

**Benchmarking Commodity Trading Advisor Performance with a
Passive Futures-Based Index**

CISDM Working Paper Series

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Abstract

This article describes a passive index methodology that can be used to construct efficient benchmarks for commodity trading advisors (CTAs). The index is designed to mimic the performance of CTAs who employ trendfollowing or counter-trend strategies. CTAs trade in a number of derivatives markets including commodity, currency, interest rate, and equity derivatives markets. Trendfollowers employ momentum strategies that are designed to capture longer-term trends in asset prices. The passive index uses a momentum trading strategy that takes hypothetical long and short positions in a number of commodity, currency, and fixed income futures contracts. The index can be tailored to CTAs who trade in particular markets or employ counter-trend or other systematic strategies. Results indicate that the tracking error between a CTA portfolio and the passive benchmark is comparable to the tracking error between a typical equity mutual fund and the S&P500 index.

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Commodity Trading Advisors (CTAs) employ a variety of strategies in a wide number of global futures, options, and OTC derivatives contracts. It has been difficult to design a passive benchmark for CTA performance that can be used in the same fashion as benchmarks in the equity or fixed-income markets. Passive benchmarks such as the S&P 500 Index or the Lehman Bond index can be used to benchmark mutual fund performance because mutual fund managers are restricted to holding only long positions and cannot employ leverage. CTAs are frequently short in various markets and can also dynamically change their leverage levels, so an index of futures prices will not provide accurate forecasts of CTA performance. The index described in this article employs a momentum-based investment strategy across a wide number of futures contracts. The strategy also employs dynamic leveraging and can be customized to track the performance of managers who focus on particular markets. The resulting indexes track many CTAs about as well as the S&P 500 index tracks equity mutual funds, and can be used by investors for manager selection, performance attribution, and asset allocation decisions.

1. Previous Research on Passive Futures-Based Benchmarks for Evaluating CTA Performance

There are several passive performance indexes derived from commodity futures prices. Most of these indexes fall into the buy-and-hold category. Indexes such as the Goldman Sachs Commodity Index, the Dow Jones Futures Index, and the Commodity Research Bureau Index, are useful as investment vehicles or as benchmarks for long-only commodity investments, but not as benchmarks for strategies that hold short positions or trade financial futures contracts (Schneeweis and Spurgin [1997]).

There are at least four other indexes that have been created to track the performance of dynamic strategies. The Mount Lucas Management Index (MLM) was created in 1989 and tracks the performance of a 12-month moving-average trading rule across twenty-five actively traded commodity and financial futures contracts. This index was designed as an investment vehicle rather than a CTA benchmark, and while it does explain some portion of CTA returns, the tracking error between the MLM index and CTAs is quite large (Schneeweis and Spurgin [1997]). Lequeux and Acar [1998] proposed another passive index. This index is designed to benchmark momentum strategies in currency markets. Only a few CTAs trade currency markets exclusively, so this index is not useful as a benchmark for most CTAs. Barclay

Futures Index (Waxman [2000]) is similar to the MLM index in that it trades twenty-five financial and commodity futures contracts. Like the MLM, it was designed primarily as an investment vehicle rather than a benchmark. The main difference is a shorter moving average trading rule -- three months for Barclay versus twelve for the MLM. Waxman [2000] reports the Barclay index has higher correlation with active CTA programs. The holding period of a typical CTA position is much shorter than one year. The fourth index, proposed by Spurgin [1999], employs three different trading rules in across six futures contracts. This index was designed to track the performance of active CTA programs, but has several limiting features. The index methodology proposed in this article uses the same trading rule as Spurgin [1999], but extends the methodology in several ways.

Several academic researchers have employed trendfollowing futures variables as explanatory variables for CTA performance rather than for use as benchmarks. Fung and Hsieh [1996, 1997, 2000] employ various trendfollowing variables including the absolute value of the change in the futures contract (Fung and Hsieh [1996, 1997]) and a trading rule based on the delta of a lookback straddle (Fung and Hsieh [2000]). The delta of a lookback straddle follows a path very similar to many momentum strategies. Schneeweis and Spurgin [1998] show that the absolute value of futures returns has explanatory power in multi-variate regressions of CTA returns.

2. Methodology: Index Construction and Optimization

The CTA benchmark index is constructed as a two-stage process. First, a series of market indexes are created from underlying futures contracts in each of the principal market segments traded by CTAs. The market indexes are based on the trading rule and rebalancing strategy outlined in Spurgin [1999]. The second stage involves finding the linear combination of market indexes that best explains the performance of a particular CTA style or specific manager. Multiplying the optimal weights for the CTA or CTA style by the market index returns yields a proxy for the CTA returns.

