Key to Trading Profits – Matching the Probability Distribution of A Contract with An Appropriate Mechanical Trading Strategy

Gary Tan

Business School, University of Adelaide

10 Pulteney Street, SA 5005, Australia

Tel: 61-(0)8-8303 7215 E-mail: g.tan@adelaide.edu.au

Abstract

Most research on technical trading strategies had centred only on testing the efficacy of common trading rules applied to various contracts. Other research on the implications of moments of distribution tends to concentrate on asset or portfolio valuation perspective as opposed to trading rules.

Given the controversy surrounding the usefulness of mechanical trading strategies per se, this paper seeks to match the distribution of a contract with an appropriate trading rule to determine the profitability or lack thereof of such an approach.

We tested this approach using Light Sweet Crude Oil futures for the period 1994 – 2008. On the whole, our results strongly support the approach employed. We also tested the results against the weak form EMH and found that there may be some non randomness in prices that one can exploit with the use of mechanical trading methods.

Keywords: Mechanical Trading Strategies, Technical Trading Rules, Futures Trading, Oil Futures

1. Introduction

Technical analysis is commonly perceived to involve the prediction of future asset price movements from an analysis of past movements, employing either qualitative methods (such as chart pattern recognition) or quantitative techniques (such as moving averages), or a combination of both.

Whether one takes a qualitative or a quantitative approach, the techniques available are many and varied, and that complicates a systematic assessment of the usefulness of technical analysis. It comes as no wonder then, that empirical tests of specific trading rules and their attendant signals are often less than satisfactory tests of the efficiency of technical analysis in general, since traders typically employ not one but a range of technical indicators. Additionally, many traders also apply considerable market intuition to complement the insight gained from technical analysis, so there will always be an element of subjectivity with its application.

Since the publication of Fama & Blume (1966) most academics have considered the usefulness of technical analysis in forecasting to be probably close to nil. For many others, the continued and widespread use of these techniques Taylor & Allen (1992); Yin-Wong Cheung & Menzie D. Chinn (2001) is even puzzling since technical analysis shuns economic fundamentals and relies only on information on past price movements. Historical information, according to the weak form market efficiency, should already be embedded in the current asset price, thus its use is unprofitable.

Burton G. Malkiel (1996), suggested that "technical strategies are usually amusing, often comforting, but of no real value". Malkiel's dismissal of technical analysis is glaringly at odds with the fact that technical analysis is widely used by market professionals.

On the other hand, Sweeney (1986, 1988) presents results consistent with some usefulness to technical rules. More recent studies have included Taylor (1992), LeBaron (1994), and Levich & Thomas (1993). The latter two employed bootstrap techniques to further emphasise the magnitude of the forecastability. Other related evidence includes that of Taylor & Allen (1992) which shows the extent to which traders continue to use technical analysis. Brock et al (1992) showed using a bootstrap methodology that the rules did at least generate statistically significant forecastability.

It is not difficult to understand why technical analysis did not or could not sustain academic interest as long as the available evidence was not of a more systematic nature. The scepticism with which academic economists initially viewed (and to some extent continue to view) technical analysis can be largely attributed to the intellectual standing of the efficient markets hypothesis (EMH), which, in its "weak form" Fama (1970),

maintains that all historical information should already be embodied in asset prices, making it impossible to earn excess returns on forecasts based on historical price movements.

If technical analysis reflects rational thinking that leads to profitable trading rules, how is it that market processes do not arbitrage these profit opportunities away? It is offered that in well functioning markets one would expect that profit opportunities will be exploited up to an extent where agents feel appropriately compensated for their risk. To take open positions is inherently risky, whether the decision is based on fundamental or technical considerations.

Or perhaps technical analysis is an indication of irrational behaviour, as can only be concluded if one follows the traditional understanding of the EMH and regards markets as at least weakly efficient; Fama (1970). However, to interpret technical analysis as an indication of irrational or even not-fully rational behaviour goes against the grain that virtually all market professionals rely on technical trading rules, albeit to varying degrees. Surely market professionals cannot all be exhibiting suboptimal behaviour, much less irrationality, even if temporarily.

