Derivatives Trading

Trading efficiency of commodity trading advisors using Data Envelopment Analysis

Greg N. Gregoriou

101 Broad Street, Plattsburgh, New York 12901, USA. Tel: +1 (518) 564 4202;
Fax: +1 (518) 564 4215; e-mail: greg.gregoriou@plattsburgh.edu

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Greg N. Gregoriou, PhD is associate professor of finance and coordinator of faculty research in the School of Business and Economics at State University of New York College at Plattsburgh. He is also Hedge Fund Editor and editorial board member for *Derivatives Use, Trading and Regulation*.

Practical applications

Investors can use Data Envelopment Analysis (DEA) as complementary performance appraisal technique to examine and rank the relative trading efficiency of commodity trading advisors (CTAs). Data Envelopment Analysis can offer added insight by observing which CTAs are best at optimising their inputs to produce the largest outputs. One of the benefits of using DEA is that it allows comparisons among CTAs without the use of external benchmarks or indices. With this in mind, investors can monitor whether the CTAs they have selected for inclusion in their portfolio possess efficient trading skills.

Abstract

This paper investigates the trading efficiency of commodity trading advisors (CTAs) during the period January 1998–June 2004. The 90 largest CTAs are analysed using the basic Data Envelopment Analysis (DEA) model, followed by the cross-efficiency and super-efficiency models. A detailed efficiency analysis of CTAs is provided, and the results indicate that only a handful of CTAs are efficient in terms of minimising trading to attain the highest compounded return.

trading advisors (CTAs) has regained ground since the collapse of the dot com bubble in March 2000. The negative correlation and lower standard deviation versus various equity markets makes them ideal diversifying vehicles for traditional stock and bond portfolios. While stocks and bonds are considered a traditional asset class for investment portfolios, they do not achieve optimal portfolio diversification.¹ Including alternative investments, such as managed futures, in traditional portfolios will diversify, reduce overall risk and enhance portfolio returns.²

INTRODUCTION

The argument in favour of diversifying a traditional portfolio with commodity

Considered as alternative investment vehicles, CTAs produce absolute returns by employing leverage, short selling, futures

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and options, etc. Typically, CTAs are classified as being either systematic or discretionary. Systematic traders use computerised mathematical models that produce buy and sell signals, whereas discretionary traders (non-systematic) use economic indicators or fundamental analysis to execute their trades.

Commodity trading advisers use proprietary trading systems to create market positions in commodity, currency markets and financial futures in global futures markets. They can assume either long or short positions and invest in futures contracts to make leveraged bets on currencies, energy, bonds, interest rates, stock market indices as well as agricultural and consumer goods.

Having an alternative performance measure such as Data Envelopment Analysis (DEA) is important, because it enables investors potentially to pinpoint the reasons behind a CTA's poor trading efficiency. For institutional investors considering using CTAs, it is critical that a measure provide not only a precise appraisal of the CTA trading efficiency, but also an idea of what the CTAs can be compared with. The single measure of performance, which takes into account the multiple measurements of inputs and outputs to estimate a CTA's efficiency level, is practical because the CTAs themselves are used as benchmarks. Specifically, DEA permits us to evaluate, appraise and rank the trading efficiency of CTAs without using traditional market indices. Among the first studies in DEA to propose the evaluation of CTA classifications followed by the development of the benchmark models were Wilkens

and Zhu³ and Zhu.⁴

Using data envelopment analysis, this paper investigates the trading efficiency of CTAs and determines whether the ranking ordering produced by three DEA models and can be used as an alternative measure of performance to the Sharpe ratio.

Institutional investors, endowments and pension funds can only benefit from this complementary measure when deciding on what CTAs they believe are efficient at trading and maintaining good performance.

The rest of the paper is organised as follows. The next section presents the literature review. Following that, the data and methodology are discussed. The second to last section presents an application to a set of 90 CTAs, and the final section concludes.

