measures the price change, in percentage, between the price n days ago and the current price (Paul and Deepika, 2022; Karasu and Altan, 2022).

2.4. Technical Analysis and Performance

A vast amount of literature exists when it comes to the success or failure of techniques such as machine learning, technical analysis, and regressions in financial markets (Kamalov et al., 2021; Gurrib and Kamalov, 2021; Gurrib et al., 2022; Kumar et al., 2022; Kamalov et al., 2024). 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. (2018) 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. Lately, 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.

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 (1964b) 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 like 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. Recent studies which applied the Sharpe performance measure in commodities markets include Gurrib et al. (2023), Gurrib (2023), Gurrib (2022), Gurrib et al. (2022), and Gurrib et al. (2020).

While various applications exist regarding the use of Sharpe (Gurrib [2016] and 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 and Price (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.

3. DATA

For the purpose of this study, we focus on the Crude oil futures prices. As per the largest derivatives marketplace - Chicago Mercantile Exchange, the West Texas Intermediate (WTI) light sweet crude oil futures is the world's most liquid oil contract. Specifically, WTI crude oil futures provides the most efficient way to trade the largest light, sweet crude oil blend, and allows hedgers (speculators) to hedge (speculate) by minimizing (maximizing) the impact of potentially adverse (favorable) price moves on the value of oil-related assets. Over 1 million contracts of WTI futures and options trade daily, with approximately 4 million contracts of open interest (Chicago Mercantile Exchange, 2024). WTI is the go-to measure for the world oil price, since U.S. is the leading consumer and producer of oil. The contract specifications for the energy commodity futures is summarized in Table 1 Data is sourced from Factset and NYMEX.

Due to the impact of weather on energy prices, it is important to conduct a preliminary seasonality analysis of both crude oil futures prices in the U.S. Table 2 reports the seasonality impact on crude oil futures prices in the U.S. A 10-year average is also estimated to capture trends over the years. As observed, the months of April tend to witness the most positive changes in crude oil, compared to the prior month. Comparatively, the months of November and December tend to witness drops in crude oil energy prices.

Table 1: Asset specification details

Energy Futures Markets	Crude Oil WTI (NYM $/bbl)
Trading Symbol	CL00
Sector	Energy
Contract unit	1,000 barrels
Currency	U.S. dollar
Tick size	$10 per contract
Contract months	Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec
Settlement	Physical
Exchange	NYMEX

Source: Factset, New York Mercantile Exchange (NYMEX)

As reported in Figure 1, 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 natural gas market and crude oil market (represented by the S&P 1500 Energy index) decoupled 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 trend observed in the S&P Composite 1500 Energy Index makes the ROC a good candidate to be used as a technical indicator.

The study is conducted, using end of month prices, over the period May 28th, 2004-April 30th, 2024. The risk-free rate is estimated using the 3-month US Treasury bill rate, which ranged from a minimum of −0.05% to 5.36% from May 2004 to April 2024, with an average of 1.48% over the period under study. The negative yield was in early 2020, where the financial players were concerned about the potential adverse impact of the coronavirus and related policy measures taken to address the flight from risky assets such as stocks to short-term Treasuries. With growing uncertainty, this led to a shift into short-term government-issued securities, where the prices rose and the yield fell, creating a inversion yield curve. The risk-free rate is sourced from the St Louis Federal Reserve (FRED) database. Energy futures prices are sourced from Factset.