2.1. Asset Selection:

Trendfollowing market indexes are constructed for four futures market segments: Currencies, interest rates, physical commodities, and stock indexes.

Currency Index (3 contracts): Euro (CME), Japanese Yen (CME), and British Pounds (CME).

Interest Index (3 contracts): Treasury Bonds (CBOT), Eurodollar Rates (CME), and German Government Bonds (EUREX).

Physical Commodity Index (5 contracts): Crude Oil (NYMEX), Natural Gas (NYMEX), Gold (COMEX), Copper (COMEX), and Corn (CBOT).

Equity Index (3 contracts): S&P 500 (CME), FTSE 100 (LIFFE), and NIKKEI 225 (OSX).

Market indexes uses historic volatility to determine allocation to each futures market. The strategy allocates equal dollar risk to each market in the index. Index weights are revised daily. Formulas for estimating volatility and for computing the notional investment in each futures contract are given in the Appendix. In each market, the index holds positions in the two nearest-to-maturity contracts. The allocations to the two contracts are changed daily to maintain a constant weighed average time-to-maturity in each market.

2.2. Trading Strategy

Long and short positions in each market are determined by a momentum the trading rule. An x -day momentum strategy takes a long position in a futures market on date t if the total return to the contract between dates t and $t-x$ is positive. Otherwise the strategy takes a short position. Three separate momentum strategies are traded in each market. The numbers of days used to compute the momentum trading rules are 15, 27, and 55.¹ Each strategy has an equal weight, so the index will either be 100% long, 33% long, 33% short, or 100% short in a given contract, depending on the signals of the three strategies.

2.3. Computing Market Index Returns

Market index returns are calculated daily using the returns to the futures contracts in the index and the weights in each contract. Returns to market indexes are not directly comparable to observed CTA returns. As is the norm for passive investment indexes, no fees, transaction costs, bid-ask spreads, or other market imperfections are assumed. Many passive indexes (e.g., GSCI, MLM) include a collateral return on invested capital because futures contracts require no direct investment. Passive market indexes do not incorporate a collateral return.

2.4. Construction of Passive Indexes to Benchmark a Particular CTA or CTA Style

The principal difference between this benchmark methodology and existing passive CTA benchmarks is in the optimization procedure. The methodology involves finding the linear combination

of the four market indexes that most closely matches a particular CTA or CTA style. The style benchmark coefficients are estimated using L1 regressions² of monthly returns on the CTA returns. The regression model is

$$r_{CTA} = \mathbf{a} + \mathbf{b}_{CURR}r_{CURR} + \mathbf{b}_{INTRAT}r_{INTRAT} + \mathbf{b}_{PHYS}r_{PHYS} + \mathbf{b}_{STOCK}r_{STOCK} + \mathbf{e} \quad (1)$$

This full model is estimated, and then re-estimated with market index coefficients that are statistically significant at the 10% level.

2.5. Out-of-Sample Index Construction

Many exiting passive futures indexes performed much better in-sample (*pro forma*) than out-of-sample. For example, the MLM index, which was created in 1989, reported in-sample excess returns (return less the risk-free rate) of about 7% per year in the ten years prior to 1989. In the subsequent ten years, annual excess returns were 3.4%. Net of fees and transactions costs associated with replicating this index, excess returns to investors have averaged less than 2% per year. Similarly, the Goldman Sachs Commodity Index, which was launched in 1991, reported in-sample excess returns of about 5% per year in the ten years prior to launch. Excess returns from the 1991 launch until June, 2000 are zero (negative if transactions costs are considered).

The historical returns to the passive CTA style benchmarks are reported on an out-of-sample basis in order to minimize the possible effects of over-fitting the model. Weights for style benchmarks are re-estimated for each year using data from the previous five years. For example, weights applicable in 1993 were estimated with market index returns from January 1988 through December 1992. Predicted returns for the CTA in 1993 are generated by multiplying the '88-'92 weights by the market index returns in 1993. Forecasts are adjusted for the mean in-sample tracking error. For example, if the average deviation between the CTA and the passive benchmark during the '88-'92 estimation period is -0.5% per month, then forecasts for '93 would be reduced by -0.5% per month.³ This process is repeated each year to generate a series of out-of-sample predicted values for the CTA. Performance of the benchmark using this historical return series is more likely to be representative of future benchmark performance than if the entire data series were used to estimate coefficients. Annual re-estimation of the model has other benefits, as changes in regression coefficients may indicate changes in a trading style.