LITERATURE REVIEW

Prior to this paper, no detailed trading efficiency analysis of CTAs has been undertaken using DEA. The literature on CTA efficiency is virtually non-existent, with only four studies touching on the subject.⁵⁻⁸

CTAs use long and short positions coupled with leverage to enhance portfolio returns. Traditionally, CTAs trade anywhere from 50 to 100 futures contracts on various global markets and attempt to minimise their losses as they occur.⁹

With fewer dollars under management, small CTAs will most likely trade less frequently and may not be as efficient as large CTAs, owing to economies of scale. In addition, Diz *et al.*¹⁰ examines the performance of CTAs and concludes that

the amount of leverage (margin- to-equity ratio) is related to performance.

More recent studies on DEA^{5,7,8} examined the performance of live CTAs using basic, cross-efficiency and super-efficiency during the period 1997–2001. They concluded that DEA is a valid technique in evaluating the performance of alternative investments. As further noted in Wilkens and Zhu,⁹ hedge funds, managed futures and other actively managed funds have neither a universally accepted performance evaluation methodology nor a consistent classification system. Therefore it is difficult to classify CTA strategies quantitatively for a variety of reasons, including changing CTA risk and skewed return distributions.

DATA

The dataset consists of the 90 largest live CTAs that reported monthly performance figures net of all management and performance fees to the Center for International Derivatives and Securities Markets (CISDM) database. The CTAs are tracked from January 1995 to June 2004, and efficiency scores using each of the three DEA models are generated. The above time frame was selected because using prior years would have resulted in too few CTAs for the analysis. Furthermore, two CTAs were removed from the analysis due to incomplete data. The definitions of the five CTA classifications are displayed in Table 1.

Because only live funds are examined, there is a possibility that survivorship bias may exist in the data. To address this, the

dead CTAs were added, and it was discovered they ranked last, had the lowest efficiency score and did not alter the best practice frontier or the rankings of the live CTAs.

METHODOLOGY

Data Envelopment Analysis lends itself naturally to CTA trading efficiency because of its employment in assessing the relative trading efficiency of CTAs using various inputs to produce outputs. In essence, DEA is an ideal method of measuring trading efficiency relative to the best-performing CTAs, allowing one to identify efficient and non-efficient CTAs.

The inputs and outputs must correspond to the activities of CTAs for DEA. Four variables are used: two for inputs and two for outputs. The inputs (1) beginning assets under management which represents the amount each CTA has at the start of the investigation period and (2) the number of futures contracts traded per million dollars net of all brokerage fees are used.

For the first output (1), compound return, is used because it identifies CTAs that have performed well during the investigation period. This will further show whether the CTA has done an efficient job of trading futures contracts throughout the examination period. The second output (2), ending assets under management, provides the assets of the CTAs at 30th June, 2004. The second output identifies which CTAs were able to increase their ending asset under management more efficiently through the use of efficient trading of futures contracts.

Table 1: Definition of commodity trading adviser classifications

Classification	Definition of investment style
Diversified	Manager trades financial futures/options, currency and forward contracts as well as commodity futures/options. Manager limits risk by holding a large number of positions
Currency	Manager trades financial futures/options as well as currency futures/options, forward contracts, and currency, interest rates, stock indexes and precious metals
Financial	Manager specialises in stock index futures and options
Agricultural	Manager specialises in agricultural futures options trading
Stock Index	Manager specialises in stock index futures and options

Source: Schneeweis, T. (2003) 'The benefits of hedge funds/CTA', presentation at IDAC Investment Dealers Association of Canada, St Andrews by-the-Sea, New Brunswick.

An input-oriented variable returns-to-scale model is used to examine the trading efficiency of CTAs. The Banker et al. (BCC)¹¹ the cross-efficiency model¹² and the super-efficiency model¹³ are used in the analyses.

