“Technical analysis and market efficiency: an empirical examination on energy markets”

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Technical analysis and market efficiency: an empirical examination on energy markets

Abstract

The main objective of this study is to investigate the validity and predictability of technical analysis in energy markets. We use bootstrap tests of White (2000) and Hansen (2005), to determine whether there is a favorable trade rules are found amongst the universe of technical trading rules of the Sullivan et al. (1999). These powerful bootstrap tests are conducted under scrutiny of non-synchronous trading and transaction costs. The empirical results strongly indicate that the three elements, data snooping, non-synchronous trading and transaction costs have a significant impact on the overall performance of technical analysis. In fact, these results support efficient market hypothesis among the thirteen energy market indices.

Keywords: technical analysis, data snooping, efficient market hypothesis.
JEL Classification: G11, G14.

Introduction

Technical analysis is a well-established method for forecasting future market movements by generating buy or sell signals based on specific information gained from previous prices. The continuing prevalence and application of technical analysis has come to be widely recognized, even amongst academic scholars, with the techniques for discovering any hidden patterns ranging from the very rudimentary analysis of moving averages, to the recognition of quite complex time series patterns. Brock et al. (1992) show that simple trading rules based upon the movements of a short-run and a long-run moving average return have significant predictive power over a century of daily data on the Dow Jones industrial average. Fifield, Power, and Sinclair (1995) went on to investigate the predictive power of the 'filter' rule and the 'moving average oscillator' rule in eleven European stock markets, covering the period from January1991 to December 2000. Their main findings indicate that four emerging markets, Greece, Hungary, Portugal and Turkey, were informationally inefficient, relative to the other seven more advanced markets. Empirical results in the past support technical analysis, among them, Blume et al. (1994), Lo et al. (2000), and Savin et al. (2007). However, such evidence may be criticized for their data snooping bias; see, for example, Lo and MacKinlay (1990) and Brock et al. (1992).

Data snooping occurs when a given set of data is used more than once for the purposes of inference or model selection. To minimize this problem, Sullivan et al. (1999) apply the White (2000) "reality check (RC)" test and find that technical trading rules lose their predictive power for major U.S. stock indices after the mid 1980's. Chen et al. (2009) find that the results of technical analysis remain valid in all Asian markets, with the exception of South Korea, even after controlling for data snooping bias through the bootstrap reality check (RC) of White (2000) and superior predictive ability (SPA) test of Hansen (2005). Hsu et al. (2010) extend the SPA test of Hansen (2005) to a stepwise SPA test that can identify predictive models without potential data snooping bias. In the present study, we set out to empirically test the efficacy of technical analysis within thirteen energy market indices, employing the two data snooping adjustment methods for non-synchronous trading and transaction costs proposed by White (2000) and Hansen (2005).

The efficient market hypothesis (EMH) has dominated empirical finance, largely as a result of the works of Fama (1970). An enormous wealth of associated literature during the 1970s provided support for the weak form of this hypothesis, in which it is suggested that changes in past share prices cannot be used to forecast future share returns. Along the same vein, energy market efficiency implies that energy prices respond quickly and accurately to relevant information. If energy prices are mean reverting, then it follows that the price level will return to its trend path over time and that it might be possible to forecast future movements in energy prices based on past behavior. By contrast, if energy prices follow a random walk process, then any shock to prices is permanent. This means that future returns cannot be predicted based on historical movements in energy prices and that volatility in energy markets would increase without limitation.

Historically, technical analysis is equally appealed among financial and agricultural commodity markets as illustrated by popular practitioner books, for examples, Murphy (1986), Arnold (1993), and Pring (2002). The most widely followed futures composite index is the Commodity Research Bureau (CRB) index, which is represented by a basket of 21 industrial and agriculture commodities. The CRB index is particularly sensitive to price movement in the grains and oil complex. However, as surveyed by Park and Irwin (2007), most empirical studies of the efficacy of technical analysis focus on the stock markets and the foreign exchange markets, there is only a smaller number of studies being devoted to the commodity markets, in particular, energy markets.

Olga and Apostolos (2008) measure deviations from the efficient market state based on an analysis of scale-dependent fractal exponent and analyze the market efficiency in two electricity markets, Alberta and Mid-Columbia (Mid-C), as well as in the AECO Alberta natural gas market. They conclude that price fluctuations in all of the markets studied are not efficient. Charles and Darné (2009) examines the random walk hypothesis for the crude oil markets over the period of 1982-2008. They find that the Brent crude oil market is under weak-form efficiency, while the WTI crude oil market seems to be inefficient during the 1994-2008 sub-period. Lee and Lee (2009) investigates the efficient market hypothesis using four disaggregated energy prices – coal, oil, gas, and electricity for OECD countries over the period of 1978-2006. They find an overwhelming amount of evidence that support energy prices are not characterized by the efficient market hypothesis. Ulrich (2009) constitutes a first analysis on the stock returns of energy corporations from the Euro-zone and finds that profitable opportunities are provided for strategic investors. Herráiz and Monroy (2009) study market efficiency in the Iberian Power Futures Market and other European Power Markets and conclude that energy markets tend to show limited levels of market efficiency. Wang and Yang (2010) utilize high frequency data to examine the intraday efficiency of four major energy (crude oil, heating oil, gasoline, natural gas) futures markets. They indicate that heating oil and natural gas futures markets lack market efficiency, in particular, during the bull market condition.

