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Do Investment Strategies Matter for Trading Global Clean Energy and Global Energy ETFs?

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Abstract: Based on technological innovation and climate change, clean energy has been paid increasing attention to by worldwide investors, thereby increasing their interest in investing in firms that specialize in clean energy. However, traditional energy still plays an important role nowadays, because extreme weather has often occurred in the winters of recent years. We thus explore whether investing the strategies adopted by diverse technical trading rules would matter for investing in energy-related ETFs. By employing two representative global ETFs with more than 10 years of data, iShares Global Clean Energy ETF as the proxy of clean energy performance and iShares Global Energy ETF as that of traditional energy performance, we then revealed that momentum strategies would be proper for buying the green energy ETF, but contrarian strategies would be appropriate for buying the energy ETF. Furthermore, based on investment strategies adopted by diverse technical trading rules, we showed that the performance of clean energy outperforms that of energy, indicating that green energy does matter for the economy. Moreover, while observing the price trend of these two ETFs, we found that such two ETFs may have opposite share price performances, implying that, while the green energy ETF reached a relatively high price, investors following the contrarian strategies suggested in this study may reap profits by investing the energy ETF.

Keywords: clean/green energy; contrarian strategies; energy-related ETFs; momentum strategies; technical trading rules

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1. Introduction

According to the efficient market hypothesis (EMH), stock prices seem difficult to predict because of all of the available information fully reflected on the market [1,2]. However, related research shows that many stock markets may not conform to the EMH. For example, many market participants who trade on the stock market believe that the market cannot be fully effective [3]. As a result, they may take additional risks and strive to do better than the market in order to get more returns by deliberately screening stocks [4]. Additionally, some investors, such as institutional traders and hedge funds, consistently beat the market, which might indicate that the EMH might not be completely right [5]. Furthermore, some investors adopting technical trading rules generate significant profits in several financial and commodity markets [6], indicating that technical trading rules widely explored in the real world seem to challenge the EMH [7].

We argue that exploiting higher profits in financial markets would be a crucial objective for many investors, resulting in technical trading rules concerned with and adopted by many market participants. As such, with the survey for the relevant studies related to technical trading, we discover that the Moving Average (MA), Stochastic Oscillator Indicator (SOI), Relative Strength Index (RSI), and KD trading rules are often employed by the technical proponents for trading stocks [8–13]. However, even though many market participants adopt these trading rules, the trading strategies employed by these trading rules might not be the same. For example, the MA and KD trading rules indicate the use of momentum strategies, but the RSI and SOI trading rules indicate the use of contrarian strategies. As a result, they might need to understand why different wisdom (i.e., adopting opposite investing strategies) of these trading rules would be widely employed by many market participants, which would be one of the motivations and aims of this study.

Furthermore, based on climate change and technological innovation, many investors are increasing their interest in investing in firms that specialize in clean energy [14]. As such, clean energy has received the attention of many governments and related parties around the world [15,16]. Even so, aside from enhancing the energy efficiency [17–19], employing proper strategies to increase profits from investments in crude oil markets is still an important issue for investors in energy finance [20], since extreme weather has often occurred in the winters of recent years. As a result, although the investment trading strategies implied by these trading rules might not be the same as mentioned above, this study is to explore whether investors would generate profits by adopting these different trading rules for trading financial commodities closely related to the performances of energy and green energy (e.g., energy ETFs and green energy ETFs), which would be another motivation and aim of this study.

Moreover, regarding market participants who are interested in investing in energy-related financial commodities (e.g., ETFs), they may be concerned with the following issues and problems, including whether investing clear energy ETFs would exploit more profits compared with energy ETFs in general, whether investing strategies matter for trading these energy-related ETFs, and whether one of the technical trading rules would outperform the others. In sum, the purpose of this study is whether investment strategies implied by diverse technical trading rules do matter for trading clean energy and energy ETFs. We argue that these issues and problems might be unanswered for energy-related ETFs, especially for clean energy ETFs, indicating that it might be necessary to understand these above-mentioned issues, since these problems would concern many market participants. However, far too little attention has been paid to these issues mentioned above.

By endeavoring to find two representative global ETFs with concerning data for more than 10 years, iShares Global Clean Energy ETF (its stock symbol: ICLN) is the proxy for the stock price performance of clean energy, as well as iShares Global Energy ETF (its stock symbol: IXC) as the proxy for the stock price performance of energy in this study. We then explored which technical trading rule (i.e., MA, RSI, SOI, or KD trading rules) would be more appropriate in trading the energy ETF (ICLN) and the green energy ETF (IXC), which investing strategy (e.g., momentum strategy or contrarian strategy) would be more proper in trading these two ETFs, and whether, based on these trading rules, trading the green energy ETF would generate a higher profit compared with trading the energy ETF, all of which would be concerned by market participants who are interested in trading energy-related ETFs (e.g., green energy ETFs and energy ETFs)

In this study, we illustrated several essential findings. First, based on the MA and KD and trading rules, we showed that the momentum strategy is suggested for market participants in buying the green energy ETF for almost all holding periods. Second, according to the SOI and RSI trading rules, a contrarian strategy would be recommended for market participants buying either the green energy ETF or energy ETF, especially for holding these ETFs for about one year. Third, when observing Figure 1 deliberately, we argued that these two ETFs may have opposite share price performances during the data period, indicating that both ETFs are somewhat like substitutions, implying that when the price of the energy (green energy) ETF reaches a relatively high price, investors may be able to buy the green energy (energy) ETF to exploit profits. For example, in early 2021, the green energy ETF ICLN (the energy ETF and IXC) reached a relatively high (low) price. If investors bought IXC at that time and still hold it for more than a year, those investors would make rather high profits, since crude oil rose above USD 100 in 2022.

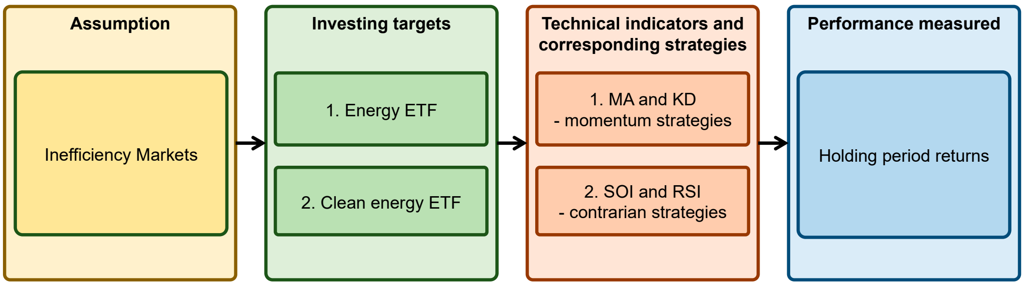

Figure 1. The conceptual framework of this study.