The notation from Zhu⁴ is adapted for basic efficiency and super-efficiency models. For basic DEA, the ratio of outputs divided by inputs in equation (1) is maximised, which forms the objective function for the particular CTA h_0^* . CTAs are denoted by $j = \{1, 2, \dots, n\}$, which uses quantities of i inputs with $i = \{1, 2, \dots, m\}$ to produce quantities of r outputs with $r = \{1, 2, \dots, s\}$; furthermore, let x_{ij} be the quantity of input i for j used to produce the quantity y_{rj} of output r . Each CTA uses a variable quantity of m different inputs ($i = 1, 2, \dots, m$) to generate s different outputs ($r = 1, 2, \dots, s$). In particular, CTA j uses amount x_{ij} of input i and generates y_{rj} of output r . It is then presumed that $x_{ij} \geq 0$, $y_{rj} \geq 0$, and that

each CTA has at least one positive input value and one positive output value. Data Envelopment Analysis optimisation handles the observed vectors of x_j and y_j as given and selects values of output and input weights for a particular CTA. In Equation (1), a free variable, denoted by u_0 , is added in the BCC¹¹ model to allow for variable returns to scale. If an increase in a CTA's inputs does not produce a proportional change in its outputs, the CTA exhibits variable returns-to-scale. Therefore, as the CTA alters its scale of operations, its efficiency will increase or decrease.

Therefore, in an input-oriented BCC model, the formulation minimises the inputs, given the outputs. The following optimisation is obtained

$$h_0^* = \max \frac{\sum_{r=1}^s u_r y_{r0} + u_0}{\sum_{i=1}^m v_i x_{i0}} \quad (1)$$

subject to

$$\frac{\sum_{r=1}^s u_r \gamma_{rj} + u_0}{\sum_{i=1}^m v_i x_{ij}} \leq 1, \quad j = 1, 2, \dots, n \quad (2)$$

where s is the number of outputs, m is the number of inputs, u_r is the weight of output r , v_i is the weight of input i , x_{ij} is the amount of i used by CTA, γ_{rj} is the amount of r used by CTA, and u_0 is the free variable.

Equation (2) is the constraint which imposes that the equivalent weight, when implemented to all CTAs does not allow any CTA to have an efficiency score greater than 1.0 (or less than one). The efficiency score falls between 0 and 1.0, and a CTA is regarded as efficient upon obtaining an efficiency score of 1.0. A best-practices frontier is then generated by the efficient CTAs. Therefore, each CTA will select weights to maximise its own self-efficiency with respect to the constraint in Equation (2).

The cross-efficiency model was first seen in Sexton *et al.*¹² and later in Doyle and Green¹⁴ and Anderson *et al.*¹⁵ It establishes the ranking procedure and computes the efficiency score of each CTA n times, using optimal weights obtained via DEA models. Count n is the number of times the problem needs to be generated to differentiate the efficiency scores. Cross-efficiency adds further insight into the performance of each CTA and determines whether they have performed well in all areas according to inputs and outputs. Essentially, cross-efficiency allows for all CTAs to cast their votes. A

cross-efficiency matrix consists of rows and columns, each equal to the number of CTAs in the analysis. The efficiency of CTA j is computed with the optimal weights for fund k . Calculating the mean of each column will provide the peer appraisal score of each CTA. The cross-efficiency model (BCC model) used here is represented by Equation (3).

$$h_{kj} = \frac{\sum_{r=1}^s \gamma_{rj} u_{rk}}{\sum_{i=1}^m x_{ij} v_{ik}}, \quad k = 1, 2, \dots, n, \quad j = 1, 2, \dots, n \quad (3)$$

where the problem is generated n times, and h_{kj} is the score of CTA j cross-evaluated by the weight of CTA k . In the cross-efficiency matrix, all CTAs are bounded by $0 < h_{kj} \leq 1$, and the components in the leading diagonal h_{kk} depict the basic DEA efficiency score, $h_{kk} = 1$ for efficient CTAs and $h_{kk} < 1$ for inefficient CTAs.