We set out in this study to test empirically the profitability of technical analysis in thirteen energy market indexes of futures and spots from November 1982 to December 2009, taking into account the relevant data snooping biases, non-synchronous trading effects and transaction costs. We reexamine the performance of technical rules by implementing the White (2000) 'reality check' and the Hansen (2005) 'superior predictive ability' test in order to fully investigate the effects that data snooping can have on trading rules. Our study extends the set of trading rules considered in Bessembinder and Chan (1995) to the 'universe' of 7846 trading spaces suggested in Sullivan, Timmermann, and White (1999).

The remainder of this paper is organized as follows. An explanation of the test algorithms and the trading rules proposed in this study are provided in section 1. This is followed in section 2 by our presentation and subsequent analysis of the empirical results. Finally, the conclusions drawn from this study are provided in the last section, along with some suggestions for further development of our approach.

1. Methodology

In this section, we describe the methodology used in our study, including the test for algorithms and the trading rules. The former comprises the 'reality check' of White (2000) and the 'superior predictive ability' test of Hansen (2005), while the latter introduces the 7846 universal rules proposed by Sullivan et al. (1999).

1.1. The reality check and superior predictive ability tests. Trading model dependence makes it difficult to construct a formal test to differentiate between a genuine model with superior predictability and other spurious models. White's 'reality check', which was initially built on Diebold and Mariano (1995) and West (1996), employed the block re-sampling procedure of Politis and Romano (1994) in a predictive power test model to account for the effect of data mining.

We begin by defining the relative performance of models k, $k = 1, ..., m$, against the benchmark at time t, $t = 1, ..., n$, as follows:

$$\pi_{k,t} \equiv \varphi(\xi_t, \delta_{k,t-1}) - \varphi(\xi_t, \delta_{0,t-1}),\ k = 0,1,\ldots,m. \quad (1)$$

$\phi(\xi_t, \delta_{k,t-1}) = \delta_{k,t-1}\ \xi_t$, where ξ_t represents the random real asset returns; $\delta_{k,t-1}$ is the trading signal of the forecasting model, k, at t-1; and k = 0 represents the market model.

Let $\mu = E(\pi_k)$ be the expected return of model k. Since our main area of interest is in determining whether any of the models have superior performance to that of the benchmark, the null hypothesis is defined as:

$$H_0 : \mu \leq 0 \quad \mu \in R^m, \quad (2)$$

which also means that none of the alternative forecasts are superior to the benchmark. The block re-sampling procedure of Politis and Romano (1994) is employed to generate 500 pseudo time-series $\pi^B_{k,\,t}$ from the observed value $\pi_{k,t}$. We construct the following two statistics from both the real series and the pseudo series:

$$\begin{aligned} T_n^{RC} &= \max_{1<k<m}(n^{1/2}\overline{\pi}_k), \\ T_n^{RC,B} &= \max_{1<k<m}(n^{1/2}(\overline{\pi}_k^B - \overline{\pi}_k)). \end{aligned} \quad (3)$$

The comparison between T_n^{RC} and the $T_n^{RC,B}$ quintiles provides the White (2000) p-value for the null hypothesis test. The 'superior predictive ability' test of Hansen (2005), the development of which was based upon White's 'reality check', provides an alternative method of correcting the findings for data snooping effects. Hansen (2005) demonstrated that the 'reality check' can be seriously manipulated by other irrelevant models, resulting in reduced test power, and therefore utilized the studentized process to remove the irrelevant models in the sample. Similar to White (2000), the two statistics are provided as:

$$T_n^{SPA} = \max[\max_{k=1\dots m} \frac{n^{1/2}\overline{\pi}\, k}{\hat{\omega}\, k}, 0],$$
$$T_n^{SPA,B} = \max[\max_{k=1\dots m} \frac{n^{1/2}(\overline{\pi}_k^B - \hat{\mu}_k^c)}{\hat{\omega}\, k}, 0], \tag{4}$$

where $\hat{\omega}\, k$ is a consistent estimator for return variance, calculated by the stationary bootstrap method of Politis and Romano (1994), and $\hat{\mu}_k^c = \overline{\pi}_k 1_{\{n^{1/2}\, \overline{\pi}_k\, / \,\hat{\omega}\, k \le -2\sqrt{\operatorname{loglo} g\, n}\}}$ is the threshold used for the removal of the irrelevant models. The comparison between T_n^{SPA} and $T_n^{SPA,B}$ quartiles provides the p-value for the Hansen (2005) 'superior predictive ability' null hypothesis test.