In addition, we argue that this study may contribute to the existing literature by several facets. First, we explore whether the performance of the green energy portfolio would have better than that of the energy portfolio, whether the performance of both portfolios would have a time-varying change, and even whether investing strategies would be varied for both portfolios. We argue that all of these issues rarely deliberately explored before may contribute to the existing literature. Second, this study would not only propose appropriate investment strategies emitted by diverse technical trading rules but also measure the short- and long-term performances of these two global representatives of energy-related ETFs (i.e., ICLN and IXC), since there are very few representatives of energy-related ETFs that have been issued for more than a decade. Third, we argue that these issues explored in this study would be interesting to investors, since their wealth might be enhanced if they learn how to employ proper investment strategies concerning holding periods for both energy ETFs and green energy ETFs.

The remainder of this paper is organized as follows. The literature review is presented in Section 2. Section 3 introduces the data and methodology employed in this study. Section 4 shows the empirical results and analysis. Section 5 provides the concluding remarks.

2. Literature Review

Since the technical trading rules triggered by MA, SOI, RSI, and KD are frequently employed by the technical supporters to trade stocks, we thus introduced the trading signals emitted by these technical indicators and investing strategies implicated by these trading rules. Based on employing energy-related financial commodities in this study, we then surveyed the above relevant literature in terms of such commodities.

2.1. Diverse Technical Trading Rules

2.1.1. Trading Signals Triggered by Moving Average (MA)

According to the trading signals emitted by MA trading rules, the golden (dead) crosses generated by MA trading rules would be employed for predicting future stock prices [21]. Such trading rules employed for forecasting future prices are mainly based on former price movements [5]. When MA trading rules are used to trade stocks in emerging stock markets, institutional investors often exhibit excellent performances [22].

We then introduce the n-day MA as below.

$$\mathrm{MA}_{t,n} = \frac{1}{n}\sum_{i=t-n+1}^{t} P_i \quad (1)$$

where $\mathrm{MA}_{t,n}$ represents the n-day moving average at time t, and P_i denotes the closing price at time t.

According to the MA trading rule, the golden cross emits as the short-term MA (SMA) increases beyond the long-term MA (LMA), indicating the end of the downward trend and the start of the new upward trend. In contrast, the dead cross emits as the SMA drops below the LMA, representing the end of the upward trend and the start of the new downward trend. As such, since these crosses are regarded as the trading signals, investors who are familiar with the MA trading rules may trade financial instruments (e.g., stocks, bonds, derivatives, etc.) as the occurrences of golden crosses (dead crosses) have been identified.

Thus, the definitions of the golden and dead crosses are presented as below.

$$\text{The golden cross is: } SMA_t > LMA_t \text{ and } SMA_{t-1} < LMA_{t-1} \tag{2}$$

$$\text{The dead cross is: } SMA_t < LMA_t \text{ and } SMA_{t-1} > LMA_{t-1} \tag{3}$$

2.1.2. Trading Signals Triggered by Stochastic Oscillator Indicators (SOI)

According to the overreaction wisdom of SOI trading rules [23], market participants following the trading signals emitted by SOI would enhance their trading performance [24]. Many institutional investors and even individual investors make profits by trading stocks based on the trading signals emitted by SOI trading rules [25].

SOI, such as K and D, are quite sensitive to the update in stock prices, which may result in K and D values being modified owing to the changes in the highest and lowest prices during a certain period (The nine-day K and D values often applied in the real world are employed in this study (i.e., N is set as 9). We would also treat $RSV_{t-1} = K_{t-1}$ for (7) when no prior K is available and $K_{t-1} = D_{t-1}$ for (8) when no prior D is available.). We present the model of SOI below:

$$CL_t = P_t - \min(P_1, P_{t-1}, \ldots, P_{t-8}) \tag{4}$$

$$HL_t = \max(P_1, P_{t-1}, \ldots, P_{t-8}) - \min(P_1, P_{t-1}, \ldots, P_{t-8}) \tag{5}$$

$$RSV = \frac{CL_t}{HL_t} \times 100 \tag{6}$$

$$K_t = \frac{2}{3}K_{t-1} + \frac{1}{3}RSV_t \tag{7}$$

$$D_t = \frac{2}{3}D_{t-1} + \frac{1}{3}K_t \tag{8}$$

where CL_t is calculated as the lowest closing price in N recent days reduced by the latest closing price, HL_t denotes the difference between the highest and the lowest closing price within N days, RSV_t is set as the CL_t over the HL_t, K value is the sum of 1/3 of the RSV value and 2/3 of the K value at lag 1, and D value is the sum of 1/3 of the K value and 2/3 of the D value at lag 1. The oversold signals are emitted as $K \leq 20$, and the overbought signals are emitted as $K \geq 80$. Based on the SOI trading rules, buying stocks would be suggested as oversold signals revealed; similarly, selling or short-selling stocks would be suggested as the overbought signals showed.

2.1.3. Trading Signals Triggered by Relative Strength Index (RSI)

RSI trading rules can yield positive risk-adjusted returns for currency markets [26]. In other words, investors are able to yield higher returns by using the RSI trading rule instead of employing buy-and-hold strategies [27]. In general, RSI could be comprised of the basic components, which are Relative strength (RS), Average Gain (AG), and Average Loss (AL). The definitions of these components are described below:

$$RSI = 100 - 100/(1 + RS) \tag{9}$$

$$RS = AG/AL \tag{10}$$

The first measurements for AG and AL are 14-day averages, which are shown below:

$$\text{First AG} = \text{Sum of Gains over the past 14 days}/14 \tag{11}$$

$$\text{First AL} = \text{Sum of Losses over the past 14 days}/14 \tag{12}$$

The second, the third, and so on measurements are based on the previous AG or AL and the current gain (CG) or current loss (CL). The models are presented below:

$$AG = [(\text{Previous AG}) \times 13 + CG]/14 \tag{13}$$

$$AL = [(\text{Previous AL}) \times 13 + CL]/14 \tag{14}$$

When RSI is 100, it shows that there are upward price movements but without downward price movements. On the contrary, as the RSI is equal to 0, it implies that there are downward price movements with no upward price movements. Therefore, the overbought phenomena would happen when the RSI is close to 100, and the oversold circumstances would occur when the RSI is close to 0. By employing 14-day measurement, RSI ≥ 70 and RSI ≤ 30 could be viewed as the overbought and oversold phenomena, respectively.

2.1.4. Trading Signals Triggered by KD

The KD trading rule, combined with the wisdom of MA and SOI, is a momentum strategy that directs the stock price moving to a high or a low point by tracing former KD values. In fact, professional institutional investors, particularly foreign investors, behave consistently with the suggested strategies by the KD trading rule, which are buying signals remitted as K lines upward cross over D lines but selling signals shown when K lines downward cross over D lines [25].