Such is the paradox, so is it any wonder then, that evidence relating to the profitability of technical analysis tends to be inconclusive? Not at all, for if technical analysis was never profitable, its widespread use would be hard to fathom; if, on the other hand, technical analysis was always profitable, it would perhaps imply that the market is inefficient to a degree that many academics would not find credible.

Clearly, technical analysis remains an intrinsic part of the market. For market practitioners, the challenge is to constantly refine technical trading strategies as potentially important tools in the search for excess returns. For academic researchers, technical analysis must be understood and integrated into economic reasoning at both the macroeconomic and the micro structural levels.

This paper hopes to contribute to the existing literature by matching the distribution of a contract with an appropriate trading rule, thus integrating the characteristics of a contract with the capability of a trading strategy. In this regard, knowing that a contract's distribution is negatively skewed, for instance, one can expect a higher probability of making many small wins and a low probability of risking a larger loss. Thus by choosing the appropriate contract to trade vis-à-vis one's risk profile, one is already ahead of the game in terms of staking the odds of winning trades in one's favour even before selecting a trading strategy. As different trading strategies cater to different characteristics of price movements, back testing with different trading rules can uncover a trading rule that best exploit the characteristics of the intended contract, thus achieving a competitive edge.

2. Data and Summary Statistics

2.1 Data

This study uses daily exchange series from Nymex as provided by Telequote Networks. The series represent the daily data for the Light Sweet Crude Oil futures extending almost 15 years and 3,714 observations. We first determine the distribution of daily lognormal returns for the in-sample period from 01 January, 1994 through to 31 December, 1998 and 1,254 observations. Based on the said distribution an appropriate trading strategy was adopted to trade subject commodity for the out-of-sample period from 01 January, 1999 through to 31 October, 2008 yielding 1,596 trades out of 2,460 observations. We also test the distribution of the out-of-sample period to determine the continuity of the distribution established for the in-sample period.

2.2 Summary Statistics

The daily return series is generated as follows:

$$R_t = \ln (P_t/P_{t-1}) \tag{1}$$

where ln is the natural logarithm operator, R_t is the return for period t, P is the closing price for period t and t is the time measured in days.

The descriptive statistics and results of the normality test for the daily returns are presented in Table 1.

The skewness coefficient, being the third moment about the mean/cube of the standard deviation is -0.0118 for in-sample period and -0.2615 for out-of-sample period, and is measured as follows:

$$S = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{y_i - \bar{y}}{\hat{\sigma}} \right)^3 \tag{2}$$

where N is the number of observations, $\bar{y}$ is the mean of the series and $\hat{\sigma}$ is an estimator for the standard deviation.

The distribution of the daily lognormal returns appeared to be slightly negatively skewed for the in-sample period, a characteristic that extended to the out-of-sample period. This suggested that wins are small and likely, and losses can be large but are far and few. In other words, there is the occasional large loss at the expense of promising consistent winnings. Negative skewness, although commonly viewed as risky, is not without its own appeal to traders as the occasional large downside can be more than mitigated by the frequent and smaller upside with appropriate trading strategies that deliver robust win/loss ratios. A trading strategy that has a high percentage of wins would generate significant profits in the long run when compounded by a robust win/loss ratio.

The kurtosis coefficient, being the fourth moment about the mean/square of the second moment is 5.6983 for in-sample period and 6.2375 for out-of-sample period, and is calculated as follows:

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{Y_i-\bar{Y}}{\hat{\sigma}}\right)^4 \tag{3}$$

where N is the number of observations, $\bar{Y}$ is the mean of the series and $\hat{\sigma}$ is an estimator for the standard deviation.

This indicates that the in-sample distribution is also more peaked than normal, a characteristic that is also carried forth into the out-of-sample period, a condition otherwise known as leptokurtic. This suggests a not so significant deviation from its mean, which implies less volatility in future returns and lower probability of extreme price movements. This implies lower risks and therefore more stable returns, thus mitigating sharp drawdown risks as is feared with a significant negatively skewed distribution.