4. RESEARCH METHODOLOGY

4.1. Rate of Change indicator (ROC)

The Rate-of-Change (ROC) indicator is applied as a measure to determine the percentage change of prices from one timeframe period to the next one, representing a momentum of a variable. ROC is broadly used in a diverse range of mathematical and scientific scenarios. In addition, it can be also employed in the finance field as it allows investors to identify security momentum as well as other trends. ROC is estimated as follows:

$$ROC=[(Close\text{-}Close\ n\ periods\ ago)/(Close\ n\ periods\ ago)]\times 100 \quad (1)$$

Furthermore, it is considered that assets with a positive ROC outperform on the market, therefore a security price is expected to increase. In contrast, a low or negative ROC shows an expected decline in a security price, typically signaling assets to sell. ROC broadens into positive region when there is an accelerating rise in asset prices. Moreover, there is not any limit to an upward price. Conversely, ROC goes deeper into negative region when there is an accelerating decline. In general, there are almost 250 trading

Table 2: Crude oil price change (%)

Years	Month-on-Month % change in price											
	January	February	March	April	May	June	July	August	September	October	November	December
10 year average	1.2	2.4	−4.3	5.8	8.1	3.2	−2.7	−0.9	0.8	−1.8	−4.5	−0.2
2023	−1.7	−2.3	−1.8	1.5	−11.3	3.7	15.8	2.2	8.6	−10.8	−6.2	−5.7
2022	17.2	8.6	4.8	4.4	9.5	−7.8	−6.8	−9.2	−11.2	8.9	−6.9	−0.4
2021	7.6	17.8	−3.8	7.5	4.3	10.8	0.7	−7.4	9.5	11.4	−20.8	13.6
2020	−15.6	−13.2	−54.2	−8.0	88.4	10.7	2.5	5.8	−5.6	−11.0	26.7	7.0
2019	18.5	6.4	5.1	6.3	−16.3	9.3	0.2	−5.9	−1.9	0.2	1.8	10.7
2018	7.1	−4.8	5.4	5.6	−2.2	10.6	−7.3	1.5	4.9	−10.8	−22.0	−10.8
2017	−1.7	2.3	−6.3	−2.5	−2.0	−4.7	9.0	−5.9	9.4	5.2	5.6	5.3
2016	−9.2	0.4	13.6	19.8	6.9	−1.6	−13.9	7.5	7.9	−2.9	5.5	8.7
2015	−9.4	3.2	−4.3	25.3	1.1	−1.4	−20.8	4.4	−8.4	3.3	−10.6	−11.1
2014	−0.9	5.2	−1.0	−1.8	3.0	2.6	−6.8	−2.3	−5.0	−11.6	−17.9	−19.5

Source: Factset

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

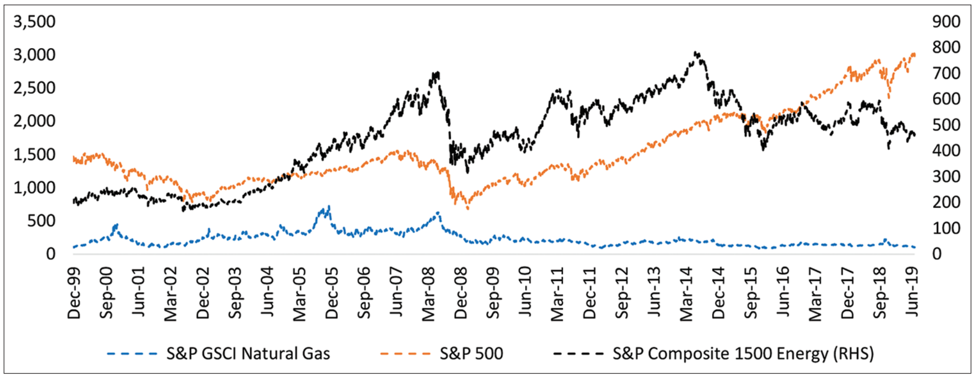


Figure 1 shows the performance of the S&P 500 market index, S&P Composite1500 Energy index and the S&P GSCI natural gas, which is displayed on the right-hand side vertical axis. Source: Factset, S&P500 Dow Jones Indices