Super-efficiency¹³ is obtained from the regular DEA model by excluding the fund under evaluation from the reference set. Super-efficiency (input-oriented) allows a highly efficient CTA to attain an efficiency score greater than 1.0 by removing the constraint $j \neq 0$ in Equation (5).

$$h_0^* = \max \frac{\sum_{r=1}^s u_r \gamma_{rj} + u_0}{\sum_{i=1}^m v_i x_{ij}} \quad (4)$$

subject to

$$\frac{\sum_{r=1}^s u_r \gamma_{rj} + u_0}{\sum_{i=1}^m v_i x_{ij}} \leq 1, \quad j = 1, 2, \dots, n \text{ and } j \neq 0 \quad (5)$$

The results of each DEA model are further compared with the Sharpe ratio (excess return over standard deviation) to see whether the rank order of the DEA models can be used as a complementary performance measure. Using the 1997–2001 Zurich hedge fund database, Gregoriou *et al.*¹⁶ conclude that DEA can be considered an alternative and robust ranking technique for ranking the performance of hedge funds. By means of simple-efficiency, cross-efficiency and super-efficiency, Diz *et al.*⁵ and Gregoriou *et al.*⁸ also conclude similar findings using CTAs.

EMPIRICAL RESULTS

Table 2 provides the results of the basic-efficiency, cross-efficiency and super-efficiency scores along with the ending assets under management, compound return and Sharpe ratio. Of the 90 CTAs, only nine are efficient using the basic DEA model. Of these efficient CTAs, three are among the largest five, and the remaining efficient CTAs range from the smallest to \$460m in ending assets under management.

A possible explanation is that larger CTAs have better performance and are more efficient at trading than smaller ones. Furthermore, large CTAs tend to take less risk, since they bring in a great deal of management and performance fees, than their smaller counterparts which typically assume more risk to grow. Moreover, a majority of the CTAs that are efficient and super efficient tend to have high Sharpe ratios. Of the nine efficient CTAs, four are diversified, two are currency, two are

financials and one is a stock index.

When investigating the basic DEA efficiency scores vs the Sharpe ratio, the Spearman rank correlation is positive and significant (0.391 at the 1 per cent level, two-tailed test). In terms of the Spearman ranking correlation, it is further found that the efficiency score vs ending assets under management is positive and significant (0.245 at the 1 per cent level, two-tailed test).

On examination of the cross-efficiency scores, it is found that Mangin Capital Mgt attains the highest cross-efficiency score (89.33), closely followed by Sunrise Capital Expanded Diversified (79.72). The basic DEA model is then compared against the cross-efficiency model to determine the consistency between models, and it is observed that the Spearman rank correlation is positive and significant (0.809 at the 1 per cent level, two-tailed test). The cross-efficiency scores are also compared with the Sharpe ratio, and the Spearman rank correlation is also found to be positive and significant (0.393 at the 1 per cent level, two-tailed test). In terms of the Spearman ranking correlation, it is further found that the cross-efficiency scores vs ending assets under management is positive and significant (0.246 at the 1 per cent level, two-tailed test).

In terms of super-efficiency, the efficient CTAs displaying a score of 1.0 using the basic DEA model now have higher efficiency scores than unity, since they can now attain a score greater than unity. The CTA with the greatest super-efficiency score is Campbell and Company (Financial/Metals/En Large) which is also

*Table 2: Basic-efficiency, cross-efficiency and super-efficiency models of CTAs
January 1995–June 2004*