The Jarque-Bera (JB) test of normality was employed to further test the normality as it is an asymptotic or large-sample test that is appropriate given the large number of observations in this study. For a normally distributed variable, $S = 0$ and $K = 3$, hence the Jarque-Bera (JB) test serve to test the joint hypothesis that $S = 0$ and $K = 3$ and thus the null hypothesis that the series is normally distributed.

$$Jarque - Bera = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{4}$$

where N is the sample size, S is the skewness coefficient and K is the kurtosis coefficient.

The JB statistic as computed is 380.4543 with a p-value of 0 for in-sample period and 1,102.3620 for out-of-sample period with a p value of 0. As to be expected from our calculation of skewness and kurtosis in the foregoing, the value of the statistic is far from zero and the p value zero. Thus, one can reject the null hypothesis of normal distribution. This only lend more credence to the significance of focusing on the third and fourth moment of distribution.

Insert Table 1: Summary Statistics

In Table 2 the autocorrelation coefficients at various lags are very high for both in-sample and out-of-sample periods, starting at 0.9980 and 0.9990 at the first lag and only declined to 0.9880 and 0.9940 at the 5th lag respectively. Autocorrelations up to 5 lags for both periods are also individually statistically significant from zero since they are all outside the 95% confidence bounds.

We also tested the statistical significance of the autocorrelation coefficients by using the Ljung-Box (LB) statistic. The LB statistic is defined as:

$$Q = T(T+2)\sum_{j=1}^{k}\frac{\tau_j^2}{T-j} \tag{5}$$

where T is the sample size and τ_j is the j-th autocorrelation.

The LB statistic tests the joint hypothesis that all the p_k up to certain lag lengths are simultaneously equal to zero. From Table 2 the value of the LB statistic up to 5 lags is 6,205 for in-sample and 12,235 for out-of-sample. There is also zero probability of obtaining such a LB value under the null hypothesis that the sum of 5 squared estimated autocorrelation coefficients is zero. Accordingly, one can conclude significant time dependence in the return series due perhaps to some form of market inefficiency. This suggests that trends and reversal tendencies are present and can be detected. As a result, patterns in short term price changes can be exploited for significant profits by the intelligent use of mechanical trading methods.

Insert Table 2: Autocorrelation

3. Mechanical Trading Model

Having established that the distribution of the contract in question is negatively skewed and leptokurtic, we next determine an appropriate trading strategy to employ. Many strategies exist to trade a negatively skewed market, with statistical arbitrage and convergence trading among the more common or popular methods.

This model seeks to initiate a trade when the current price breaks above the previous high or below the previous low. So if one is trading on the basis of daily time frames as is envisaged in this paper, one would be comparing the current price with the previous day high and previous day low.

This can be expressed as follow:

$$Buy\ if: P_t \geq max\ (P_{t-1}) + 1\ tick \qquad (6)$$

$$Sell\ if: P_t \leq min\ (P_{t-1}) - 1\ tick \qquad (7)$$

where P_t the price at time t and 1 tick refers to the minimum price fluctuation of the contract.

Once a trade is entered, say to buy one contract, in accordance with the rule specified in the foregoing, hold until an opposite signal is given by the market (again in accordance with the rules above) to sell. When that occurs, sell two contracts – one to square the earlier position and the other to simultaneously enter a new short position. The process is then repeated every time the rule is triggered.

Insert Table 3: Examples of Trade Selection

As a result net position is always one contract, long or short, at any one time. This also means no adding to positions when consecutive long signals or consecutive short signals are given by the model.

The model works on the premise that the breaking of a prior high signifies new buying interest which in turn will drive prices even higher. Conversely, the breaking of a prior low is indication of renewed selling interests which would then force prices down. Being aligned with the flow complements the high incidence of wins given by the contract characteristics as determined in subsection 2.2. Accordingly, if the rule takes you long in the market, remain in that position until the rule takes you out. This will allow the market to work on your trade and more importantly allow one to be constantly in the market so as to be able to ride the big move when it comes as opposed to trying to "second-guess" when that might be, thus increasing the likelihood of achieving a robust win/loss ratio.