As defined in Section 2.1.2, K_t (the trend of K values) and D_t (the trend of D values) are rather similar to SMA and LMA. In essence, K_t and D_t are frequently used as indicators to decide when to buy (sell) stocks. A buying signal is initiated when K_t crosses up through D_t, whereas a selling signal is revealed as K_t crosses down through D_t. In other words, the buying (selling) signals would be emitted as K-lines crossed over D-lines upward (downward) following the KD trading rule. In sum, D_t is a trigger point for K_t, and the buying (selling) signals are defined below:

$$\text{The buying signal is } K_t > D_t \text{ and } K_{t-1} < D_{t-1} \tag{15}$$

$$\text{The selling signal is: } K_t < D_t \text{ and } K_{t-1} > D_{t-1} \tag{16}$$

2.2. Investing Strategies

A deterministic trading strategy can be viewed as a signal processing element that uses external information and past prices as inputs and incorporates them into future prices [28]. While generating a profitable portfolio seems to be a challenging issue for many market participants, establishing an investment strategy is crucial for investors. In essence, momentum and contrarian strategies are two major investment strategies widely debated by investment strategists across the world [29] and can be adopted for ways of making profits [30]. For example, Duxbury and Yao [31] stated that investors may make profits by adopting momentum strategies when adding stocks to their portfolios and contrarian strategies when selling stocks from their portfolios.

In general, momentum or contrarian strategies have been shown to produce abnormal profits over varying time horizons in the U.S. [32–34], the U.K. [35], and other European stock markets [36]. For example, while a contrarian strategy likely generates profits at long horizons, a momentum strategy is usually profitable at the medium (3–12 months) horizon [37], indicating that the adoption of an investment strategy might depend on the time frame of the investment.

2.2.1. Momentum Strategies

Regarding momentum strategies, Hong and Stein [38] argued that momentum traders have conditions based on past price changes, and stock returns appear to exhibit the momentum in the short to medium runs. If the momentum in stock returns does come from gradual information flow, then the momentum strategy would be the most profitable among these stocks, especially for the information flow moving most slowly across the investing public.

Chui, Titman, and Wei [39] showed that momentum profits positively relate to analyst forecast dispersion, transaction costs, and the familiarity of the market to foreigners but negatively relate to firm size, and volatility. Asness, Moskowitz, and Pedersen [40] find that a momentum return premier exists across diverse markets. Novy-Marx [41] claims that momentum phenomena can be observed from different U.S. and international financial markets, including stock, bond, currency, and commodity markets.

Menkhoff et al. [42] showed that there are significant excess returns for past winner currencies in foreign exchange markets, indicating that momentum strategies might matter for the currency markets. Vayanos and Woolley [43] indicated that momentum arises if the rational prices underreact to expect future flows. Ni, Liao, and Huang [44] revealed that, with 80% of the trading volume contributed by individual investors, these investors may employ momentum strategies for trading stocks in the Chinese stock markets because of their overoptimistic moods.

In sum, the application of momentum investing trading may give some useful information for market participants [45–47], revealing that momentum trends following these techniques might have beaten the market in previous studies [48–51].

2.2.2. Contrarian Strategies

The contrarian strategy has been one of the most mature investing strategies in financial research, suggesting buying stocks with low prices to earnings, cash flows, or other measures of fundamental values [52]. Gopal [53] indicated that a contrarian strategy consists of buying stocks that have been losers and selling short stocks that have been winners. This strategy is based on the premise that the stock market tends to overreact to news, so winner stocks are probably overvalued, and loser stocks are likely undervalued. Contrarian strategies are mainly based on price reversals, a movement in the reverse direction of the price of a share from one period to the next. As such, investors may take the opportunity from the reversals to earn an extra return from the market [34]. Moreover, contrarian strategies may generate profits by taking both short positions with recent winners and long positions with the recent losers together [54].

Meanwhile, overreaction allows the price to fluctuate more than its reasonable range, which would cause the price to drop or increase at a later period towards the true price, thereby likely generating profits by employing contrarian strategies [55]. Besides, Vieru, Perttunen, and Schadewitz [56] reported that most overconfident market participants are also contrarian investors. DeHaan and Kakes [57] indicated that all the three institutional investors in The Netherlands, including pension funds, life insurers, and non-life insurers, tend to be contrarian traders, indicating that they buy past losers and sell past winners. Cho et al. [58] found that market makers and institutional traders use the contrarian strategy due to the reason that the contrarian strategy dampens the volatility. As such, institutional traders engage more actively in contrarian trading when individual traders cause excessive volatility.

Besides, Shi and Zhou [59] reported that the trading strategies based on contrarian portfolios are dependent on market conditions. Kumar [54] argued that the portfolios based on the contrarian strategy were providing a significant positive return across all the holding periods, likely resulting in mainly bearing the systematic risk of the formed portfolio only or the over-expectation of the investors from the past winners. Portfolios based on inverse strategies provide significant positive returns across all holding periods, which may be due to the systemic risk of forming the portfolio or the investor's excessive expectation of past winners. Yu, Fung, and Leung [60] also revealed that employing contrarian strategies would generate a better outperformance in Chinese stock markets. To sum up, contrarian strategies might perform well because investors overestimate past performances, resulting in stocks that have underperformed in the past being undervalued and those that have performed well in the past being overvalued [61].

2.3. Investing Strategies and Trading Rules for Energy and Green Energy Portfolios

As for the effectiveness of trading rules in energy markets, Lubnau and Todorova [62] showed that employing simple technical trading can be employed profitably for energy futures, and, as such, whether energy futures markets can be considered weakly efficient in the short-term would be doubtful. Narayan [63] also showed that the technical trading strategy revealed a profitable oil market during the COVID-19 period. Moreover, Wang et al. [64] explored whether MA trading rules can obtain excess returns in crude oil futures markets and determined that such trading rules help traders make profits when there are obvious price fluctuations. Regarding the technical trading rules for clean energy markets, Sadorsky [14] accurately displayed the stock price direction of clean energy ETFs by using some technical indicators. Bouri et al. [65] exhibited the predictive information of climate policy uncertainty for price dynamics of green and brown energy equity. Liu et al. [66] indicated that generated trading rules by employing MA trading rules can adapt to price changes and make profits in carbon emission future markets treated as a key tool to combat climate change cost-effectively.

Based on strategies to increase profits from investments in energy markets that have become an important issue for investors in energy finance, Wang et al. [20] found that dynamic trading rules can help traders make profits in crude oil futures markets, and dynamic MA trading rules are more favorable to traders than static trading rules, indicating that momentum strategies might be appropriate for trading such markets. However, Chang et al. [67] showed that MA timing outperforms random timing for the ETF of renewable energy companies but not for the ETF of fossil energy companies, suggesting that momentum strategies would be proper for renewable and green energy firms instead of traditional energy firms.

Since climate change, green consumers, energy security, fossil fuel divestment, and technological innovation are powerful forces shaping an increased interest in investing in firms that specialize in clean energy [14], we thus explore whether the investment performance of green energy portfolios would have better than those of traditional energy portfolios, whether the performance of both portfolios (e.g., green energy ETFs and energy ETFs) would have a time-varying change, and even whether investing strategies would be varied for both portfolios. As such, the issues mentioned above would be worthwhile for further investigation, since our explored issues would be concerned by those who are interested in investing in both portfolios and even the prospect of green energy if investors can derive satisfactory rewards.