3. Data

The methodology for passive style benchmark construction can be applied to individual CTAs as well as benchmarks constructed from CTA performance such as those compiled by Managed Account Reports (MAR), Barclay Trading Group, or TASS management. The CTA data analyzed in this report are monthly composite indexes for several CTA strategies. Included in the analysis are two broad-based CTA indexes and several style composites (Currency, Discretionary, Diversified, Financial, Systematic, and Trendfollowing).⁴ A short description of each strategy is given in the Appendix. MAR returns are net of all management fees and expenses.

Market momentum indexes were constructed from January 1988 to December 2000 using futures prices from Datastream. Market indexes are computed daily, so the methodology can be used to estimate coefficients from daily CTA data. Most CTAs currently distribute returns to investors on a daily basis. Estimating the style benchmarks from daily returns should offer considerably more precision than the monthly returns used in this report.

4. Results and Discussion

In this section, style benchmarks are shown to explain a considerable portion of out-of-sample CTA returns, suggesting that the passive style methodology is a useful tool for benchmarking and analyzing some active CTA programs. Momentum-based CTA styles had the highest correlation with passive style benchmarks, while strategies that are based on fundamental or economic analysis had the lowest correlation. Results also indicate that CTA trading styles are relatively stable through time.

4.1. Performance Characteristics of Market Momentum Indexes

Exhibit 1 provides descriptive statistics of the market momentum indexes used to construct the style benchmarks and the MAR CTA Indexes. Also included in Exhibit 1 is a monthly average of the four momentum indexes. Correlations are reported for the momentum and CTA indexes as well as with three other indexes, the MLM index, the GSCI, and the S&P 500. Physical commodities and interest rates generated the bulk of momentum index returns. Total return to the stock index strategy was about zero. Exhibit 1 reports that correlations among the market indexes are low, so allocating across these strategies offers diversification benefits. While the momentum indexes have fairly low returns on notional capital, low correlation between momentum strategies allows CTAs to employ leverage without

experiencing a proportionate increase in volatility. This is evident from the performance of the momentum index average, which has a standard deviation about half the average standard deviation of the momentum indexes.

Insert Exhibit 1 about here

Correlation between the market momentum indexes and the MAR Indexes are generally in the .20 to .50 range. Exceptions are the Discretionary index, which has low correlation with all market indexes, and the Currency index, which has correlation of 0.73 with the currency market index and no correlation with the others. Although for most styles no single momentum index explains more than 25% of a MAR Index return, a simple average of the indexes generates correlations in the 0.60-0.70 range. Finding the optimal mix of momentum indexes will be shown to offer additional explanatory power. Fixed benchmark strategies such as the MLM Index (Exhibit 1) have relatively low correlation with CTA Indexes. The highest correlation between the MLM and an active CTA index is 0.26 (MAR Diversified). The SP500 and Goldman Sachs Commodity Index have low correlations with both momentum indexes and active CTA Indexes. The source of return to momentum strategies appears unrelated to the buy-and-hold strategies in either equity or commodity markets.

4.2. Performance of Style Benchmarks

Exhibits 2 and 3 report the regression coefficients as well as a comparison of in-sample and out-of-sample performance for each of the MAR Indexes studied. Exhibit 2 shows summary results for each MAR Index, and Exhibit 3 details the performance of each style benchmark in each year studied. The first two columns in Exhibit 3 are the estimation period and sample period. The weights used to construct the passive index for each year are in columns (3-6). Statistically insignificant coefficients (10% confidence level) are left blank. Insufficient data is marked "NA". Column (7) contains the in-sample regression R-squares. The implied leverage of the CTA style, which is the sum of the estimated coefficients, is column (8). Remaining columns focus on the performance of out-of-sample forecasts as a benchmark for the CTA style. Columns (9-10) report the results of OLS regression with the 12 forecasted returns as independent variables, and the observed CTA returns the dependent variable. Beta (9) and R-square (10) are reported. Significance of the slope at the 95% and 99.5% level are indicated. The difference between the average CTA return and the passive index return is reported in columns (11-

12). Column (11) is the difference between the means in the five-year estimation period, and (12) is the difference between the means in the twelve-month sample period. A measure of benchmark performance, the mean absolute deviation (MAD), is reported in columns (13-14). Exhibit 2 summarizes the performance of each passive style benchmark over the full sample period. The in-sample columns in Panel I are the average of the annual in-sample results from Exhibit 3. Out-of-sample results (sample beta and r-square, mean deviation, and MAD) are calculated over the full sample period (three years for Systematic, five years for Currency, seven years for remaining MAR Indexes).