It is further assumed that one is able to buy at the ask and sell at the bid, with no slippage given that the i) contract in question is liquid and its bid-ask spread had been consistently 1 tick difference for most parts, and ii) bid-ask volume can easily absorb your trade size (in this paper this isn't an issue since we are looking at only one contract). In other words, one can hope to get in and out of a trade at relative ease.

4. The Results

4.1 Results from Trading the Model

The model generated net profits for every single year in the out-of-sample period from January 1999 to October 2008, no matter long or short positions. Combined, long and short trades netted profits of USD590,690, USD323,220 and USD267,470 respectively for the period sampled. Such sterling results were achieved on the back of robust win/loss ratios compounded by a high probability of winning trades.

Transaction costs were assumed to be USD30 per round turn. Note also that the average profit per trade of USD770 can more than cover any transaction costs and still be profitable. Consequently, slippage from execution, if any, is unlikely to have a material negative impact on profits.

Win/loss ratio is defined as gross win/gross loss and averaged 4 times for all trades, indicating the dollar value of winnings was 4 times that of losses in the period sampled. Long trades performed better than short trades, averaging 5 times compared to 4 times for shorts. The lowest win/loss ratio in a given year was still a healthy 2 times. Such robust win/loss ratios can be attributed to the efficacy of the trading model. The trading model as enumerated in section 3 is designed such that a position once initiated and profitable is allowed to run thus maximising its profit potential. Consequently, the model was able to exploit the opportunities offered by the market, thus compounding the many "small" wins envisaged by the distribution characteristics of the contract. Such favourable win/loss ratios are certain to result in longer term profitability for any trading model that has an even chance of winning, more so when we have a high probability of wins as is the case here.

% winning trades is defined as the total number of winning trades/total number of trades and was 55% of a total of 798 trades taken during the sample period. It is further noted that annual trades generated by the model were winning at least half the time to two thirds of the time. It must also be pointed out that % wins are less

encouraging in short trades primarily because crude oil was on a long term uptrend for much of the period sampled. However, profits were still achieved every single year on short trades due to a robust win/loss ratio. Long trades were more profitable, averaging 61% wins for the sample period. Again as explained in subsection 2.2, the subject contract exhibited significant time dependencies. By aiming to capitalise on new buying and new selling interests the trading model was able to capture the trends and reversal tendencies displayed, thus resulting in a high probability of wins.

Maximum continuous winning streak was 9 trades and totalled USD60,240 while maximum continuous losing trades totalled 6 trades and was USD10,620. Consistent with the leptokurtic nature described in subsection 2.2 drawdown was kept in check. Together with the strong win/loss ratios and higher probability of wins, the trading model provides one with positive expectations and hence the confidence to trade.

There is no open position as the last trade was closed out at the end of the sample period.

Insert Tables 4: Trading Results of Combined Trades

Insert Tables 5: Trading Results of Long Trades Only

Insert Tables 6: Trading Results of Short Trades Only

To be sure, one can improve the results by employing risk/money management strategies such as trade sizing, trailing stops, pyramiding etc. Results can also be enhanced by the use of appropriate filters in the trade rules and by employing other confirmation signals which is out of the scope of this paper.

4.2. Results Evaluated Against the Weak Form EMH

As described above, the model had consistently generated positive excess return. The question remains if these excess returns were due to the efficacy of the model or did they happen by chance? And if they were due to the efficacy of the model, just how significant are they? To address these concerns, we evaluated the results in the context of the framework developed by Peterson & Leuthold (1982), a framework that essentially evolve from the works of Samuelson (1965) and Mandelbrot (1963, 1966) and Fama (1970).