CTA	Classification	Basic efficiency	Cross- efficiency	Super- efficiency	Ending millions under management	Compound return	Sharpe ratio
CAMPBELL & CO (FIN/MET/EN LARGE)	FIN	1.00000	75.55	2.98898	7,009.20	332.97	0.85
FX CONCEPTS (DEVELOPED MARKETS CUR)	CUR	0.37014	21.33	–	3,300.00	218.46	0.56
ASTMAX CO (PRELUDE)	DIV	0.46602	29.09	–	2,086.67	56.76	0.06
SUNRISE CAPITAL (EXPANDED DIVERSIFIED)	CUR	1.00000	79.72	2.73269	1,673.41	255.5	0.69
CRABEL CAPITAL MGT (DIV FUT UNLEV)	DIV	1.00000	43.05	1.78315	1,617.72	110.77	0.70
ROTELLA CAPITAL (STANDARD LEV)	DIV	0.54147	26.22	–	1,528.30	303.27	0.93
GRINHAM MANAGED FUNDS PTY	DIV	0.75460	26.63	–	1,230.00	172.66	0.65
BEACH CAPITAL MGT (DISCRETIONARY)	DIV	0.84894	32.10	–	1,208.03	384.24	0.91
R.G NIEDERHOFFER CAPITAL MGT	DIV	0.06062	4.26	–	985.86	145.16	0.30
MILLBURN RIDGEFIELD (DIVERSIFIED)	DIV	0.12905	7.80	–	690.61	108.63	0.23
FIRST QUADRANT (MANAGED FUTURES)	DIV	0.15880	9.11	–	672.59	38.73	–1.00
DUNN CAPITAL MGT (WMA)	DIV	0.19139	11.57	–	625.94	526.03	0.46
CAMPBELL & CO (GL/DIVERSIFIED LARGE)	DIV	0.29416	20.07	–	562.00	202.98	0.59
WILLOWBRIDGE ASSOCIATES (ARGO)	DIV	0.27142	17.10	–	501.82	305.45	0.34
RABAR MARKET RESEARCH	DIV	0.11333	6.58	–	487.34	97.76	0.17
ECLIPSE CAPITAL (GLOBAL MONETARY)	FIN	0.15589	9.57	–	476.84	172.11	0.45
DUNN CAPITAL MGT (TOPS)	FIN	0.11492	7.21	–	473.63	285.61	0.30
CIPHER INVESTMENT MGT	DIV	1.00000	33.93	1.07176	460.00	436.92	0.79
ALLIED IRISH CAPITAL MGT (FOREX)	CUR	0.89966	53.51	–	424.00	83.11	0.78
ECKHARDT TRADING (STANDARD)	DIV	0.03880	2.61	–	390.01	471.49	0.78

Table 2: (Continued)

CTA	Classification	Basic efficiency	Cross- efficiency	Super- efficiency	Ending millions under management	Compound return	Sharpe ratio
SUNRISE CAPITAL (DIVERSIFIED)	DIV	0.31699	19.46	–	339.46	285.65	0.66
JOHN W HENRY & CO (FIN & METALS)	FIN	0.15520	4.10	–	337.60	205.69	0.33
SUNRISE CAPITAL (CURRENCY)	CUR	0.36950	11.92	–	230.12	136.48	0.32
MORGAN STANLEY MANAGED FUT (GLOBAL)	DIV	0.11203	5.59	–	228.57	74.59	0.09
JOHN W HENRY & CO (INTL FX)	CUR	0.23180	9.02	–	200.06	235.13	0.46
ALLIED IRISH CAPITAL MGT (WORLDWIDE)	FIN	0.25685	10.20	–	194.00	77.86	0.93
SUNRISE CAPITAL (FINANCIALS–CIMCO)	FIN	0.20541	8.74	–	179.24	173.35	0.35
BAREP ASSET MGT (EPSILON EURO)	DIV	1.00000	53.61	1.47249	169.00	113.79	0.38
TRANSTREND (STANDARD RISK USD)	DIV	0.09789	5.19	–	153	207.68	0.87
CORAL ROCK INVESTMENT (WHITE CORAL)	CUR	0.66667	18.86	–	136.5	51.42	0.20
WILLOWBRIDGE ASSOCIATES (PRIMARY)	DIV	0.13667	7.58	–	128.13	357.13	0.38
EMC CAPITAL MGT (CLASSIC)	DIV	0.03125	0.99	–	106.71	85.3	0.09
SANGAMON TRADING	DIV	0.02979	1.04	–	106.6	120.26	0.70
BLENHEIM CAPITAL MGT	DIV	0.04178	1.74	–	105.23	348.27	0.37
NORTHFIELD TRADING (DIVERSIFIED)	DIV	0.08052	2.39	–	95.96	46.94	0.01
HILL-CRABEL FINANCIAL (GDP)	DIV	0.05262	1.85	–	87	108.08	0.44
ANSBACHER INVESTMENT MGT	STX	1.00000	23.40	1.58902	81.5	622.57	0.84
JOHN W HENRY & CO (G-7 CURRENCY)	CUR	0.25090	5.28	–	75.46	115.62	0.21
ER CAPITAL MGT (GLOBAL XL)	DIV	0.10238	3.73	–	73.3	289.8	0.39
QUICKSILVER TRADING (DIVERSIFIED)	DIV	0.83756	22.12	–	71.41	864.75	0.95
WILLOWBRIDGE ASSOCIATES (SIREN)	DIV	0.13106	3.73	–	70.22	93.97	0.16