As mentioned in the introduction, we realize that whether the market is efficient or not is still without consensus. However, market inefficiency has been found in many previous studies. Therefore, we constructed the conceptual framework of this study based on the assumption of inefficient markets. Afterwards, we employed two ETFs (representing the performance of either clean energy or energy) as our investing targets, adopted investing strategies implied by diverse technical trading rules (momentum strategies implied by MA and KD trading rules and contrarian strategies implied by the SOI and RSI trading rules) as trading signals emitted by these diverse trading rules, and then measured the diverse holding period returns of these ETFs. As such, the conceptual framework of this study is presented in Figure 1

3. Data and Methodology

We argue that examining the performances of these trading rules concerning the investing strategies implicated in these trading rules would be an interesting issue, since, even though the investing strategies of these technical trading rules might not be the same (i.e., momentum strategies employed by MA and KD trading rules and contrarian strategies adopted by SOI and RSI trading rules), these technical trading rules are still widely employed in many market participants. As such, we then endeavor to find two representative global ETFs (i.e., iShares Global Clean Energy ETF and iShares Global Energy ETF) with data concerning more than 10 years (i.e., 2010–2021). Regarding iShares Global Energy ETF, the ETF seeks to track the S&P Global 1200 Energy Index. The fund generally invests at least 80% of its assets in the component securities of its underlying index. The index measures the performances of companies that the index provider deems as the energy sector of the economy. Concerning iShares Global Clean Energy ETF, this ETF aims to achieve investment outcomes that are broadly consistent with the price and yield performance of the S&P Global Clean Energy Index. The index is developed to evaluate the performance of around 30 of the world's most liquid and tradable firms, representing the listed clean energy universe. As such, by employing iShares Global Clean Energy ETF (ICLN) as the proxy for the stock price performance of clean energy, as well as iShares Global Energy ETF (IXC) as the proxy for the stock price performance of energy), we then compared the share price performance of clean energy with that of energy in the recent decade.

Moreover, even though these technical trading rules (i.e., MA, KD, RSI, and SOI trading rules) are widely employed by many market participants, the wisdom of these trading rules might not be the same as presented in Table 1. As such, exploring and comparing the performance of trading these two ETFs would be a worthwhile further investigation, since these technical trading rules may not adopt the same investing strategies.

Table 1. Technical trading signals in terms of momentum and contrarian strategies.

Technical Trading Rules	Investing Strategies Adopted and Buying Signals Emitted
MA trading rules	Momentum strategies are adopted when the golden cross appears (i.e., the SMA increases beyond the LMA).
KD trading rules	Momentum strategies are adopted when the golden cross appears (i.e., the K line crosses up the D line).
SOI trading rules	Contrarian strategies are adopted when SOI falls into the oversold zone (i.e., $K \leq 20$).
RSI trading rules	Contrarian strategies are adopted when RSI falls into the oversold zone (i.e., $RSI \leq 30$).

In addition, Conrad and Kaul [37] showed that, while a contrarian strategy nets statistically significant profits at long horizons, a momentum strategy is usually profitable at the medium (3–12 months) horizon [37], indicating that the adoption of an investment strategy might depend on the time frame of the investment. In addition, similar findings are also shown in previous studies [36,60,67–69]. We thus use different holding period returns to measure stock price performances while buying these ETFs as buying signals are emitted by diverse trading rules (i.e., MA, ROI, SOI, and KD trading rules). By setting day 0 as the day of the buying signals triggered by diverse technical trading rules, we then measured 5, 10, 25, 50, 100, 150, 200, and 250-day HPRs (approximately 250 trading days in a year) to measure diverse holding period returns (HPRs) based on the study of Conrad and Kaul [37].

In addition, the returns for regular time intervals can be calculated below:

$$(1 + \mathrm{HPR}) = (1 + r_1) \times (1 + r_2) \times (1 + r_3) \times (1 + r_4) \ldots \times (1 + r_n) \quad (17)$$

where r_1, r_2, r_3, r_4 … are the periodic returns (the daily holding period returns).

It also can be represented as:

$$\mathrm{HPR}_n = [(1 + r_1) \times (1 + r_2) \times (1 + r_3) \times \ldots (1 + r_n)] - 1 \quad (18)$$

where n = 5, 10, 25, 50, 100, 150, 200, and 250.

We thus can measure the HPR_5, HPR_{10}, HPR_{25}, HPR_{50}, HPR_{100}, HPR_{150}, HPR_{200}, and HPR_{250} in this study.

4. Empirical Results and Analysis

4.1. Descriptive Statistics

By employing daily data of these two representative global ETFs (i.e., ICLN and IXC) from Datastream as our samples, Table 2 shows the mean, median, SD, CV, Min, and Max for these two ETFs from 2010 to 2021 (using 12-year data). We then reveal the enormous difference between the Max and Min for both ETFs, indicating that the movements of these two ETFs might be rather volatile. Based on portfolio theory, portfolios (e.g., ETFs) are expected to have a lower price volatility, but the descriptive statistics show that energy-related ETFs are not low-volatility financial commodities. In addition, after plotting the stock prices of these two ETFs in Figures 2 and 3, we still showed high price volatilities for both ETFs. However, we also found that these two ETFs may have opposite share price performance during the data period, implying that these ETFs (i.e., ICLN and IXC) are somewhat like substitutions. In addition, we stated that the above phenomenon may be an interesting finding in this study, which means that when the price of the energy (green energy) ETF reached a relatively high price, investors may be able to buy the green energy (energy) ETF.

Table 2. Descriptive statistics. Table 2 reports the means, standard deviations (SD), coefficient of variance (CV), median, minimum (Min), and maximum (Max) for iShares Global Clean Energy ETF (ICLN) and iShares Global Energy ETF (IXC) prices over the data period 2010–2021.

Energy ETFs	Sample	Mean	SD	CV	Median	Min	Max
ICLN	3021	10.82	4.99	46.09%	9.04	5.00	33.04
IXC	3021	26.45	3.88	14.67%	26.97	11.71	36.47

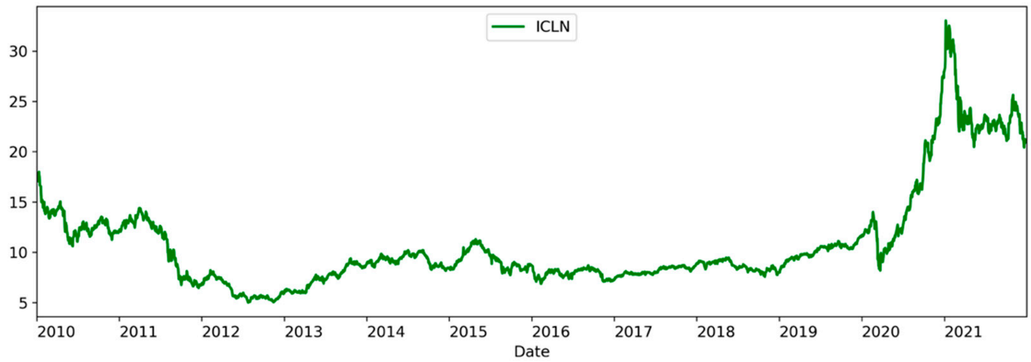

Figure 2. The trend of the iShares Global Clean Energy ETF (ICLN) prices from 2010 to 2021.