days during a year, it can be decomposed as 125 days for 6 months, 63 days per one quarter leading to 21 days per month. A trend reversal spreads on the shortest timeframe and progressively extends to encompass broader timeframes. When ROC for both the 250-day and 125-day periods are positive caused by the long-term uptrend. This implies that current prices surpass those ones of 6 and 12 months prior. Therefore, long positions placed 6 and 12 months should remain profitable leaving an investor in a positive mood. Typically, when the price of an asset reaches a new highs or lows, however, ROC does not mimic the same, it can be a signal of a weakening trend leading to a potential reversal. The extremely high level of ROC can illustrate that a security is overbought, contrarily, the extremely low level of ROC demonstrates that a security is oversold indicating a possible price reversal. In addition, when traders see how ROC crosses above a zero-mark, they tend to buy securities. In contrast, when traders observe how ROC crosses below a zero-mark signalling to sell securities. Besides, with the usage of ROC traders can confirm a direction of a trend when it follows suit a price movement. In conclusion, ROC is beneficial indicator to determine a price momentum and possible reversals on the security market. However, taking into consideration limitations of ROC, traders should also actively apply other technical and fundamental methods to make correct decisions (Rate of Change [ROC], n.d.).

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:

$$Sortino\,ratio = \frac{\overline{R_A} - MAR_A}{\sigma_A^d} \quad (2)$$

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.

5. RESEARCH FINDINGS

5.1. Descriptive Statistics

As summarized in Table 3, the average monthly price of crude oil futures was nearly \$71.2/bbl with a median of \$69.57/bbl over the period May 28th, 2004 to April 30th, 2024. The average risk was \$21.71, with an average price to risk ratio of 3.28. The price behaviour had a kurtosis value of 2.52, positioning it towards a playkurtic distribution. The positive skewness value suggests a distribution skewed to the right, with more positive values. The relatively low probability of the Jarque-Bera test statistic support a normal distribution at 10% level. The low P-value of the Augmented Dickey-Fuller (ADF) test support the data is stationary at levels.

5.2. ROC

It is important to note that an investment or trading horizon would differ among different traders and investors, based on their trading/investment risk appetite and trading/investment objectives. For example, for an investment analyst on the trading pit, the long-term horizon is completely different from that of an institutional investor. While for a trader, long-term can mean several days, for an investor, it can mean 12-18 months. While it is beyond the scope of this study to tackle all possible x periods, due to the use of monthly data, we position our analysis to a long-term investment horizon. Nonetheless, to allow the study to provide sufficient insights, we initially estimate the ROC using 9, 10, 11, 12, 13, and 14 months as n periods. Figure 2 displays the ROC values under each of the 6 scenarios. Noticeably, the ROC dropped significantly in values in the later part of 2008, 2010, 2014 and 2022, consistent in price drops in the U.S. WTI crude oil prices during these specific periods. The drops in ROC values are witnessed from positive to negative ROCs, compared to 2010 where ROC dropped but hardly turned negative. Importantly, while ROC drops fluctuated between −67% (10-months ROC) and −70% (13-months ROC), ROC spikes fluctuated between 154% (9-months ROC) and 249% (14-months ROC). This can be found in Figure 2 where the 14 month-based ROC model (in green) tends to dominate in terms of more negative and more positive values during the period of 2004-2024. This suggests that the selection of ROC, particularly during periods of increases, is particularly important for profit-maximizing investors, where different ROC-based models do not significantly differ during price falls. ROC can drop to −1 (with a 100% fall in prices), with however no upper boundary as prices can rise indefinitely.

Table 3: Descriptive statistics of west Texas intermediate crude oil futures price

Mean	71.1984
Median	69.5700
Standard deviation	21.7089
Kurtosis	2.5223
Skewness	0.2816
Jarque-Bera	5.4760
P-value	0.0640
ADF	-3.3465
P-value	0.0139
Observations	241