4.3. Performance of Passive Indexes as Benchmarks for Active CTA Programs

Passive style benchmarks generally performed well enough to be useful tools for analyzing and benchmarking active CTAs. Benchmark accuracy is generally measured by mean absolute deviation (MAD), which is the average absolute tracking error between the program and the benchmark. In order to be useful as a benchmark, an index must have *ex ante* tracking error low enough for investors to have confidence that the benchmark contains useful information about the performance of the active program.

For the style benchmarks, the degree of success varies with the individual styles. This is expected because the style benchmarks are based on a trendfollowing strategy, while many of the advisors in the MAR indexes employ different active strategies. The most obvious example is the discretionary style. Regressing MAR Discretionary returns (Exhibit 2 and Exhibit 3D) on the momentum indexes provided consistently low R-square values (0.17 on average) and a high proportion of insignificant coefficients. Out-of-sample R-square (0.04 on average) suggests the model's forecasts have little value in benchmarking this style.

Insert Exhibit 2 about here

Exhibit 2 suggests that there are considerable differences in the performance different MAR indexes, and that indexes performance is consistent with the strategy descriptions. Currency CTAs demonstrate no exposure to physical commodity or stock index. The passive currency and interest rate strategies explain 62% of out-of-sample MAR Currency returns. Financial CTAs are heavily weighted towards interest rate and currency momentum indexes, with a small exposure to physical commodities (many financial CTAs trade precious metals). Broad-based categories (Dollar Wt, Equal Wt, Diversified,

Systematic, and Trendfollowing) have statistically significant exposure to all four market indexes. Discretionary CTAs follow other strategies besides momentum-based strategies.

All strategies report lower R-square coefficients in the sample period than in the estimation period. However, even with this drop in out-of-sample explanatory power, the style benchmark r-squares for most of the strategies are above 0.50. Four are higher than 0.60, which imply correlation coefficients above 0.75. Furthermore, the mean absolute tracking errors for the out-of-sample forecasts is lower than the in-sample tracking error for all but one of the strategies. This is surprising, as lower out-of-sample r-squares would be expected to cause higher tracking error.

Mean absolute tracking errors during the sample period were mostly in a range of 1.5-2% per month. This level of tracking error is about the same as the tracking error between stock mutual funds and equity benchmarks. For example, the ICD database contains 213 Long-Term Growth equity mutual funds with continuous returns spanning our sample period of 1993-2000. The mean absolute deviation of these funds with the SP500 Index averages 1.9%. This is larger than the tracking error of all but one of the passive style benchmarks in absolute terms, and about the same after adjusting for the higher standard deviation of equity mutual funds.

Exhibit 2 also indicates one of the weaknesses of the methodology. For many of the strategies, the in-sample return of the style benchmark is higher than the out-of-sample return. For example, the average in-sample return for the Trendfollowing strategy was higher than the MAR Trendfollowing return by 0.9% per month. This meant that trendfollowing index forecasts for the following year were adjusted lower by 0.9% per month, on average. While the MAR Trendfollowing index did underperform as predicted, the level was only about half the predicted amount, so the MAR trendfollowing index ended up returning 0.44% more per month than the style benchmark. While the passive style benchmarks explain a considerable portion of the variation in CTA returns, the model is less successful in tracking the level of CTA returns.

4.4. Return Attribution and Style Drift Analysis for CTA Indexes

Exhibit 3 provides a detailed analysis of the performance of the eight style benchmarks during the sample period. This analysis provides information about the effectiveness of the style benchmarking methodology as well as the information about changes in the trading style and strategy of CTAs. For the broad-based CTA indexes, out-of-sample performance appears correlated with CTA returns. The lowest

r-squares are in 1994 and 1999 -- when aggregate CTA returns were near zero and return volatility among the lowest in the sample period (see Exhibit 4). Style benchmarks appear to be more effective when there is considerable variation in CTA returns.

Insert Exhibit 3 about here

Changes in regression weights provide evidence of style shift for CTAs during the sample period. Most CTA indexes show declining exposure to physical commodities and increased exposure to equities. For example the EqualWt and Diversified indexes had no exposure to the stock index market index in 1993 and exposure to physical commodities of similar order to the interest rate momentum index. By 1999, commodity and equity market index exposures were about the same.