1.2. Technical analysis. Sullivan et al. (1999) extended the sample rules proposed by Brock et al. (1992), to a larger universal technical analysis space. In this paper, we adopt the two sets of rule spaces proposed in these two studies, and undertake a comprehensive comparison of their performance. The Sullivan et al. (1999) trading set comprises of 7846 universal trading rules belonging to five technical analysis catalogs, as shown in the following sub-sections, each of which provides a brief overview of these rules; the standard filter rule can be explained as in Fama and Blume (1966). We define an X per cent filter as follows: if the daily closing price of a particular security moves up by at least X per cent, then an investor buys and holds the security until its price moves down at least X per cent from the subsequent high, at which time the investor simultaneously sells and takes up a short position; a moving average strategy (MA) is designed to detect a trend, with a buy (sell) signal being generated when the short-term average price crosses the long-term average price from below (above); a 'support and resistance' strategy supplies details on the market movements relating to historical support and resistance lines. A buy (sell) signal is generated when the closing price exceeds (falls below) the historical maximum (minimum) within a given time frame; a 'channel breakout' strategy is similar to the support and resistance rule. The buy (sell) signal is generated when the closing price moves up (down) the upper (lower) channel; an 'on-balance volume averages' strategy (OBV) is a volume-based version of the moving average rules. A buy (sell) signal is generated when the short-term average volume crosses the on-term average volume from below (above). The parameter required in the on-balance volume averages strategy is similar to those for the moving average rules. This category has a total of 2040 rules.

2. Empirical results and analysis

We set out in this study to test empirically the profitability of technical analysis brought forward by Sullivan et al. (1999) in energy market indices over the period of 1982-2009, taking into account the relevant data snooping biases, non-synchronous trading effects and transaction costs. Our empirical sample of the testing markets indices cover thirteen energy markets which are comprised of two futures Light Crude Oil Futures Index and Natural Gas Futures Index, and eleven spots which are listed in Table 1 (see Appendix). The empirical market data of daily prices and daily volumes utilized in this study are obtained from Datastream. Moreover, the actual research horizon for each index, which referred to Table 1, is trimmed according the data availability from Datastream. Meanwhile, the entire universal set of trading rules are employed in the futures markets while only part of them are tested in the spot markets due to the lack of volume data in the latter. Ultimately, the trading rules for the futures and spot markets amounts to 7846 and 5806 respectively. The summary statistics of the daily returns for thirteen energy market indices are reported in Table 1.

2.1. Optimum rules for the thirteen energy market indices. This section reports the characteristics of the best trading rules and their associated profits within the energy market indices. With no consideration of the issues of non-synchronous trading biases or transaction costs, the optimal trading rules for the spot markets and futures markets are rather distinct. The OBV and MA rules are best served in the futures and spot markets respectively. Among the best MA rules in spot markets, the windows of moving averages are diversified, ranging from two- through 125-day, which contrast sharply with about two- through five-day windows reported in the U.S. markets by Sullivan et al. (1999) and in Asian markets by Chen et al. (2009). As the standard example, MA (1, 15, 0, 5, 0) is the best among the Sullivan et al. (1999) for Brent Crude Oil Spot Index. The picture alters a bit in the futures markets due to the more long-run oriented best

OBV rules. For instance, Natural Gas Futures Index has found the best rule as OBV (15, 150, 0, 0, 25). In consequence, the resultant trading signals for energy market indices tend to be diversified; of these, the lowest frequency is found in the S&P GSCI Crude Oil Spot Index, where the total number of buy and sell signals are 20 and 21; the highest frequency is found in the No. 2 Heating Oil NYH Spot Index, where the total number of buy and sell signals are 263 and 255. Moreover, almost all best trading rules exhibit significant mean returns at 5% level except WTI Cushing Crude Oil Spot Index only reaching 10% significance. The mean daily returns of the best rules range from a high of 0.18% for the Brent Crude Oil Spot Index, to a low of 0.11% for S&P GSCI Heating Oil Spot Index; all of these easily outperform a buy-and-hold strategy across their various market indices.

We further decompose the results on trading signals into buy-signals and sell-signals in order to examine, in some detail, the characteristic features of these buy and sell signals, and find that the frequency of buy and sell signals is approximately equal for each market. For instance, No. 2 Heating Oil USG Spot Index results in a total of 259 (258) buy (sell) signals for the best rules. However, the frequency of buy and sell signals varies across the different markets; for example, the figures for the S&P GSCI Crude Oil Spot Index, 20:21, is the lowest of all of the energy market indices under examination, whereas there is a very high ratio of 263:255 between the buy and sell signals in the No. 2 Heating Oil NYH Spot Index. As a result, there are also significant variations in the ratios of the average holding horizons for buy and sell signals across markets. It is found to be highest in the S&P GSCI Crude Oil Spot Index, with a ratio of 155:125.14, and lowest in the No. 2 Heating Oil NYH Spot Index, where the ratio is 11.24:10.24.