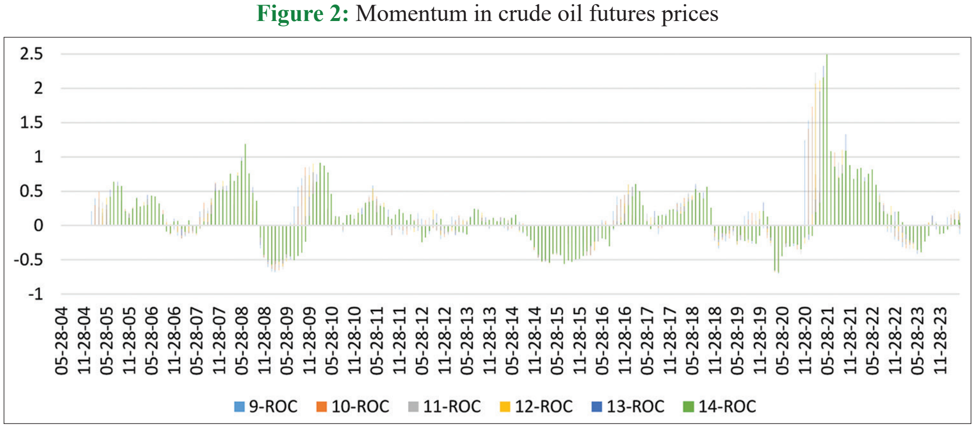
Source: Authors

While Figure 2 shows a relatively dominant ROC model based on 14 months for the crude oil futures market, statistical analysis is needed to confirm the model selection. As seen in Table 4, end of month crude oil futures prices are positively correlated with all the ROC models, ranging from 0.374 for the 9-ROC to 0.448 for the 14-ROC model. Moreover, the 14-ROC model is strongly positively correlated with all other ROC-periods models, ranging from 0.609 to 0.902. This confirms the selection of the ROC model which is based on 14-month estimations.

5.3. Trading System Based on Momentum

To be able to assess the performance of the ROC model, it is critical to determine overbought and oversold extremes, by taking into account the volatility of the asset's rate of change. With a standard deviation of the ROC-14 model of 42% and an average of the standard deviation of all other ROCs from Table 4 at 38%, we assume an overbought/oversold level at +40%/−40%. It is critical to note that while we used a 40% overbought and −40% oversold level, these levels differ from different financial assets, and thus cannot be applied blindly across the wide spectrum of financial products. Figure 3 Panels A and B displays the crude oil futures prices and the rate of change technical indicator over the monthly periods of May 2004-April 2024. Panel A shows that crude oil prices have fluctuated drastically from nearly \$40/bbl to nearly \$80/bbl over the two decades, with prices fluctuating significantly to reach highs of nearly \$140/bbl in June 2008. On average, the WTI crude oil futures was priced around \$71/bbl. Panel B includes the overbought and oversold levels as mentioned above. As observed in Panel B, the momentum indicator tends to turn close to the overbought and oversold levels. This suggests that the overbought and oversold are relatively correctly specified to determine selling (overbought) and buying (oversold) signals. Alternatively stated, a selling (buying) signal from the technical indicator is captured when the previous period (say month) is lower (higher) than current period's momentum. Narrowing (widening) the band would result in more (less) trading signals. Since any