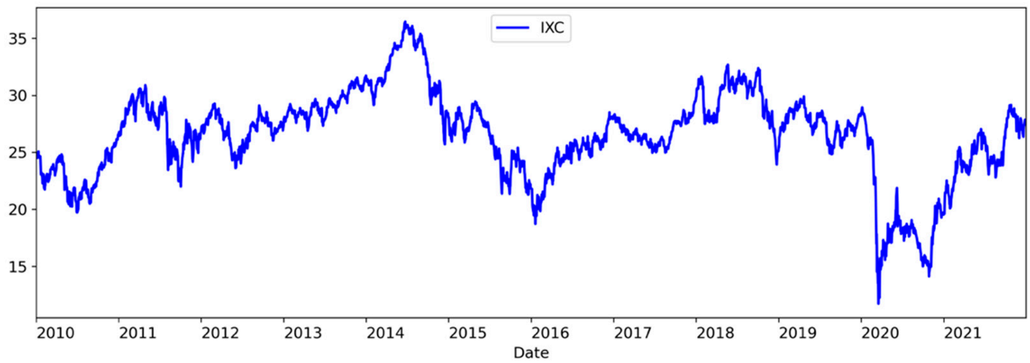

Figure 3. The trend of the iShares Global Energy ETF (IXC) prices from 2010 to 2021.

4.2. Empirical Results

4.2.1. Momentum Strategies

We employed the buying signals emitted by MA and KD trading rules that are based on momentum strategies. According to the MA trading rule, the golden cross (i.e., buying signal) emerged when the SMA increases beyond the LMA, indicating the end of the downward trend and the start of the new upward trend. Since K and D are somewhat similar to SMA and LMA, a buy signal is initiated when K crosses through D based on the KD trading rule.

Concerning whether the performances of both portfolios (e.g., green energy and energy ETFs) would have a time-varying change, we then adopted 5, 10, 25, 50, 100, 150, 200, and 250-day HPRs to measure diverse HPRs after buying signals emitted by these trading signals based on the suggestion of previous studies [36,37,60,67,69]. We revealed that, while employing momentum strategies, the performance of the global clean energy ETF (i.e., ICLN) is better than that of the global energy ETF (i.e., IXC) for either almost all of the HPRs based on the MA trading rule or long-term HPRs according to the KD trading rules in Table 3. The revealed results indicate that momentum strategies would be proper in buying and holding ICLN over 100-day holding periods, as revealed in that the long-run holding period returns of ICLN (including 100, 150, 200, and 250-day HPRs) are much higher than those of IXC.

Table 3. Momentum strategies for trading energy-related ETFs according to MA and KD trading rules. By employing the financial commodities closely related to the performance of green energy (iShares Global Clean Energy ETF and its stock symbol: ICLN) or traditional energy (iShares Global Energy ETF and its stock symbol: IXC) over the data period 2010–2021, we then investigate whether these HRRs, including 5, 10, 25, 50, 100, 150, 200, and 250-day HPRs, would be different from zero if investors employ momentum strategies to buy these ETFs as the buying signals (i.e., golden crosses triggered by either MA trading rules (i.e., MA-GC) or KD trading rules (KD-GC). We also present the statistics of *t*-tests for these HPRs. In addition, *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

		iShares Global Clean Energy ETF (ICLN)				iShares Global Energy ETF (IXC)			
Strategy	**Holding Period**	**Count**	**Mean**	***p*-Value**	**Sig.**	**Count**	**Mean**	***p*-Value**	**Sig.**
MA-GC	5	85	0.03%	0.9461		84	0.18%	0.5762	
MA-GC	10	85	0.36%	0.5379		84	0.25%	0.5975	
MA-GC	25	85	1.21%	0.2252		83	1.05%	0.1775	
MA-GC	50	85	2.88%	0.0551	*	83	0.78%	0.5124	
MA-GC	100	83	4.61%	0.0498	**	82	1.20%	0.5033	
MA-GC	150	82	7.40%	0.0143	**	80	2.95%	0.1247	
MA-GC	200	78	9.03%	0.0262	**	79	4.10%	0.0709	*
MA-GC	250	78	10.31%	0.0079	***	77	3.73%	0.1601	
KD-GC	5	221	0.13%	0.6703		213	0.29%	0.2126	
KD-GC	10	220	0.14%	0.7091		212	0.58%	0.0857	*
KD-GC	25	219	0.57%	0.3568		211	0.87%	0.1094	
KD-GC	50	218	1.19%	0.2097		209	1.78%	0.0162	**
KD-GC	100	215	3.18%	0.0446	**	203	1.74%	0.0830	*
KD-GC	150	213	5.20%	0.0121	**	198	2.80%	0.0209	**
KD-GC	200	209	7.97%	0.0035	***	194	3.00%	0.0341	**
KD-GC	250	205	10.25%	0.0002	***	192	3.70%	0.0225	**

4.2.2. Contrarian Strategies

According to the trading signal emitted by either the SOI or RSI trading rules, the buying signal would occur when either the SOI or RSI value falls to an oversold zero (i.e., $K \leq 20$ or $RSI \leq 30$). In other words, investors would be suggested to buy a stock as the price of the stock falls into oversold zero defined by either the SOI or RSI trading rules, indicating that, based on SOI and RSI trading rules, investors buy financial commodities (e.g., stocks and ETFs) based on contrarian strategies.

Table 4 reveals that, when we adopted the contrarian strategies, the performance of either the global clean energy ETF (i.e., ICLN) or the global energy ETF (i.e., IXC) were all positive for all of HPRs based on the SOI trading rule. However, as for long-term HPRs (i.e., 150, 200, and 250-day HPRs), ICLN outperforms IXC, indicating that investing and holding the green energy ETF for over 150 days might generate higher profits compared with the energy ETF. Similar findings are also revealed for the RSI trading rule (i.e., ICLN outperforms IXC for holding 150, 200, and 250 days), but investors might not generate positive profits for holding both ETFs that are less than 100 days. The results might indicate that, based on the buying signals triggered by SOI and RSI trading rules, holding these ETFs for about one year (i.e., 250 trading days) might not be a bad idea, revealing over 7% of HPRs for either ICLN or IXC.