Table 2: (Continued)

CTA	Classification	Basic efficiency	Cross-efficiency	Super-efficiency	Ending millions under management	Compound return	Sharpe ratio
WILLOWBRIDGE ASSOCIATES (VULCAN)	DIV	0.06994	2.49	–	66.92	218.48	0.23
HATHERSAGE CAPITAL MGT (LONG-TERM)	CUR	0.75083	15.37	–	63.2	292.03	0.96
ABRAHAM TRADING	DIV	0.09037	3.26	–	63.2	294.1	0.42
ECKHARDT TRADING (HIGHER LEVERAGE)	DIV	0.10489	2.80	–	62.68	891.88	0.80
ARA PORTFOLIO MGT (GAMMA)	DIV	0.08333	1.93	–	60.47	84.32	0.15
JOHN W HENRY & CO (ORIGINAL)	DIV	0.11111	2.10	–	58.22	64.99	0.05
COMPUCOM FINANCE	CUR	1.00000	28.86	2.19130	53	99.15	0.16
WILLOWBRIDGE ASSOCIATES (TITAN)	DIV	0.11489	4.23	–	51.56	261.53	0.26
MARK J WALSH & CO (STANDARD)	DIV	0.05505	2.59	–	45.6	520.41	0.47
SAXON INVEST (AGGRESSIVE DIVERSIFIED)	DIV	0.07351	1.34	–	41.7	248.02	0.21
HAWKSBILL CAPITAL (GL DIVERSIFIED)	DIV	0.02025	0.62	–	36.42	202.39	0.18
MILBURN RIDGEFIELD (CURRENCY)	CUR	0.06667	1.02	–	35.62	70.69	0.10
AIS FUTURES MGT (2:4 LEVERAGED)	DIV	0.13445	3.28	–	33.77	152.13	0.29
MISSISSIPPI RIVER INVESTMENTS	DIV	0.18642	4.76	–	31.5	422.76	0.78
JOHN W HENRY & CO (GLOBAL FIN & EN)	FIN	0.22164	7.51	–	31.01	258.41	0.35
RANGE WISE	AG	0.05739	1.13	–	30.28	130.51	0.29
FRIEDBERG COMMODITY MGT (CURRENCY)	CUR	0.07377	0.86	–	29.49	37.68	–1.00
DOLPHIN CAPITAL (GL DIVERSIFIED I)	DIV	0.07053	2.49	–	27.4	315.8	0.42
HANSEN CAPITAL MGT	DIV	0.14531	1.47	–	24.64	106.22	0.28
TACTICAL INVESTMENT (INSTITUTIONAL)	DIV	0.14871	4.3	–	24.14	430.89	0.61
JPD ENTERPRISES (GLOBAL DIVERSIFIED)	DIV	0.07801	1.41	–	22.34	118.11	0.36

Table 2: (Continued)