Figure 2: Momentum in crude oil futures prices



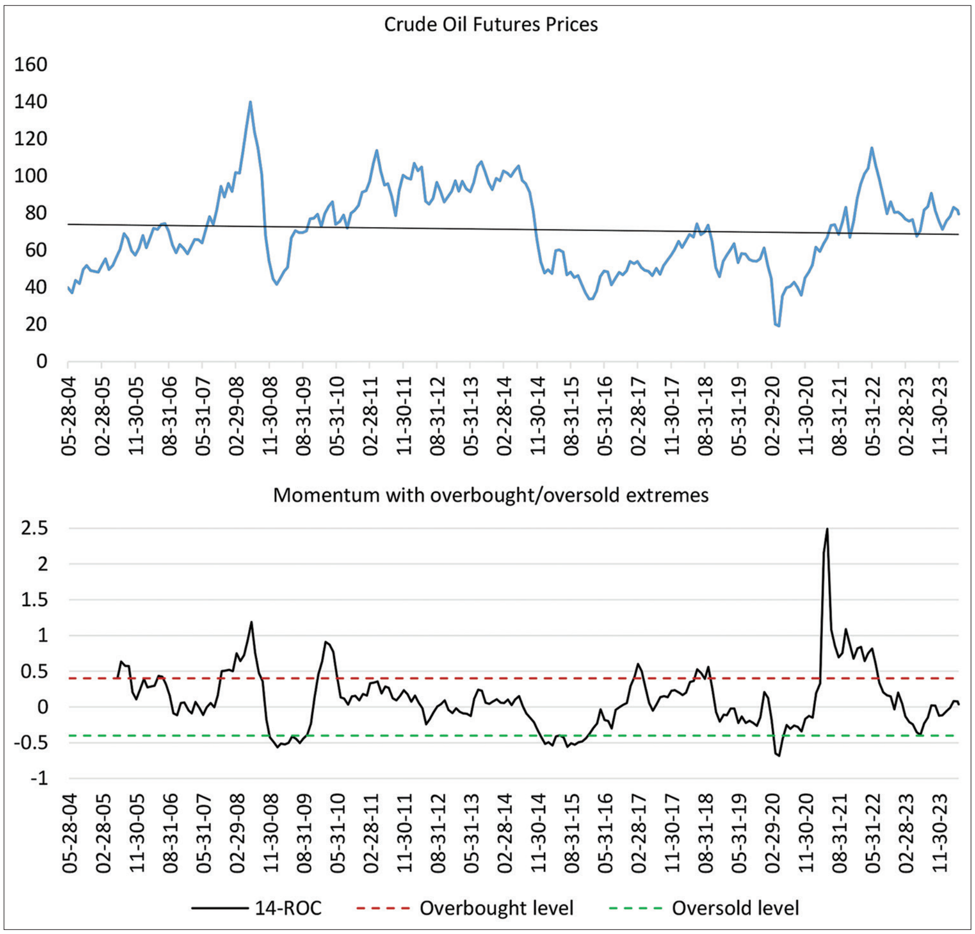
Source: Authors

Table 4: Relationships between crude oil futures prices and momentum

Variables	9-ROC	10-ROC	11-ROC	12-ROC	13-ROC	14-ROC	CL-WTI
9-ROC	1.000						
10-ROC	0.890	1.000					
11-ROC	0.754	0.891	1.000				
12-ROC	0.688	0.764	0.900	1.000			
13-ROC	0.636	0.700	0.764	0.892	1.000		
14-ROC	0.609	0.648	0.698	0.768	0.902	1.000	
CL-WTI	0.374	0.392	0.404	0.419	0.436	0.448	1.000

Source: authors

Figure 3: Crude oil prices and momentum levels



Source: Authors

transaction results in transaction costs, it is vital to select proper overbought and oversold levels to avoid transaction costs reducing the total returns significantly and making the trading model not profitable. To validate the performance of the ROC-14 model, we build a trading system and report the total return, average return, average risk, and Sharpe performance measure.

Figure 4 reports the returns achieved upon implementing the ROC-14 model in the crude oil futures market. To estimate any return, an open trade position is required to be closed, i.e. a buy offset against the next sell, or a sale matched against the next purchase. In the event(s) of a buying signal, followed by another buying signal, or a selling signal followed by another selling signal, a return is calculated by offsetting a buy with the next available selling signal, and vice versa. Last, but not least, in the event of any open position at the end of the April 2024 period, the position is closed with the last price in the study period. As observed in Figure 4, the returns generated from the technical analysis indicator were all positive initially reaching the highest return of 295% in December 2009. However, as depicted in the waterfall representation in Figure 4, the effect of positive returns on total returns were reduced with the trading system posting negative returns from 2017 to 2024. Specifically, the 4 next trading positions since 2017 posted negative returns of −34%, −7%, −8% and −20% respectively.