Table 4. Contrarian strategies for trading energy-related ETFs according to the SOI and RSI trading rules. By employing the financial commodities closely related to the performance of green energy (iShares Global Clean Energy ETF and its stock symbol is ICLN) or traditional energy (iShares Global Energy ETF and its stock symbol is IXC) over the data period 2010–2021, we then investigate whether these HRRs, including 5, 10, 25, 50, 100, 150, 200, and 250-day HPRs would be different from zero if investors employ contrarian strategies to buy these ETFs as the buying signals (i.e., oversold signals triggered by either SOI trading rules (i.e., K $\leq$ 20) or RSI trading rules (RSI $\leq$ 30). We also present the statistics of *t*-tests for these HPRs. In addition, *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively.

		iShares Global Clean Energy ETF (ICLN)				iShares Global Energy ETF (IXC)			
Strategy	**Holding Period**	**Count**	**Mean**	***p*-Value**	**Sig.**	**Count**	**Mean**	***p*-Value**	**Sig.**
K $\leq$ 20	5	274	0.20%	0.4377		218	0.59%	0.1714	
K $\leq$ 20	10	273	0.49%	0.1152		218	1.23%	0.0245	**
K $\leq$ 20	25	270	1.75%	0.0002	***	218	1.03%	0.1859	
K $\leq$ 20	50	270	1.73%	0.0346	**	216	3.47%	0.0034	***
K $\leq$ 20	100	268	2.85%	0.0253	**	216	5.91%	0.0000	***
K $\leq$ 20	150	268	5.17%	0.0047	***	213	2.81%	0.0986	*
K $\leq$ 20	200	265	8.55%	0.0020	***	213	4.57%	0.0164	**
K $\leq$ 20	250	265	8.31%	0.0014	***	211	7.10%	0.0014	***
RSI $\leq$ 30	5	200	0.45%	0.1846		186	−0.46%	0.3842	
RSI $\leq$ 30	10	196	0.35%	0.3458		186	−0.54%	0.4028	
RSI $\leq$ 30	25	195	0.26%	0.6648		186	−1.95%	0.0921	*
RSI $\leq$ 30	50	195	−0.39%	0.6740		186	3.78%	0.0086	***
RSI $\leq$ 30	100	195	4.77%	0.0019	***	186	6.05%	0.0002	***
RSI $\leq$ 30	150	195	6.56%	0.0001	***	186	0.28%	0.8885	
RSI $\leq$ 30	200	195	7.43%	0.0029	***	186	3.10%	0.1426	
RSI $\leq$ 30	250	184	8.96%	0.0001	***	186	8.60%	0.0009	***

5. Discussion and Conclusions

By employing two representative global portfolios (i.e., ICLN and IXC) with more than 10 years of data, we explored whether the investment performance of the green energy portfolio would be better than those of the traditional energy portfolio, whether the performance of both portfolios would have a time-varying change, and even whether investing strategies would be varied for both portfolios. Afterwards, we came up with the following important conclusions.

5.1. Main Conclusions

First, we showed that, based on the MA trading rule, the momentum strategy is suggested for market participants in investing in the green energy ETF (i.e., ICLN) for almost all holding periods, except the 5-day holding period. Previous studies showed that employing MA trading rules can adapt to price changes and make profits in carbon emission futures markets [66]. MA timing outperforms random timing for the ETF of renewable energy companies [67]. As such, consistent with previous studies, we revealed that momentum strategies would be proper for trading clean energy ETFs.

Second, based on momentum strategies triggered by MA trading rules, Wang et al. [64] showed that momentum strategies can obtain excess returns in the crude oil future market, and such strategies help traders make profits when there are obvious price fluctuations.

Chang et al. [70] also showed that momentum strategies are useful in trading European energy markets However, different from previous studies, we revealed that contrarian strategies emitted by SOI and RSI trading rules would be appropriate for buying the energy ETF. As such, whether the investing strategies would be varied by either different energy-related commodities or different technical trading rules might be worthwhile for further investigations.

Third, when observing Figure 1 deliberately, we argued that these two ETFs may have opposite share price performances during the data period, indicating that energy ETFs and green energy ETFs are somewhat like substitutions, implying that, when the price of an energy (green energy) ETF reaches a relatively high price, investors may be able to buy a green energy (energy) ETF to exploit the profits. For example, in early 2021, the green energy ETF ICLN (the energy ETF and IXC) reached a relatively high (low) price. If investors bought IXC at that time and still hold it after more than a year, those investors would make rather high profits, since crude oil rose above USD 100 in 2022. After surveying previous studies, to our understanding, such an interesting finding might not have been disclosed before, which may shed light on the seemingly opposite performances of these two ETFs.

5.2. Study Strength and Contributions

Concerning the strengths and contributions of this study, we argue that understanding energy-related financial markets, (i.e., energy-related stocks and ETFs), investing strategies (i.e., momentum and contrarian strategies adopted by diverse technical trading rules), and screening numerous outcomes (i.e., derived from big data analytics) may provide a beneficial thinking process of investing energy-related commodities for market participants, since they rarely seem concerned by investors before they make investment strategies in energy-related financial commodities and even other financial commodities. In addition, we examined whether the performance of the green energy portfolio would be better than that of the energy portfolio, whether the performances of both portfolios (ETFs) would have a time-varying change, and even whether the investing strategies would be varied for both ETFs, all of which may contribute to the existing literature because of these essential issues rarely explored in energy-related financial commodities. Moreover, we argue that these issues explored in this study would be concern and interest investors, since their wealth might be enhanced if they know to employ proper investment strategies concerning holding periods for these two global representatives of energy-related ETFs (i.e., ICLN and IXC), as the evidence showed for the short- and long-term performances of both the green energy ETF (i.e., ICLN) and the energy ETF (i.e., IXC) in this study.

5.3. Research Implications

In addition, this study may have the following valuable practical implications. First, we argue that investors might derive higher returns for investing in financial commodities whose performances are closely related to green energy and traditional energy (e.g., green energy and traditional energy ETFs) if they can measure different HPRs according to investing strategies associated with diverse technical trading rules (i.e., momentum strategies implicated by MA and KD trading rules and contrarian strategies implicated by RSI and SOI trading rules). Second, because of deriving numerous HPRs by using diverse technical trading rules, investors might present these plentiful outcomes derived from big data analytics, classify these outcomes, and then adopt appropriate investment strategies and technical trading rules in investing in green energy and energy ETFs and even other financial instruments. Third, this study may provide valuable information for investors to enhance the profitability in trading energy-related ETFs (e.g., green energy ETFs or energy ETTs), since we argued that well preparation would be a prerequisite for enhancing the profitability and even reducing the risks in trading energy-related commodities, especially for those energy-related with rather higher volatilities. Four, we argue that, if history may repeat itself, our revealed results may encourage some investors to trade energy-related

ETFs, since investors may generate satisfactory profits by trading such ETFs, thereby likely broadening their investment horizons.

5.4. Future Research and Limitation

In addition, we argue that future research and possible research extensions for this study might be concerning as follows. First, by employing big data analytics, we would extend the holding period and shorten the interval to derive more information. Second, we would compare the performances of energy-related commodities with other financial commodities. As such, we may find similarities and differences among various financial commodities. Third, we argue that energy prices and even green energy prices may have a price cap, since oil prices soared as high as USD 147 in 2008, and once, oil prices fell to less than USD 10, and even oil futures fell to the negatives in 2020. As such, whether energy-related commodities belong to long-term investment instruments would be worthwhile for future studies. Besides, we may consider a robustness test by including different proxies for clean and dirty energies if we can derive these data shortly. Moreover, we would discuss the limitations and insufficiencies of this study. Due to the sharp rise in crude oil prices in 2022, we would be interested in the results after incorporating the 2022 data. However, since the whole year data for 2022 is not available now, we might not be able to derive the results now. Additionally, aside from employing four technical trading rules, we are still able to employ more technical trading rules and more HPR results by either extending our HPRs (e.g., more than 250-day HPRs) or shortening our interval to 25 even small instead of 50 after 50-day HPR (e.g., incorporating 75, 125, 175, and 225-day HPRs).