The sum of the regression coefficients, which are a proxy for leverage, remained relatively stable for most of the strategies. While this measure is correlated with r-square (more in-sample explanatory power will tend to increase coefficients and leverage estimates) there does not seem to be much variation in leverage. So while there has been a measurable shift in the markets CTAs trade, total risk allocation has remained stable.⁵

Insert Exhibit 4 about here

Exhibit 4 shows the predicted and actual CTA and style benchmark returns and standard deviations for each year. The difference between predicted and actual return and the ratio of the standard deviations is also reported. The standard deviation columns indicate that for the broad-based indexes as well as several of the MAR style indexes, the forecast volatility is less than realized volatility. For example, the observed volatility for the MAR financial index is higher than model volatility in all seven of years studied. However, volatility forecasts for the Trendfollowing index are more consistent with observation. The MAR Indexes whose trading strategy is best captured by the model have predicted volatility which is closer to observed. This suggests the model is underspecified, and that other explanatory factors can improve the benchmark performance.

MAR Index returns (Exhibit 4) consistently outperformed the predicted returns, particularly the Trendfollowing, Diversified, and EqualWt CTA Indexes. As noted earlier, the benchmarking

methodology appears to overestimate in-sample returns for the style benchmarks, which leads to underestimation of out-of-sample returns.

5. Conclusion and Suggestions for Further Research

Passive style benchmarks are shown to explain a considerable portion of observed CTA returns, with tracking errors of similar magnitude to equity benchmarks. These style benchmarks have a number of practical uses, including assisting in manager selection, monitoring, and multi-manager portfolio construction. Diversification can be improved by insuring a portfolio is diversified across factors rather simply across a number of managers. Incentive compensation could be tied to performance relative to the benchmark rather than absolute return, as is common in traditional investments. This methodology can be extended to other investment strategies. Many relative value strategies employed by hedge funds, such as currency convergence or convertible bond arbitrage, can be approximated with passive trading rules.

Benchmarks can provide information about the expected distribution of CTA returns. Style benchmarks have no skill. Historical returns of style benchmarks may be a better proxy for the excess returns of a particular strategy than the actual returns, just as historical returns to passive stock and bond indexes are more likely to be used as proxies for expected returns to these asset classes than the historical performance of mutual funds.

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Appendices

Historic Volatility Estimator

The method of estimating historic volatility incorporates the average of the trading range (Parkinson, 1980). A period of 200 trading days is used to estimate volatility from observed trading ranges l . The equation for the volatility of an individual commodity is

$$\hat{s}^2 = \frac{(\sum l_i / N)^2}{(8/p)}, \quad (2)$$

Computing Asset Allocations

In order to insure equal risk in each commodity, the percentage allocation (x_i) to each of the n commodities must satisfy two constraints. The solution to this system of equations gives the notional amount of each underlying futures contract.

$$\text{Constraints: } x_i \mathbf{s}_i = C, \quad \sum_{i=1}^n x_i = 1 \quad \text{Optimal Weights: } x_i = \frac{1}{n} \frac{1}{\mathbf{s}_i} \quad (3)$$

Description of Managed Accounts Reports Active CTA Index Strategies

Dollar Weight	All qualified ¹ CTAs, weighted by assets under management
Equal Weight	All qualified CTAs, equally weighted
Currency ²	Specialize in currency trading
Discretionary	Use fundamental/economic analysis to make trading decisions
Diversified	Limit risk by holding a large number of positions
Financial	Currency, interest rate, stock index, and precious metals
Stock Index ³	Specialize in stock index futures and options
Systematic ⁴	Use systematic, but not purely trendfollowing strategies
Trendfollow	Focus only on trendfollowing strategies

¹Satisfy minimum requirements for length of track record and assets under management

²Excluded because of insufficient data history

³Lacks full data history, began 1990

⁴Lacks full data history, began 1992

Exhibit 1. Descriptive Statistics for Momentum Indexes and MAR Indexes, 1993-2000