As any mechanical trading system must yield zero profits under the weak form efficient market conditions, the null hypothesis must be zero and any non zero results deemed a contradiction. Additionally, a zero benchmark seemed in order given that futures trading are a zero sum game, Leuthold (1976). Further, Samuelson (1965) argued that "on average … there is no way of making an expected profit" and Fama (1970) also ruled out excess profits under the assumptions of the weak form efficient market. Bachelier (1900) also concluded that "the mathematical expectation of the speculator is zero" and he described this condition as a "fair game." Accordingly, the following hypothesis is tested:

Ho: mean profit = 0

Ha: mean profit ≠ 0

A trading system that consistently produces losses can just as easily be used to consistently produce profits by adopting a contrarian approach, i.e. by simply buying on a sell signal and selling on a buy signal. Such a move would obviously result in an opposite effect of the same magnitude.

Accordingly, a two-tailed Z-test is chosen to measure the significance:

$$Z = \frac{X - X_0}{\sqrt{\frac{s^2}{n}}} \ (n > 30) \tag{8}$$

where is the actual mean gross profit/loss from the Model, X_0 is the expected mean gross profit/loss (= 0), s^2 is the variance of gross profits per trade and n is the number of round-turn trades.

As tabulated in Tables 4, 5 and 6 the calculated z-statistic for combined trades, long trades and short trades in the sample period was 9.43, 8.61 and 5.34 respectively. For all years in the sample period, combined trades generated net profits significantly different from 0 at the 1% level.

Long trades also exhibited the same results as above for all years. Short trades were more erratic but most years were still significant, at least at the 10% level.

The results indicate that the null hypothesis should be rejected, at least at the 10% level. The ability of the model to generate significant excess profits suggest non random price movements and accordingly, it can be concluded that the Light Sweet Crude Oil futures failed the weak form efficiency test.

5. Conclusion

This study confirmed that it is possible to match the distribution of a contract with an appropriate trading strategy to provide a competitive edge. Simple trading rules that are complementary to the distribution of the contract, when consistently applied, can systematically produce excess profits in the long run. The appeal of mechanical trading methods lies also in that they help set the rules and remove or at least keep guesswork and emotions to a minimum, thereby making simulation easy.

To be sure there can be more than one trading rule that matches any given distribution and vice versa. Perhaps the successful trader differs from the unsuccessful one, not because of the superiority of one model over another, but because he or she has found a model that is in-tune with his or her basic personality, outlook and experience sets. Because these models of market success are drawn from our fundamental views and aversions, I suspect they are far less amenable to modification than is commonly appreciated, which explains why market participants can and do get different results from trading identical models.

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Notes

Table 1. Light Sweet Crude Oil Futures - Summary Statistics

Descriptive Statistics	In-sample Jan 1994 – 98	Out-of-sample Jan 1999 – Oct 2008
Observations	1254	2460
Mean	-0.0002	0.0007
Median	0.0000	0.0015
Maximum	0.1223	0.1772
Minimum	-0.0854	-0.1654
Std. Dev	0.0198	0.0232
Skewness	-0.0118	-0.2615
Kurtosis	5.6983	6.2375
Jarque-Bera	380.4543*	1102.3620 *
Probability	0.0000	0.0000

Notes: Summary statistic for raw data for in-sample period 01 January 1994 – 31 December 1998 and out-of-sample period 01 January 1999 – 31 October 2008; * denotes statistical significance at the 5% level; Skewness = 0 and kurtosis = 3 in a normal distribution; Jarque-Bera tests if the series is normally distributed.

Table 2. Light Sweet Crude Oil Futures - Auto-Correlation

		In-sample Jan 1994 – 98			Out-of-sample Jan 1999 – Oct 2008	
p(lag)	AC	Q-Statistic	Probability	AC	Q-Statistic	Probability
1	0.9980*	1 251	0.0000	0.9990*	2 457	0.0000
2	0.9950*	2 497	0.0000	0.9980*	4 909	0.0000
3	0.9930*	3 738	0.0000	0.9960*	7 356	0.0000
4	0.9900*	4 974	0.0000	0.9950*	9 798	0.0000
5	0.9880*	6 205	0.0000	0.9940*	12 235	0.0000

Notes: p (lag) refers to the first 5 autocorrelations for the return series; AC refers to autocorrelation; Q-statistic refers to the Ljung-Box statistic; * denotes statistical significance at the 5% level.