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References

1. Fama, E.F. The behavior of stock-market prices. *J. Bus.* **1965**, *38*, 34–105. [CrossRef]
2. Fama, E.F. Efficient capital markets: A review of theory and empirical work. *J. Financ.* **1970**, *25*, 383–417. [CrossRef]
3. Latif, M.; Arshad, S.; Fatima, M.; Farooq, S. Market efficiency, market anomalies, causes, evidences, and some behavioral aspects of market anomalies. *Res. J. Financ. Account.* **2011**, *2*, 1–13.
4. Phan, K.C.; Zhou, J. Market efficiency in emerging stock markets: A case study of the Vietnamese stock market. *IOSR J. Bus. Manag.* **2014**, *16*, 61–73. [CrossRef]
5. Masteika, S.; Rutkauskas, A.V. Research on futures trend trading strategy based on short term chart pattern. *J. Bus. Econ. Manag.* **2012**, *13*, 915–930. [CrossRef]
6. Narayan, P.K.; Narayan, S.; Sharma, S.S. An analysis of commodity markets: What gain for investors? *J. Bank. Financ.* **2013**, *37*, 3878–3889. [CrossRef]
7. Bessembinder, H.; Chan, K. The profitability of technical trading rules in the Asian stock markets. *Pac.-Basin Financ. J.* **1995**, *3*, 257–284. [CrossRef]
8. Gencay, R. Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. *J. Int. Econ.* **1999**, *47*, 91–107. [CrossRef]

9. Lo, A.W.; Mamaysky, H.; Wang, J. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *J. Financ.* **2000**, *55*, 1705–1765. [CrossRef]
10. Lento, C.; Gradojevic, N. The profitability of technical trading rules: A combined signal approach. *J. Appl. Bus. Res.* **2007**, *23*, 13–27. [CrossRef]
11. Metghalchi, M.; Marcucci, J.; Chang, Y.-H. Are moving average trading rules profitable? Evidence from the European stock markets. *Appl. Econ.* **2012**, *44*, 1539–1559. [CrossRef]
12. Ni, Y.-S.; Lee, J.-T.; Liao, Y.-C. Do variable length moving average trading rules matter during a financial crisis period? *Appl. Econ. Lett.* **2013**, *20*, 135–141. [CrossRef]
13. Yu, H.; Nartea, G.V.; Gan, C.; Yao, L.J. Predictive ability and profitability of simple technical trading rules: Recent evidence from Southeast Asian stock markets. *Int. Rev. Econ. Financ.* **2013**, *25*, 356–371. [CrossRef]
14. Sadorsky, P. A random forests approach to predicting clean energy stock prices. *J. Risk Financ. Manag.* **2021**, *14*, 48. [CrossRef]
15. Chien, T.; Hu, J.-L. Renewable energy and macroeconomic efficiency of OECD and non-OECD economies. *Energy Policy* **2007**, *35*, 3606–3615. [CrossRef]
16. Hsiao, W.-L.; Hu, J.-L.; Hsiao, C.; Chang, M.-C. Energy efficiency of the Baltic Sea countries: An application of stochastic frontier analysis. *Energies* **2018**, *12*, 104. [CrossRef]
17. Chang, T.-P.; Hu, J.-L. Total-factor energy productivity growth, technical progress, and efficiency change: An empirical study of China. *Appl. Energy* **2010**, *87*, 3262–3270. [CrossRef]
18. Hu, J.-L.; Kao, C.-H. Efficient energy-saving targets for APEC economies. *Energy Policy* **2007**, *35*, 373–382. [CrossRef]
19. Li, L.-B.; Hu, J.-L. Ecological total-factor energy efficiency of regions in China. *Energy Policy* **2012**, *46*, 216–224. [CrossRef]
20. Wang, L.; An, H.; Liu, X.; Huang, X. Selecting dynamic moving average trading rules in the crude oil futures market using a genetic approach. *Appl. Energy* **2016**, *162*, 1608–1618. [CrossRef]
21. Shintani, M.; Yabu, T.; Nagakura, D. Spurious regressions in technical trading. *J. Econom.* **2012**, *169*, 301–309. [CrossRef]
22. Fifield, S.G.; Power, D.M.; Donald Sinclair, C. An analysis of trading strategies in eleven European stock markets. *Eur. J. Financ.* **2005**, *11*, 531–548. [CrossRef]
23. Ni, Y.; Cheng, Y.; Liao, Y.; Huang, P. Does board structure affect stock price overshooting informativeness measured by stochastic oscillator indicators? *Int. J. Financ. Econ.* **2020**, *27*, 2290–2302. [CrossRef]
24. Chiang, Y.-C.; Ke, M.-C.; Liao, T.L.; Wang, C.-D. Are technical trading strategies still profitable? Evidence from the Taiwan Stock Index Futures Market. *Appl. Financ. Econ.* **2012**, *22*, 955–965. [CrossRef]
25. Wang, Z.-M.; Chiao, C.; Chang, Y.-T. Technical analyses and order submission behaviors: Evidence from an emerging market. *Int. Rev. Econ. Financ.* **2012**, *24*, 109–128. [CrossRef]
26. Shik, T.C.; Chong, T.T.-L. A comparison of MA and RSI returns with exchange rate intervention. *Appl. Econ. Lett.* **2007**, *14*, 371–383. [CrossRef]
27. Chong, T.T.-L.; Ng, W.-K. Technical analysis and the London stock exchange: Testing the MACD and RSI rules using the FT30. *Appl. Econ. Lett.* **2008**, *15*, 1111–1114. [CrossRef]
28. Farmer, J.D.; Joshi, S. The price dynamics of common trading strategies. *J. Econ. Behav. Organ.* **2002**, *49*, 149–171. [CrossRef]
29. Aravind, M. Contrarian and momentum strategies: An investigation with reference to sectoral portfolios in NSE. *NMIMS Manag. Rev.* **2016**, *29*, 102–117.
30. Liao, C.-C. Momentum trading, contrarian trading and smart money manipulation. *Int. Bus. Res.* **2017**, *10*, 53–62. [CrossRef]
31. Duxbury, D.; Yao, S. Are investors consistent in their trading strategies? An examination of individual investor-level data. *Int. Rev. Financ. Anal.* **2017**, *52*, 77–87. [CrossRef]
32. De Bondt, W.F.; Thaler, R. Does the stock market overreact? *J. Financ.* **1985**, *40*, 793–805. [CrossRef]
33. De Bondt, W.F.; Thaler, R.H. Further evidence on investor overreaction and stock market seasonality. *J. Financ.* **1987**, *42*, 557–581. [CrossRef]
34. Jegadeesh, N.; Titman, S. Returns to buying winners and selling losers: Implications for stock market efficiency. *J. Financ.* **1993**, *48*, 65–91. [CrossRef]
35. Galariotis, E.C.; Holmes, P.; Ma, X.S. Contrarian and momentum profitability revisited: Evidence from the London Stock Exchange 1964–2005. *J. Multinatl. Financ. Manag.* **2007**, *17*, 432–447. [CrossRef]
36. Rouwenhorst, K.G. International momentum strategies. *J. Financ.* **1998**, *53*, 267–284. [CrossRef]
37. Conrad, J.; Kaul, G. An anatomy of trading strategies. *Rev. Financ. Stud.* **1998**, *11*, 489–519. [CrossRef]
38. Hong, H.; Stein, J.C. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *J. Financ.* **1999**, *54*, 2143–2184. [CrossRef]
39. Chui, A.C.; Titman, S.; Wei, K.J. Individualism and momentum around the world. *J. Financ.* **2010**, *65*, 361–392. [CrossRef]
40. Asness, C.S.; Moskowitz, T.J.; Pedersen, L.H. Value and momentum everywhere. *J. Financ.* **2013**, *68*, 929–985. [CrossRef]
41. Novy-Marx, R. Is momentum really momentum? *J. Financ. Econ.* **2012**, *103*, 429–453. [CrossRef]
42. Menkhoff, L.; Sarno, L.; Schmeling, M.; Schrimpf, A. Carry trades and global foreign exchange volatility. *J. Financ.* **2012**, *67*, 681–718. [CrossRef]
43. Vayanos, D.; Woolley, P. An institutional theory of momentum and reversal. *Rev. Financ. Stud.* **2013**, *26*, 1087–1145. [CrossRef]
44. Ni, Y.; Liao, Y.-C.; Huang, P. MA trading rules, herding behaviors, and stock market overreaction. *Int. Rev. Econ. Financ.* **2015**, *39*, 253–265. [CrossRef]