	Performance Measures				Correlation with Market Momentum Indexes					Correlation with Asset Benchmarks		
	Ann. Return	Ann. StDev	Min Month	Max Month	Curr	IntRate	Phys	Stock	Avg.	SP500 Index	MLM Index	GSCI Index
<i>Market Momentum Indexes</i>												
Currency	1.2	5.0	-2.6	5.0	1.00	-.09	-.01	-.16	.21	-.06	-.13	.04
InterestRate	4.3	5.1	-2.6	5.6	-.09	1.00	-.19	.23	.38	.04	-.02	.05
Physical	6.9	7.2	-5.6	6.3	-.01	-.19	1.00	.27	.60	-.24	.39	-.14
Stock Index	0.5	8.9	-6.4	12.7	-.16	.23	.27	1.00	.79	-.07	.25	-.07
Index Avg	3.2	3.6	-1.9	5.6	.21	.38	.60	.79	1.00	-.18	.30	-.09
<i>MAR CTA Indexes</i>												
Dollar Wt	10.0	8.8	-4.8	8.2	.49	.44	.22	.24	.59	.00	.13	.13
Equal Wt	9.1	8.3	-4.5	7.2	.52	.43	.26	.32	.67	-.05	.18	.12
Currency	4.4	9.3	-6.7	10.5	.73	-.02	.00	-.14	.16	.05	-.01	.04
Discretionary	11.7	6.4	-3.5	6.9	.16	.22	.14	.06	.24	.17	.09	.16
Diversified	11.4	11.3	-6.1	10.8	.32	.45	.36	.39	.70	-.09	.26	.11
Financial	11.7	11.4	-5.1	9.9	.52	.54	.10	.21	.55	-.01	-.04	.16
Systematic	8.6	10.4	-5.4	9.6	.45	.40	.33	.27	.63	-.05	.21	.09
Trendfollow	9.8	13.7	-6.8	11.9	.50	.48	.23	.30	.65	-.06	.14	.12

Exhibit 2: Composite Performance of Style Benchmarks

MAR Index	Average Annual Sub-Index Weights (%)				Panel Averages		Sample Period		Mean Deviation		Mean Absolute	
	IntRate	Curr	Phys	Stock	Rsq	Leverg.	Beta	Rsq	Estim.	Sample	Estim.	Sample
Dollar Weight	99.6	100.6	48.5	1.6	.68	2.5	.89	.54	-.05	.14	1.41	1.41
Equal Weight	82.5	104.4	42.0	11.6	.71	2.4	.86	.60	-.23	.37	1.29	1.26
Currency	60.3	146.8	-	-	.64	1.6	.69	.62	.23	.23	1.65	1.15
Discretionary	36.8	30.4	24.2	-	.17	.9	.33	.04	.83	-.13	1.69	1.46
Diversified	107.3	93.0	60.8	13.4	.60	2.7	.85	.50	-.43	.60	1.86	1.90
Financial	142.2	120.6	45.6	-	.66	3.1	1.06	.62	-.18	.30	1.75	1.60
Systematic	128.8	109.3	68.9	13.8	.61	3.2	.58	.58	-.50	.14	1.64	1.42
Trendfollow	154.3	167.5	77.7	19.2	.72	4.2	.82	.62	-.90	.44	2.07	2.03

Exhibit 3. Passive Style Benchmarks for MAR CTA Indexes

Panel A: MAR Dollar Weight Index

Estimation and Sample		Sub-Index Weights (%)				Estimation Statistics		Sample Period		Mean Deviation		Mean Absolute	
Estim.	Sample	IntRate	Curr	Phys	Stock	Rsq	Leverg.	Beta	Rsq	Estim.	Sample	Estim.	Sample
88-92	93	57.2	98.7	63.7	-	.80	2.2	.63	.38	.01	.43	1.54	1.85
89-93	94	98.7	91.3	51.5	-	.75	2.4	.82	.32	-.01	-.55	1.44	1.63
90-94	95	105.2	90.9	51.7	-	.70	2.5	1.26	.69	-.09	.05	1.47	1.32
91-95	96	106.1	86.8	41.0	-	.70	2.3	1.29	.73	-.11	.48	1.45	1.60
92-96	97	124.3	109.1	55.1	-	.62	2.9	1.01	.81	-.23	-.31	1.48	.91
93-97	98	114.3	119.2	40.0	-	.60	2.7	.70	.72	.00	.16	1.32	1.01
94-98	99	91.5	108.4	42.8	-	.63	2.4	.53	.21	.05	.31	1.21	1.47
95-99	NA	99.6	100.2	42.6	12.9	.67	2.6	NA	NA	NA	NA	NA	NA