Table 3. Examples of Trade Selection

Date	High	Low	Trade
25-03-08	101.40	99.30	Assume no position yet
26-03-08	106.20	101.15	Long 1 contract at 101.41 as price had broken 25-03-08 day high
27-03-08	108.10	105.20	Hold as price did not break 26-03-08 day low
28-03-08	107.65	104.35	Sell 2 contracts at 105.19 as price had broken 27-03-08 day low; one contract to square the long trade taken on 26-03-08 and the other contract to initiate a new short trade
31-03-08	106.60	100.45	Hold as price did not break 28-03-08 day high
01-04-08	102.50	99.70	Continue to hold as price did not break 31-03-08 day high
02-04-08	104.85	100.87	Long 2 contracts at 102.51 as price had broken 01-04-08 day high

Note: High refers to Day High Price and Low refers to Day Low Price.

Table 4. Light Sweet Crude Oil Futures – Trading Results of Combined Trades

Year	Net Profit USD	Transaction Costs @$30/rt USD	Gross Profit USD	Gross Win USD	Gross Loss USD	Win/Loss Ratio	Total Num Trades	% Win Trades	Mean (X) Profit USD	Std Dev USD	Var (S²) USD	Z Test
1999	22,140	-2,670	24,810	34,410	-9,600	4	89	55%	279	694	481,420	3.79
2000	41,740	-2,670	44,410	62,120	-17,710	4	89	47%	499	1,262	1,592,118	3.73
2001	30,360	-2,670	33,030	47,190	-14,160	3	89	51%	371	992	984,562	3.53
2002	25,420	-2,700	28,120	41,670	-13,550	3	90	51%	312	773	598,210	3.83
2003	30,800	-2,670	33,470	53,740	-20,270	3	89	52%	376	1,269	1,609,899	2.80
2004	45,800	-2,370	48,170	69,310	-21,140	3	79	53%	610	1,697	2,880,241	3.19
2005	71,860	-2,250	74,110	95,240	-21,130	5	75	60%	988	1,911	3,650,691	4.48
2006	71,090	-2,490	73,580	97,540	-23,960	4	83	59%	887	1,804	3,255,460	4.48
2007	84,870	-1,740	86,610	102,670	-16,060	6	58	66%	1,493	2,740	7,508,475	4.15
2008	166,610	-1,710	168,320	202,520	-34,200	6	57	58%	2,953	6,278	39,408,386	3.55
1999-2008	590,690	-23,940	614,630	806,410	-191,780	4	798	55%	770	2,308	5,325,164	9.43

Notes: (1) Net Profit = Gross Profit – Transaction Costs; (2) Transaction costs is assumed to be USD30 per round turn; (3) Gross Profit = Gross Win – Gross Loss; (4) Gross Win = Gross Total Dollar Value of Winning Trades; Gross Loss = Gross Total Dollar Value of Losing Trades; Win/Loss Ratio = Gross Win/Gross Loss; Total Number of Trades = Total Number of New Trades; % Win Trades = Total Number f Winning Trades/Total Number of Trades; Mean Profit = Average Gross Profit per Trade; Z-Test is two-tailed.