45. Harris, R.D.; Yilmaz, F. A momentum trading strategy based on the low frequency component of the exchange rate. *J. Bank. Financ.* **2009**, *33*, 1575–1585. [CrossRef]
46. Miffre, J.; Rallis, G. Momentum strategies in commodity futures markets. *J. Bank. Financ.* **2007**, *31*, 1863–1886. [CrossRef]
47. Szakmary, A.C.; Shen, Q.; Sharma, S.C. Trend-following trading strategies in commodity futures: A re-examination. *J. Bank. Financ.* **2010**, *34*, 409–426. [CrossRef]
48. Friesen, G.C.; Weller, P.A.; Dunham, L.M. Price trends and patterns in technical analysis: A theoretical and empirical examination. *J. Bank. Financ.* **2009**, *33*, 1089–1100. [CrossRef]
49. Lee, S.J.; Oh, K.J.; Kim, T.Y. How many reference patterns can improve profitability for real-time trading in futures market? *Expert Syst. Appl.* **2012**, *39*, 7458–7470. [CrossRef]
50. Leigh, W.; Paz, N.; Purvis, R. Market timing: A test of a charting heuristic. *Econ. Lett.* **2002**, *77*, 55–63. [CrossRef]
51. Gregory-Williams, J.; Williams, B.M. *Trading Chaos: Maximize Profits with Proven Technical Techniques*; John Wiley & Sons: Hoboken, NJ, USA, 2004; Volume 161.
52. Zou, L.; Chen, R. Earnings surprises, investor sentiments and contrarian strategies. *Int. J. Econ. Financ. Issues* **2017**, *7*, 133–143.
53. Gopal, K. A Review of Contrarian Strategies in Capital Markets. *Int. J. Manag. Bus. Soc. Sci.* **2016**, *4*, 115–120.
54. Kumar, V.V.P. A study of momentum and contrarian strategies based portfolios in US market. *Int. J. Inf. Bus. Manag.* **2016**, *8*, 61–73.
55. Asif, J.; Yahya, M.; Muhammad, J. The Performance of Contrarian Strategy in Mature and Immature Stocks: Evidence from Malaysia. *J. Econ. Manag. Perspect.* **2018**, *12*, 395–405.
56. Vieru, M.; Perttunen, J.; Schadewitz, H. How investors trade around interim earnings announcements. *J. Bus. Financ. Account.* **2006**, *33*, 145–178. [CrossRef]
57. De Haan, L.; Kakes, J. Momentum or contrarian investment strategies: Evidence from Dutch institutional investors. *J. Bank. Financ.* **2011**, *35*, 2245–2251. [CrossRef]
58. Cho, J.H.; Daigler, R.; Ki, Y.; Zaima, J. Destabilizing momentum trading and counterbalancing contrarian strategy by large trader groups. *Rev. Account. Financ.* **2019**, *19*, 83–106. [CrossRef]
59. Shi, H.-L.; Zhou, W.-X. Time series momentum and contrarian effects in the Chinese stock market. *Physica A* **2017**, *483*, 309–318. [CrossRef]
60. Yu, L.; Fung, H.-G.; Leung, W.K. Momentum or contrarian trading strategy: Which one works better in the Chinese stock market. *Int. Rev. Econ. Financ.* **2019**, *62*, 87–105. [CrossRef]
61. Lakonishok, J.; Shleifer, A.; Vishny, R.W. Contrarian investment, extrapolation, and risk. *J. Financ.* **1994**, *49*, 1541–1578. [CrossRef]
62. Lubnau, T.; Todorova, N. Trading on mean-reversion in energy futures markets. *Energy Econ.* **2015**, *51*, 312–319. [CrossRef]
63. Narayan, P.K. Evidence of oil market price clustering during the COVID-19 pandemic. *Int. Rev. Financ. Anal.* **2022**, *80*, 102009. [CrossRef]
64. Wang, L.; An, H.; Xia, X.; Liu, X.; Sun, X.; Huang, X. Generating moving average trading rules on the oil futures market with genetic algorithms. *Math. Probl. Eng.* **2014**, *2014*, 101808. [CrossRef]
65. Bouri, E.; Iqbal, N.; Klein, T. Climate policy uncertainty and the price dynamics of green and brown energy stocks. *Financ. Res. Lett.* **2022**, 102740. [CrossRef]
66. Liu, X.; An, H.; Wang, L.; Jia, X. An integrated approach to optimize moving average rules in the EUA futures market based on particle swarm optimization and genetic algorithms. *Appl. Energy* **2017**, *185*, 1778–1787. [CrossRef]
67. Chang, C.-L.; Ilomäki, J.; Laurila, H.; McAleer, M. Market timing with moving averages for fossil fuel and renewable energy stocks. *Energy Rep.* **2020**, *6*, 1798–1810. [CrossRef]
68. He, X.-Z.; Li, K. Profitability of time series momentum. *J. Bank. Financ.* **2015**, *53*, 140–157. [CrossRef]
69. Kosc, K.; Sakowski, P.; Ślepaczuk, R. Momentum and contrarian effects on the cryptocurrency market. *Physica A* **2019**, *523*, 691–701. [CrossRef]
70. Chang, C.-L.; Ilomäki, J.; Laurila, H.; McAleer, M. Moving average market timing in European energy markets: Production versus emissions. *Energies* **2018**, *11*, 3281. [CrossRef]