Panel B: MAR Equal Weight Index

Estimation and Sample		Sub-Index Weights (%)				Estimation Statistics		Sample Period		Mean Deviation		Mean Absolute	
Estim.	Sample	IntRate	Curr	Phys	Stock	Rsq	Leverg.	Beta	Rsq	Estim.	Sample	Estim.	Sample
88-92	93	70.8	118.9	50.0	-	.70	2.4	.76	.69	-.42	-.09	1.88	1.03
89-93	94	68.0	122.7	42.1	-	.76	2.3	.59	.32	-.40	-.04	1.37	1.46
90-94	95	71.1	106.1	56.3	-	.73	2.3	.90	.65	-.35	.15	1.29	1.24
91-95	96	79.4	91.8	35.0	-	.73	2.1	1.37	.73	-.31	.36	1.20	1.43
92-96	97	82.0	87.3	35.0	22.0	.62	2.3	1.57	.90	-.13	.18	1.20	.98
93-97	98	99.0	100.0	54.2	33.6	.67	2.9	.64	.69	-.13	.10	1.05	1.49
94-98	99	95.1	101.4	33.3	16.9	.70	2.5	1.08	.53	.11	.30	1.01	1.14
95-99	NA	94.4	107.1	30.2	20.5	.73	2.5	NA	NA	NA	NA	NA	NA

Panel C: MAR Currency Index

Estimation and Sample		Sub-Index Weights (%)				Estimation Statistics		Sample Period		Mean Deviation		Mean Absolute	
Estim.	Sample	IntRate	Curr	Phys	Stock	Rsq	Leverg.	Beta	Rsq	Estim.	Sample	Estim.	Sample
88-92	93	NA	NA	NA	NA	NA	NA	NA	NA	NA	-.12	NA	NA
89-93	94	NA	NA	NA	NA	NA	NA	NA	NA	NA	-1.15	NA	NA
90-94	95	-	187.2	-	-	.74	1.9	.68	.62	.42	1.21	2.09	1.91
91-95	96	60.3	178.7	-	-	.73	2.4	.70	.79	-.03	.33	1.93	1.02
92-96	97	-	166.1	-	-	.65	1.7	.73	.64	.31	.11	1.70	.88
93-97	98	-	124.5	-	-	.54	1.2	.86	.63	.18	.37	1.41	1.05
94-98	99	-	122.9	-	-	.61	1.2	.37	.35	.29	.31	1.10	.85
95-99	NA	-	101.0	-	-	.59	1.0	NA	NA	NA	NA	NA	NA

Exhibit 3. (cont.)

Panel D: MAR Discretionary Index

Estimation and Sample		Sub-Index Weights (%)				Estimation Statistics		Sample Period		Mean Deviation		Mean Absolute	
Estim.	Sample	IntRate	Curr	Phys	Stock	Rsq	Leverg.	Beta	Rsq	Estim.	Sample	Estim.	Sample
88-92	93	-	34.6	38.2	-	.26	.7	-.01	.00	1.33	1.89	2.17	2.24
89-93	94	56.5	-	-	-	.13	.6	-1.23	.24	1.49	-.34	2.17	2.17
90-94	95	-	45.1	52.3	-	.17	1.0	.61	.20	.79	.82	1.85	1.18
91-95	96	46.5	45.0	32.6	-	.24	1.2	.90	.38	.60	.70	1.60	1.00
92-96	97	54.0	-	24.1	-	.15	.8	1.32	.35	.75	.22	1.56	1.21
93-97	98	53.3	41.7	24.4	-	.15	1.2	.34	.11	.52	.33	1.35	.98
94-98	99	41.2	38.8	22.1	-	.14	1.0	.27	.01	.30	1.23	1.12	1.36
95-99	NA	43.1	38.2	-	-	.09	.8	NA	NA	NA	NA	NA	NA

Panel E: MAR Diversified Index

Estimation and Sample		Sub-Index Weights (%)				Estimation Statistics		Sample Period		Mean Deviation		Mean Absolute	
Estim.	Sample	IntRate	Curr	Phys	Stock	Rsq	Leverg.	Beta	Rsq	Estim.	Sample	Estim.	Sample
88-92	93	58.2	121.4	80.6	-	.73	2.6	.61	.53	-.76	.38	1.99	1.93
89-93	94	52.7	120.0	43.5	-	.66	2.2	.93	.19	-.36	.22	1.87	2.53
90-94	95	82.2	108.5	55.2	-	.57	2.5	1.23	.43	-.36	.24	1.94	2.48
91-95	96	106.4	84.8	44.2	-	.53	2.4	1.44	.62	-.34	.31	2.05	2.10
92-96	97	143.6	70.5	80.9	30.9	.51	3.3	1.12	.78	-.59	-.78	1.93	1.01
93-97	98	160.5	73.8	93.6	25.0	.55	3.5	.70	.83	-.50	-.03	1.61	1.70
94-98	99	133.9	77.0	49.4	21.1	.59	2.8	.87	.44	-.10	.73	1.62	1.41
95-99	NA	120.7	88.3	39.3	30.6	.65	2.8	NA	NA	NA	NA	NA	NA