CTA	Classification	Basic efficiency	Cross- efficiency	Super- efficiency	Ending millions under management	Compound return	Sharpe ratio
WILLOWBRIDGE ASSOCIATES (CURRENCY)	CUR	0.09091	1.20	–	18.49	68.71	0.11
IJU BREAKOUT PROGRAM	FIN	0.28571	2.82	–	14	68.23	0.21
AIS FUTURES MGT (3:6 LEVERAGED)	DIV	0.11922	3.23	–	13.74	233.03	0.27
SPACKENKILL TRADING CO (DIVERSIFIED)	DIV	0.09487	2.31	–	13.60	192.04	0.74
EICKELBERG & ASSOCIATES (PHOENIX)	DIV	0.12652	1.29	–	13.5	199.67	0.62
HATHERSAGE CAPITAL (DAILY GROWTH)	CUR	0.76099	15.89	–	13.00	243.42	0.96
MILLBURN RIDGEFIELD (GLOBAL FINANCIAL)	FIN	0.05556	0.52	–	12.7	68.33	0.09
JOHN W HENRY & CO (GL DIVERSIFIED)	DIV	0.08464	1.29	–	11.41	121.73	0.17
STRATEGIC INVESTMENTS (EQUITY HEDGE)	STX	0.81363	7.03	–	10.5	208.20	0.57
WITTER & LESTER (INTERMEDIATE)	STX	0.20000	0.38	–	10.19	4.90	–1.00
FORT ORANGE CAPITAL (GL STRATEGIC)	DIV	0.04809	1.33	–	8.28	240.80	0.34
RED OAK COMMODITY ADVISERS	DIV	0.12268	3.87	–	7.2	384.35	0.38
ASHLEY CAPITAL MGT	FIN	0.07771	0.89	–	7.05	175.17	0.42
SAXON INVEST (DIVERSIFIED)	DIV	0.09323	1.28	–	5.8	215.37	0.32
DANIEL R MEYER & CO	DIV	0.11802	0.89	–	4.68	311.89	0.51
MANGIN CAPITAL MGT	DIV	1.00000	89.33	2.95785	4.6	5,945.29	0.8
RAM MGT GROUP (CONSERVATIVE MRTP 1X)	DIV	0.17320	0.72	–	4.47	62.88	0.12
ALLIED IRISH CAPITAL MGT (EQUITY INDEX)	STX	0.58106	3.27	–	4	37.63	–1.00
MICHAEL J FRISCHMEYER (ICL FEE)	DIV	0.05683	0.06	–	3.55	0.7	–1.00
DREISS RESEARCH	DIV	0.13970	1.75	–	2.35	208.06	0.29
WITTER & LESTER (REDSTONE)	STX	0.23084	2.39	–	1.83	80.1	0.39

Table 2: (Continued)

CTA	Classification	Basic efficiency	Cross- efficiency	Super- efficiency	Ending millions under management	Compound return	Sharpe ratio
VISIONEERING R & D CO (V-100)	FIN	0.06574	1.03	–	0.95	164.11	0.19
AGTECH TRADING COMPANY	AG	0.38312	4.90	–	0.94	182.96	0.29
WITTER & LESTER (STOCK INDEX)	STX	0.16248	2.90	–	0.75	157.07	0.42
KOTTKE ASSOCIATES (CRUSH)	AG	0.04848	0.30	–	0.5	79.16	0.18
KOTTKE ASSOCIATES (AG SPREAD)	AG	0.06942	0.19	–	0.5	53.61	0.05
STRATEGIC INVESTMENTS (MODIFIED)	FIN	0.98128	3.75	–	0.45	175.84	0.54
INTL TRADING ADVISERS (RATES)	FIN	1.00000	4.86	1.49955	0.39	113.31	0.22

the largest CTA. The remaining CTAs in basic DEA that are not efficient (less than unity) keep the same efficiency score in the super-efficiency model. The Spearman correlation rankings of the super-efficiency model vs the Sharpe ratio are also examined, and it is found to be positive and significant (0.393 at the 1 per cent level, two-tailed test).

Although we find a few weak positive correlations, they in fact are significantly different from zero at the 1 per cent level. If it were attributed to chance, we would expect half the significant correlations to be positive and half to be negative. This validates the precision of the various models used.

CONCLUSION

This paper demonstrates that DEA can be used as an alternative selection tool to assist pension funds, institutional investors, FOF managers and high-net-worth individuals in selecting the CTAs that are the most efficient in trading futures contracts. The author believes that DEA is a valuable addition to other risk-adjusted measures in that it widens the picture of CTA trading efficiency/performance appraisal. As a relative performance efficiency measure, DEA can certainly be used as a validating technique to complement traditional performance analysis as well as monitor the trading efficiency of CTAs. The empirical results support the contention that, even when using non-normal returns in a risk-return framework, DEA can provide reliable and consistent results.

Future research using other DEA models

could examine managed futures classifications as well as measure the efficiency of various CTA indices.

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