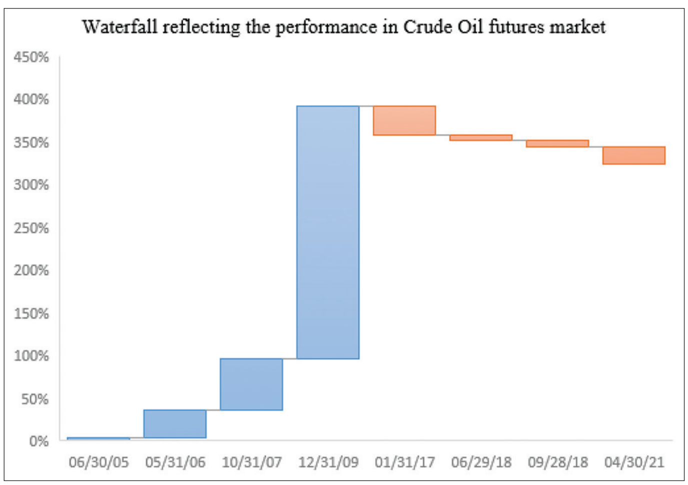
The total returns achieved were 323%, with an average return of 40% over the 8 trades. Despite the relatively low level of transactions, the average risk was 107%, resulting in a low Sharpe performance value of 0.364. Compared with a naïve buy-and-hold strategy which generated a positive return of 99% during the whole period, the momentum indicator performance was superior. Since some returns were negative, this meant that the Sortino ratio can be estimated to reflect the impact of downside risk as a performance measure. Alternatively stated, while the Sharpe ratio considers both upside and downside volatility in its calculation, the Sortino lays emphasis on downside volatility, which has been apparent due to the negative returns observed in trading system for the crude oil energy market since 2017. After adjusting for the negative returns, the downside risk or semi-deviation amounted to 8.5%, and a Sortino value of 4.58. While this result suggests crude oil performed well when adjusting for downside risk, it is important to know that the 295% return of 2009 impacted the Sortino value significantly. For instance, without this return of 2009, the Sortino value would drop to 0.25. Taking into account all the returns available, the low Sharpe and highly Sortino value points to the inclusion of additional filters into the trading system.

5.4. Trading System with Momentum with a MA Filter

To make the trading system more robust, we include a moving average price crossover strategy as a confirmation filter to the existing system which is based on momentum. Specifically, a buy (sell) signal is generated if the energy futures price crossover (cross under) the moving average indicator together with the momentum indicator crossing under (crossing over) the oversold (overbought) level. Results show that the combined use of the ROC-14 with the MA-14 did not yield any trading signal. To ensure this is not due to model specification or the lagged impact of moving averages-based indicators, we also test for different MA periods ranging from MA (5) to MA (13). Results did not change. This suggests that the MA did not enhance the existing trading model, but rather deterred the likelihood of deriving positive returns from the crude oil futures market.

Finally, we compare the use of a trading model based on the conditions meeting either a price/moving average crossover strategy or a ROC-14 model strategy. Consistent with the above, we compare the distinct ROC and MA models, which are based on 14 periods. Alternatively stated, we constructed a model where trading signals are derived as long as either the ROC overbought/oversold or MA crossover/cross-under threshold levels are violated. The waterfall in Figure 5 reports the results. With 41 (29) selling (buying) signals, the trading system yields a total return of 1125% over the 2004-2024 period over an average yearly return of nearly 7.71%, and an average return per closed position of 12.66%. Trading returns ranged from −39% in November 2018 to 270% in June 2018. This resulted in a relatively high average risk value of 65%, and a relatively low Sharpe of 0.17. Compared to the naïve buy-and-hold strategy which yielded 99% return, the trading system which considers either ROC or MA price crossover strategies outperformed significantly. All in, despite the first model which relies only on ROC model yielded a slightly lower cumulative return of 323%, the Sharpe performance measure was almost doubled (0.364). Therefore, the use of ROC-14 model without MA is recommended for the crude oil futures market.