As noted by Bessembinder and Chan (1995), significant return differentials between buy and sell signals indicate that the technical rules in energy market indices are capable of conveying economic information. The differentials in the daily returns resulting from buy and sell signals for the best rules found in this study are sufficiently wide to generate significant economic profits across the energy market indices; for example, the mean difference between buy and sell signals in the Brent Crude Oil Spot Index reaches 0.35%, whilst the S&P GSCI Heating Oil Spot Index, which has the lowest figure, still manages to achieve a 0.10% return differential.

2.2. The effects of data snooping on trading rules. We examine the profitability of technical analysis in greater depth in this section by taking into account the level of dependence that exists between the trading models, adjusting for data snooping bias by employing the White (2000) 'reality check' and the Hansen (2005) 'superior predictive ability' test.

As shown in Table 3 (see Appendix), the mean daily return of the best rule in thirteen energy market indices all are significantly higher than the buy-and-hold mean daily returns. The notable examples include Brent Crude Oil Spot Index, No. 2 Heating Oil USG Spot Index, MLCX Natural Gas Spot Index, and No. 2 Heating Oil NYH Spot Index respectively amounting to 44.90%, 39.64%, 38.91%, and 33.93% comparing to 6.08%, 6.65%, 6.03%, and 7.05% of the indices in annual returns. All the four energy spot indices above provide abnormal returns significantly in terms of nominal reality check. However, only Brent Crude Oil Spot Index and No. 2 Heating Oil USG Spot Index are significantly better than the market indices in the SPA test and RC test. The fact clearly delineates the tendency of over-optimism toward the acceptance of superior trading rules as well as the neglect of the potential data snooping effect among the universe of technical analysis. Table 3 shows that, as in the majority of prior empirical studies within the finance literature, all of the best rules in the energy market indices significantly outperform their buy-and-hold alternatives; however, our empirical results also reveal quite a striking finding in energy markets, that when controlling for the dependence in the trading models of the Sullivan et al. (1999) 'universe', most of the energy market indices in our sample, with the two exceptions of Brent Crude Oil Spot Index and No. 2 Heating Oil USG Spot Index, confirm the non-existence of a superior technical rule.

2.3. The effects of non-synchronous trading bias on technical analysis. Technical analysis trading profits arise mainly from positive serial dependence on stock index returns. However, as demonstrated by Scholes and Williams (1977), non-synchronous trading amongst component stocks may give rise to spurious positive serial dependence in the index returns, leading to the resultant measurement error potentially overestimating the trading profits of technical analysis.

We adopt the one-day lag adjustment proposed by Bessembinder and Chan (1995) in the present study to partially calibrate the non-synchronous bias. Specifically, we associate the day $t + 2$ return with the initial trading signal emitted at the close of day t, thereby allowing the component goods of the index to be fully traded on the intervening days. Our empirical results, which are reported in Table 4 (see Appendix), reveal that the non-synchronous effect is considerable and results in a significant alteration to the best rules selected for the samples.

After calibrating the non-synchronous bias, we can find the best rules still lie in the original rule categories except WTI Cushing Oil Spot Index changing from the MA rule to the Filter rule. However, the parameter structures of best rules indeed move slightly around the original ones. For example, the best rule in Brent Crude Oil Spot Index changes from MA (1, 15, 0, 5, 0) to MA (5, 15, 0, 3, 0). Furthermore, controlling for the non-synchronous effect is also found to have adverse effects on the performance of the best rules reported in Table 3; for instance, the highest mean return for the No. 2 Heating Oil USG Spot Index in Table 3, which is achieved by the MA (1, 10, 0, 0, 5) rule, declines from 0.160% to -0.020% when taking the non-synchronous effect into account, whilst the new optimal rule, MA (1, 5, 0.001, 0, 0), mean daily return is 0.150%, the gap between the two best rules is not obvious. In fact, the effect of non-synchronous has much change for the best trading rules, but the mean daily returns are not significantly affected. The nominal RC test provides a similar result to Table 3 that only three out four previous indices, namely Brent Crude Oil Spot Index, No. 2 Heating Oil USG Spot Index, and No. 2 Heating Oil NYH Spot Index, remain significantly better than the buy-and-hold strategy.

We also take the model dependence into consideration by carrying out the reality check and superior predictive ability test. As shown in Table 4, when ignoring the potential model dependence in the Sullivan et al. (1999) 'universe' of technical analysis, only three indices which are the same with Table 3 are still superior, in terms of the 'nominal reality check'. However, the picture is rather different after controlling for the data snooping effect, only two indices which have the best rule, through the reality check and the superior predictive ability test. The evidence presented in Table 4 provides support for Sullivan et al. (1999) and White (2000) on the need for bootstrap testing when assessing the performance of technical analysis. The evidence also reinforces the fact that data snooping has a potentially serious bias when assessing the profitability of technical analysis rules.