Table 5. Light Sweet Crude Oil Futures – Trading Results of Long Trades Only

Year	Net Profit USD	Transaction Costs @$30/rt USD	Gross Profit USD	Gross Win USD	Gross Loss USD	Win/Loss Ratio	Total Num Trades	% Win Trades	Mean (X) Profit USD	Std Dev USD	Var (S²) USD	Z Test
1999	17,440	-1,320	18,760	21,920	-3,160	7	44	75%	426	680	462,121	4.16
2000	22,400	-1,350	23,750	32,050	-8,300	4	45	51%	528	1,216	1,479,845	2.91
2001	11,490	-1,320	12,810	19,750	-6,940	3	44	52%	291	748	559,922	2.58
2002	18,170	-1,350	19,520	25,620	-6,100	4	45	56%	434	828	684,910	3.52
2003	16,350	-1,350	17,700	26,970	-9,270	3	45	60%	393	947	896,559	2.79
2004	27,400	-1,170	28,570	35,800	-7,230	5	39	64%	733	1,418	2,010,441	3.23
2005	46,680	-1,140	47,820	56,040	-8,220	7	38	71%	1,258	1,998	3,990,624	3.88
2006	31,870	-1,230	33,100	43,450	-10,350	4	41	61%	807	1,680	2,820,865	3.08
2007	62,610	-870	63,480	68,520	-5,040	14	29	72%	2,189	3,184	10,136,431	3.70
2008	68,810	-870	69,680	86,160	-16,480	5	29	55%	2,403	4,396	19,320,585	2.94
1999-2008	323,220	-11,970	335,190	416,280	-81,090	5	399	61%	840	1,950	3,800,610	8.61

Notes: (1) Net Profit = Gross Profit – Transaction Costs; (2) Transaction costs is assumed to be USD30 per round turn; (3) Gross Profit = Gross Win – Gross Loss; (4) Gross Win = Gross Total Dollar Value of Winning Trades; Gross Loss = Gross Total Dollar Value of Losing Trades; Win/Loss Ratio = Gross Win/Gross Loss; Total Number of Trades = Total Number of New Trades; % Win Trades = Total Number f Winning Trades/Total Number of Trades; Mean Profit = Average Gross Profit per Trade; Z-Test is two-tailed

Table 6. Light Sweet Crude Oil Futures – Trading Results of Short Trades Only

Year	Net	Transaction	Gross	Gross	Gross	Win/Loss	Total Num	% Win	Mean (X)	Std	Var (S²)	Z Test
	Profit	Costs @$30/rt	Profit	Win	Loss	Ratio	Trades	Trades	Profit	Dev		
	USD	USD	USD	USD	USD				USD	USD	USD	
1999	4,700	-1,350	6,050	12,490	-6,440	2	45	42%	134	684	468,134	1.32
2000	19,340	-1,320	20,660	30,070	-9,410	3	44	45%	470	1,320	1,742,274	2.36
2001	18,870	-1,350	20,220	27,440	-7,220	4	45	51%	449	1,187	1,409,275	2.54
2002	7,250	-1,350	8,600	16,050	-7,450	2	45	47%	191	704	494,992	1.82
2003	14,450	-1,320	15,770	26,770	-11,000	2	44	43%	358	1,542	2,376,637	1.54
2004	18,400	-1,200	19,600	33,510	-13,910	2	40	45%	490	1,942	3,771,800	1.60
2005	25,180	-1,110	26,290	39,200	-12,910	3	37	49%	711	1,802	3,246,411	2.40
2006	39,220	-1,260	40,480	54,090	-13,610	4	42	57%	964	1,936	3,746,463	3.23
2007	22,260	-870	23,130	34,150	-11,020	3	29	59%	798	2,036	4,146,140	2.11
2008	97,800	-840	98,640	116,360	-17,720	7	28	61%	3,523	7,813	61,037,792	2.39
1999-2008	267,470	-11,970	279,440	390,130	-110,690	4	399	49%	700	262	6,853,312	5.34

Notes: (1) Net Profit = Gross Profit – Transaction Costs; (2) Transaction costs is assumed to be USD30 per round turn; (3) Gross Profit = Gross Win – Gross Loss; (4) Gross Win = Gross Total Dollar Value of Winning Trades; Gross Loss = Gross Total Dollar Value of Losing Trades; Win/Loss Ratio = Gross Win/Gross Loss; Total Number of Trades = Total Number of New Trades; % Win Trades = Total Number f Winning Trades/Total Number of Trades; Mean Profit = Average Gross Profit per Trade; Z-Test is two-tailed.