Figure 4: Performance based on momentum

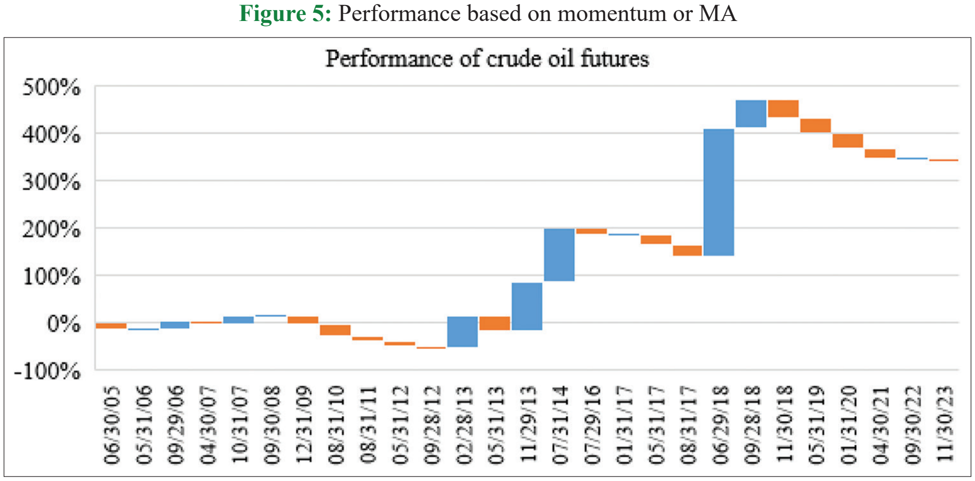


Source: Authors

6. CONCLUSIVE REMARKS

Crude oil prices have fluctuated drastically from nearly \$40/bbl to nearly \$80/bbl over the two decades, with prices fluctuating significantly to reach highs of nearly \$140/bbl in June 2008. On average, the WTI crude oil futures was priced around \$71/bbl.

Figure 5: Performance based on momentum or MA



Source: Authors

Energy commodities such as crude oil 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 to gain profits through a set of strategies. This paper focuses on the rate of change as a technical analysis tool. It has not been documented sufficiently in the existing literature, especially in the energy derivatives market. Our analysis looks at its performance during May 2004 - April 2024 for the U.S. WTI crude oil futures market.

Following a Pearson correlation analysis, we opted for a 14-month momentum indicator, with overbought (oversold) levels of 40% (−40%) capturing various turning points in the momentum indicator. Cumulative returns under the select model was 323%, with an average return of 40% over eight closed positions. Despite the relatively low level of transactions, the average risk was 107%, resulting in a low Sharpe performance value of 0.364. Compared with a naïve buy-and-hold strategy which generated a positive return of 99% during the whole period, the momentum indicator performance was superior. To reflect negative returns, the downside risk was estimated at 8.5% with a Sortino value of 4.58. While this value suggests crude oil performed well when adjusting for downside risk, it is important to know that the 295% return of 2009 impacted the Sortino value significantly. For instance, without this return of 2009, the Sortino value would drop to 0.25. Considering all available returns, the low Sharpe and highly Sortino value points to the inclusion of additional filters into the trading system. The inclusion of a price-crossover moving average strategy in the momentum-based trading system did not improve the performance. Relative to the naïve buy-and-hold strategy which yielded 99% return, the trading system which considers either ROC or MA price crossover strategies outperformed significantly. Despite the first model which relies only on ROC model yielded a slightly lower cumulative return of 323%, the Sharpe performance measure was almost doubled at 0.364. Therefore, the use of ROC-14 model without MA is recommended for the crude oil futures market.

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 rate of change indicator can provide a profitable trading strategy even during periods of significant drop in energy 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 phases of price fluctuations in energy prices. With the U.S. economy being a leading consumer and exporter of crude oil globally, it is recommended, as future research, to venture in analysis the combined impact of other technical analysis tools such as Fibonacci retracements in assessing model performance in crude oil energy markets.

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