2.4. The effects of transaction costs on technical analysis. It has been argued by many researchers that transaction costs are a critical element in the overall appraisal of the economic significance of trading rules, particularly with regard to those rules which tend to generate frequent trades. We incorporate the transaction costs of the thirteen energy market indices into the analysis of the profitability of technical analysis in this study. The round-trip costs utilized in this study are drawn from the member fees of CME Group and range from the highest Brent Cruel Oil Spot Index of 1.88% to the lowest MLCX Natural Gas Spot Index of 0.15%, the details referred to Table 2 (see Appendix).

When considering transaction costs, the best rules differ markedly from those without any consideration of transaction costs; in particular, as shown in Table 5 (see Appendix), the best rules of two futures indices regularly switch to the long-run strategies in order to avoid the frequently traded rules which attract high transaction costs. We also find that transaction costs exert great impacts on the profitability of technical analysis and results in the highest mean daily return (0.15%) to MLCX Natural Gas Spot Index which have the lowest transaction cost (0.15%).

We go on to further explore the effects of data snooping bias under a setting in which transaction costs are taken into consideration. Even in the nominal sense of the reality check, the trading rules in only two of the thirteen energy market indices (No. 2 Heating Oil USG Spot Index and MLCX Natural Gas Spot Index) continue to exhibit superior profitability, as compared to their corresponding buy-and-hold strategy. However, the picture is rather different after controlling for the data snooping effect, no indices which have the best rule, through the reality check and the superior predictive ability test. The finding arrogantly maintains the assertion of efficient market hypothesis among thirteen more developed energy markets under examination.

Conclusions

We carry out a detailed investigation on the profitability of technical analysis amongst thirteen energy market indices over the period of 1982-2009. We employ the bootstrap results of the White (2000) 'reality check' and the Hansen (2005) 'superior predictive ability' test in order to determine whether any profitable trading rule exists, drawing from the 'universe' of technical strategies proposed by Sullivan et al. (1999). Our empirical findings first indicate that, when non-synchronous trading bias and transaction costs are ignored, the best strategies in our sample are provided by short-window 'moving averages' rules. Second, we find that when a one-day lag scheme is implemented to account for non-synchronous trading bias, there are changes in the optimal trading rules, but they are similar in trading profits. Third, when transaction costs are taken into account, there is a substantial decline in trading profits. As a result, both the reality check and the superior predictive ability test reject the existence of economically profitable rules in all of the energy market indices.

This study brings together powerful bootstrap tests, along with two institutional adjustments (non-synchronous trading and transaction costs) to ascertain the profitability of technical analysis in thirteen energy market indices. The empirical results indicate that these adjustments have an enormous impact on the performance of the technical analysis rules. Indeed, our findings amongst the thirteen energy market indices examined in this study provide further support for the efficient market hypothesis; our results clearly show that economic profits are unlikely to be earned from the use of technical analysis within these particular markets.

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Appendix

Table 1. Summary statistics of the energy market future and spot indices

	Data period	No. of observations	Variables[b]							
			Mean (%)	S.D.	Skewness	Kurtosis	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$
Light Crude Oil Futures Index (NYM)	1983/03-2009/12	6964	0.0130	0.0242	-0.8495	19.3827	-0.0197	-0.0569	-0.0229**	0.0304
Natural Gas Futures Index (NYM)	1990/04-2009/12	5135	0.0171	0.0361	-0.0667	12.5488	-0.0386	-0.0110	-0.0557	0.0325
Brent Crude Oil Spot Index (NYM)	1987/05-2009/12	5892	0.0243	0.0214	-0.0065	64.3333	-0.0203	-0.0021	-0.0566**	0.0034
No. 2 Heating Oil USG Spot Index	1986/06-2009/12	6137	0.0266	0.0217	0.4744	49.3929	-0.0088	-0.0044	-0.0238	0.0019
No. 2 Heating Oil NYH Spot Index	1986/06-2009/12	6137	0.0282	0.0210	0.0624	37.4696	-0.0112	-0.0042	-0.0328	0.0022
MLCX Crude Oil (WTI) Spot Index	1990/06-2009/12	5075	0.0279	0.0209	-1.1270	20.9126	-0.0041	-0.0243	-0.0233	0.0131
MLCX Heating Oil Spot Index	1990/06-2009/12	5075	0.0267	0.0202	-0.8783	17.6403	-0.0156	0.0001	-0.0097	0.0103
MLCX Natural Gas Spot Index	1990/06-2009/12	5075	0.0241	0.0265	-0.0477	5.2357	0.0024	0.0308**	0.0101	0.0288**
S&P GSCI Crude Oil Spot Index	1987/01-2009/12	5979	0.0233	0.0221	-1.0632	22.1504	-0.0107	-0.0357	-0.0303	0.0080
S&P GSCI Heating Oil Spot Index	1982/12-2009/12	7030	0.0121	0.0210	-0.7164	16.8263	-0.0005	-0.0104	-0.0227	0.0132
S&P GSCI Natural Gas Spot Index	1994/01-2009/12	4155	0.0216	0.0328	0.0343	5.3643	-0.0090	0.0442***	0.0060	0.0381**
WTI Crude Oil Spot Index (NYM)	1986/01-2009/12	6248	0.0160	0.0260	-0.8000	18.1787	-0.0200	-0.0285	-0.0276	0.0110
WTI Cushing Crude Oil Spot Index (NYM)	1984/12-2009/12	6522	0.0151	0.0266	-0.9964	25.4741	-0.0502	-0.0329	-0.0430	0.0236

Notes: [b] $\rho(i)$ is the estimated autocorrelation at lag i for each series. * Significance of the two-tailed test at the 10% level. ** Significance at the 5% level. *** Significance at the 1% level.

Table 2. Standard test results for the technical rules amongst the energy market future and spot indices

	Best rule[a]	Order[b]	Mean		Long day[c]/Buy signals		Buy return[d]		Short day[c]/ Sell signals		Sell return[d]		BAHD[e]/SAHD		Buy-Sell[d]		Round-trip cost
			(%)	*t*-value			(%)	*t*-value			(%)	*t*-value			(%)	*t*-value	(%)
Light Crude Oil Futures Index (NYM)	OBV (20, 30, 0, 0, 10)	7551	0.08	2.57	3310	188	0.12	2.78	3403	188	0.03	2.78	17.61	18.10	0.15	2.58	1.72
Natural Gas Futures Index (NYM)	OBV (15, 150, 0, 0, 25)	7706	0.15	2.79	2334	42	0.25	3.04	2550	41	0.05	3.04	55.57	62.20	0.30	2.86	1.36
Brent Crude Oil Spot Index (NYM)	MA (1, 15, 0, 5, 0)	1626	0.18	6.20	3019	135	0.22	5.30	2618	135	0.14	5.30	22.36	19.39	0.35	6.09	1.88
No. 2 Heating Oil USG Spot Index	MA (1, 10, 0, 0, 5)	2060	0.16	5.56	3096	259	0.19	4.58	2790	258	0.12	4.58	11.95	10.81	0.31	5.49	0.61
No. 2 Heating Oil NYH Spot Index	MA (5, 10, 0.01, 0, 0)	740	0.14	5.01	2957	263	0.18	4.08	2612	255	0.11	4.08	11.24	10.24	0.28	5.07	0.63
MLCX Crude Oil (WTI) Spot Index	MA (1, 125, 0, 0, 5)	2069	0.06	2.20	2890	35	0.09	2.75	1934	35	0.02	2.75	82.57	55.26	0.11	1.92	0.27
MLCX Heating Oil Spot Index	MA (1, 125, 0, 0, 0)	509	0.07	2.37	2794	80	0.09	2.74	2030	80	0.03	2.74	34.93	25.38	0.12	2.15	0.28
MLCX Natural Gas Spot Index	MA (1, 40, 0, 2, 0)	1585	0.16	4.03	2593	137	0.21	3.98	2230	137	0.10	3.98	18.93	16.28	0.30	3.91	0.15
S&P GSCI Crude Oil Spot Index	MA (20, 25, 0, 0, 50)	2447	0.06	2.18	3100	20	0.11	2.88	2628	21	0.01	2.88	155.00	125.14	0.12	2.04	0.30
S&P GSCI Heating Oil Spot Index	MA (15, 20, 0, 0, 50)	2442	0.05	2.01	3700	30	0.08	2.49	3079	31	0.02	2.49	123.33	99.32	0.10	1.89	0.51
S&P GSCI Natural Gas Spot Index	MA (1, 30, 0, 2, 0)	1584	0.13	2.43	2028	139	0.21	2.77	1875	139	0.05	2.77	14.59	13.49	0.25	2.37	0.19
WTI Crude Oil Spot Index (NYM)	MA (1, 2, 0, 0, 50)	2103	0.07	2.04	3746	29	0.10	2.35	2251	29	0.01	2.35	129.17	77.62	0.11	1.66	1.70
WTI Cushing Crude Oil Spot Index (NYM)	MA (15, 20, 0, 0, 5)	2127	0.06	1.71	3364	168	0.10	2.37	2907	168	0.01	2.37	20.02	17.30	0.11	1.61	1.71

Notes: [a] 'Best rule MA' denotes the moving average with five parameters (*n*, *m*, *b*, *d*, *c*), where *n*-days is the short-term horizon line; *m*-days is the long-term horizon line; *b* is the filter rate (%); *d*-days is the time delay; and *c*-days is the holding days. 'Best rule OBV' denotes *t* on-balance volume averages with five parameters (*n*, *m*, *b*, *d*, *c*) with the same definition as 'Best rule MA'. [b] 'Order' refers to the location of the best universal rule. [c] 'Long (short) day' refers to the number of buying days for the best rule. [d] 'Buy (sell) signals' referring to the number of buy (sell) signals for the best rule, with the *t*-values referring to the two-tailed *t*-test. [e] 'BAHD (SAHD)' denotes the average holding days for the buy (sell) signals. f The transaction (round-trip) costs for thirteen energy market indices are adopted from member fees of CME Group.

Table 3. Bootstrapped test results for the technical rules amongst the energy market future and spot indices

	Best rule[a]	Order[b]	Daily return[c] (%)	Daily return[c] t-value	Annual return (%)	Index (%)	SPA[d]	RC[e]	Nominal RC[f]
Light Crude Oil Futures Index (NYM)	OBV (20, 30, 0, 0, 10)	7551	0.08	2.57	19.14	3.25	0.97	0.98	0.18
Natural Gas Futures Index (NYM)	OBV (15, 150, 0, 0, 25)	7706	0.15	2.79	36.84	4.28	0.99	1.00	0.21
Brent Crude Oil Spot Index (NYM)	MA (1, 15, 0, 5, 0)	1626	0.18	6.20	44.90	6.08	0.04	0.04	0.00
No. 2 Heating Oil USG Spot Index	MA (1, 10, 0, 0, 5)	2060	0.16	5.56	39.64	6.65	0.07	0.07	0.00
No. 2 Heating Oil NYH Spot Index	MA (5, 10, 0.01, 0, 0)	740	0.14	5.01	33.93	7.05	0.16	0.23	0.00
MLCX Crude Oil (WTI) Spot Index	MA (1, 125, 0, 0, 5)	2069	0.06	2.20	15.58	6.97	0.99	1.00	0.35
MLCX Heating Oil Spot Index	MA (1, 125, 0, 0, 0)	509	0.07	2.37	16.37	6.68	0.96	0.99	0.31
MLCX Natural Gas Spot Index	MA (1, 40, 0, 2, 0)	1585	0.16	4.03	38.91	6.03	0.62	0.65	0.03
S&P GSCI Crude Oil Spot Index	MA (20, 25, 0, 0, 50)	2447	0.06	2.18	15.95	5.82	1.00	1.00	0.32
S&P GSCI Heating Oil Spot Index	MA (15, 20, 0, 0, 50)	2442	0.05	2.01	12.94	3.03	0.98	1.00	0.33
S&P GSCI Natural Gas Spot Index	MA (1, 30, 0, 2, 0)	1584	0.13	2.43	32.44	5.39	0.98	0.99	0.27
WTI Crude Oil Spot Index (NYM)	MA (1, 2, 0, 0, 50)	2103	0.07	2.04	16.39	4.00	1.00	1.00	0.36
WTI Cushing Crude Oil Spot Index (NYM)	MA (15, 20, 0, 0, 5)	2127	0.06	1.71	14.42	3.78	0.99	1.00	0.43

Notes: [a] 'Best rule MA' denotes the moving average with five parameters (n, m, b, d, c), where n-days is the short-term horizon line; m-days is the long-term horizon line; b is the filter rate (%); d-days is the time delay; and c-days is the holding days. 'Best rule OBV' denotes t on-balance volume averages with five parameters (n, m, b, d, c) with the same definition as 'Best rule MA'. [b] 'Order' refers to the location of the best universal rule. [c] The t-value refers to the two-tailed t-test. [d] 'RC' refers to the p-value for the White (2000) 'reality check' to the full universe. [e] 'SPA' refers to the p-value for the Hansen (2005) 'superior predictive ability' test to the full universe. [f] 'Nominal RC' refers to the p-value obtained by applying the 'reality check' to the best rule only, without relating it to the full set of rules.

Table 4. Bootstrapped test results for the technical rules amongst the energy market future and spot indices with non-synchronous adjustment

	Best rule[a]	Order[c]	Daily return		Old best rule return[b]		SPA[d]	RC[e]	Nominal RC[f]
			(%)	*t*-value	(%)	*t*-value			
Light Crude Oil Futures Index (NYM)	OBV (15, 50, 0, 0, 25)	7668	0.09	3.12	0.08	2.70	0.84	0.94	0.08
Natural Gas Futures Index (NYM)	OBV (15, 150, 0, 0, 25)	7706	0.14	2.68	0.14	2.68	0.99	1.00	0.22
Brent Crude Oil Spot Index (NYM)	MA (5, 15, 0, 3, 0)	1747	0.18	6.27	0.18	6.11	0.03	0.03	0.00
No. 2 Heating Oil USG Spot Index	MA (1, 5, 0.001, 0, 0)	619	0.15	5.50	-0.02	-0.53	0.10	0.10	0.00
No. 2 Heating Oil NYH Spot Index	MA (2, 5, 0, 4, 0)	1848	0.13	4.82	0.11	4.23	0.18	0.25	0.01
MLCX Crude Oil (WTI) Spot Index	MA (1, 100, 0, 3, 0)	1603	0.06	2.15	0.05	1.69	0.97	1.00	0.33
MLCX Heating Oil Spot Index	MA (2, 125, 0, 0, 0)	568	0.06	2.22	0.06	2.12	0.97	0.99	0.28
MLCX Natural Gas Spot Index	MA (1, 30, 0.02, 0, 0)	684	0.13	3.70	0.12	3.02	0.81	0.88	0.10
S&P GSCI Crude Oil Spot Index	MA (1, 20, 0, 0, 0)	2077	0.06	2.22	0.06	2.02	0.99	1.00	0.41
S&P GSCI Heating Oil Spot Index	MA (5, 30, 0, 0, 10)	2239	0.05	1.91	0.05	1.80	1.00	1.00	0.34
S&P GSCI Natural Gas Spot Index	MA (1, 5, 0, 0, 0)	499	0.13	2.38	0.10	1.88	0.98	0.99	0.26
WTI Crude Oil Spot Index (NYM)	MA (20, 25, 0, 0, 5)	2132	0.05	1.71	0.05	1.69	1.00	1.00	0.48
WTI Cushing Crude Oil Spot Index (NYM)	Filter (0.005, 0, 20, 0)	193	0.07	2.23	0.06	1.69	0.98	1.00	0.35

Notes: [a] 'Best rule MA' denotes the moving average with five parameters (n, m, b, d, c), where n-days is the short-term horizon line; m-days is the long-term horizon line; b is the filter rate (%); d-days is the time delay; and c-days is the holding days. 'Best rule OBV' denotes t on-balance volume averages with five parameters (n, m, b, d, c) with the same definition as 'Best rule MA'. [b] 'Old best rule return' refers to the return of the best rule without institutional adjustments, as indicated in Table 2. [c] 'Order' refers to the location of the best universal rule. [d] 'RC' refers to the p-value for the White (2000) 'reality check' to the full universe. [e] 'SPA' refers to the p-value for the Hansen (2005) 'superior predictive ability' test to the full universe. [f] 'Nominal RC' refers to the p-value obtained by applying the 'reality check' to the best rule only, without relating it to the full set of rules.

Table 5. Bootstrapped test results for the technical rules amongst the energy market future and spot indices with transaction costs adjustment

	Best rule[a]	Order[c]	Daily return		Old best rule return[b]		SPA[d]	RC[e]	Nominal RC[f]
			(%)	*t*-value	(%)	*t*-value			
Light Crude Oil Futures Index (NYM)	OBV (20, 100, 0, 0, 50)	7787	0.05	1.68	-0.02	-0.64	1.00	1.00	0.45
Natural Gas Futures Index (NYM)	OBV (125, 150, 0, 0, 50)	7819	0.02	0.45	-0.08	-1.40	1.00	1.00	0.87
Brent Crude Oil Spot Index (NYM)	MA (5, 15, 0, 5, 0)	1957	0.09	3.19	0.09	3.03	0.85	0.95	0.14
No. 2 Heating Oil USG Spot Index	MA (1, 10, 0, 0, 5)	2060	0.11	3.72	0.11	3.72	0.65	0.71	0.06*
No. 2 Heating Oil NYH Spot Index	MA (5, 10, 0, 0, 0)	515	0.08	2.82	0.05	2.01	0.89	0.97	0.20
MLCX Crude Oil (WTI) Spot Index	MA (1, 125, 0, 0, 5)	2069	0.06	2.06	0.06	2.06	0.99	1.00	0.36
MLCX Heating Oil Spot Index	MA (1, 125, 0, 0, 0)	509	0.06	2.04	0.06	2.04	0.99	0.99	0.35
MLCX Natural Gas Spot Index	MA (1, 40, 0, 2, 0)	1585	0.15	3.81	0.15	3.81	0.73	0.77	0.06*
S&P GSCI Crude Oil Spot Index	MA (20, 25, 0, 0, 50)	2447	0.06	2.11	0.06	2.11	0.99	1.00	0.37
S&P GSCI Heating Oil Spot Index	MA (15, 20, 0, 0, 50)	2442	0.05	1.83	0.05	1.83	0.99	1.00	0.37
S&P GSCI Natural Gas Spot Index	MA (1, 30, 0, 2, 0)	1584	0.12	2.18	0.12	2.18	0.99	1.00	0.32
WTI Crude Oil Spot Index (NYM)	MA (1, 2, 0, 0, 50)	2103	0.05	1.54	0.05	1.54	1.00	1.00	0.58
WTI Cushing Crude Oil Spot Index (NYM)	MA (2, 5, 0, 0, 50)	2433	0.03	0.99	-0.03	-0.98	1.00	1.00	0.63

Notes: [a] 'Best rule MA' denotes the moving average with five parameters (n, m, b, d, c), where n-days is the short-term horizon line; m-days is the long-termhorizon line; b is the filter rate (%); d-days is the time delay; and c-days is the holding days. 'Best rule OBV' denotes t on-balance volume averages with five parameters (n, m, b, d, c) with the same definition as 'Best rule MA'. [b] 'Old best rule return' refers to the return of the best rule without institutional adjustments, as indicated in Table 2. [c] 'Order' refers to the location of the best universal rule. [d] 'RC' refers to the p-value for the White (2000) 'reality check' to the full universe. [e] 'SPA' refers to the p-value for the Hansen (2005) 'superior predictive ability' test to the full universe. [f] 'Nominal RC' refers to the p-value obtained by applying the 'reality check' to the best rule only, without relating it to the full set of rules.