Panel F: MAR Financial Index

Estimation and Sample		Sub-Index Weights (%)				Estimation Statistics		Sample Period		Mean Deviation		Mean Absolute	
Estim.	Sample	IntRate	Curr	Phys	Stock	Rsq	Leverg.	Beta	Rsq	Estim.	Sample	Estim.	Sample
88-92	93	112.5	84.4	39.5	-	.63	2.4	1.14	.69	-.01	.71	1.94	1.38
89-93	94	126.2	90.7	43.5	-	.66	2.6	.70	.41	-.04	-.87	1.92	1.49
90-94	95	137.5	96.2	46.9	-	.67	2.8	1.08	.65	-.31	-.09	1.91	1.27
91-95	96	148.6	114.6	40.3	-	.69	3.0	1.31	.73	-.43	.86	1.84	2.20
92-96	97	140.9	133.4	50.2	-	.59	3.2	1.27	.83	-.34	.02	1.85	1.25
93-97	98	144.5	146.2	45.7	-	.67	3.4	1.04	.78	.02	.02	1.43	1.23
94-98	99	156.1	150.7	50.6	-	.70	3.6	.39	.12	-.14	.06	1.38	2.20
95-99	NA	171.0	148.8	47.8	-	.68	3.7	NA	NA	NA	NA	NA	NA

Exhibit 3. (cont.)

Panel G: MAR Systematic Index

Estimation and Sample		Estimation					Sample Period		Deviation		Mean	
Estim.		IntRate	Curr	Stock	Rsq	Beta	Rsq	Sample	Estim.			
88-92	93	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
89-93	94		NA	NA	NA	NA	NA	NA	NA	NA	NA	
	95	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
91-95		NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
92-96	97		123.3	86.9	.62	3.8	0.83		-.79		1.88 .83	
	98	131.7		76.9	29.3			0.48	-.48	-.12	1.97	
94-98		121.2	110.5	-	.58			0.53	0.27	-.01	1.57	
95-99	NA		98.4	53.6	.60	2.7			NA	NA	NA	

Panel H: MAR Trend Following Index

Estimation and Sample		Estimation Statistics					Period		Deviation		Mean	
Estim.		IntRate	Curr	Stock	Rsq	Beta	Rsq	Sample	Estim.			
88-92	93		179.3	115.9	.80	4.2	.59		-1.30		2.27 2.40	
	94	137.3		93.2	-		.75		-1.13	-1.18	2.04	
90-94		136.6	177.2	12.4	.73		1.05	.66		-.07	2.16	
91-95	96		162.7	81.7	.72	4.1		.73	-1.02		2.25 1.95	
	97	164.2		69.6	35.9		1.15		-.82	-.47	.77	
93-97		190.8	156.2		51.0	.67		.63	.68	-.67	1.69	
94-98	99		167.4	49.4	.72	3.9		.37	-.33		1.59 2.04	
	NA	161.3		46.0	28.4			NA	NA	NA	NA	

Exhibit 4. Annual Observed and Predicted Returns and Standard Deviation for CTA Indexes

		Annual Returns							Standard Deviation						
		1993	1994	1995	1996	1997	1998	1999	1993	1994	1995	1996	1997	1998	1999
Dollar Wt	MAR	18.6	-0.4	14.7	14.3	10.0	9.3	3.9	8.8	8.5	10.5	11.4	8.6	7.8	6.1
	Predicted	13.5	6.0	12.7	6.8	10.9	7.4	0.9	8.5	5.8	6.8	7.5	7.7	9.5	5.3
	<i>Difference/Ratio</i>	<i>5.1</i>	<i>-6.3</i>	<i>1.9</i>	<i>7.5</i>	<i>-0.9</i>	<i>1.9</i>	<i>3.0</i>	<i>1.0</i>	<i>1.5</i>	<i>1.5</i>	<i>1.5</i>	<i>1.1</i>	<i>0.8</i>	<i>1.1</i>
Equal Wt	MAR	11.5	2.9	12.1	12.3	12.9	10.5	1.5	7.9	6.4	7.8	10.7	9.0	9.5	7.6
	Predicted	7.5	-1.4	6.0	4.0	8.8	8.1	-0.7	8.7	6.2	7.0	6.6	5.4	12.7	5.1
	<i>Difference/Ratio</i>	<i>4.0</i>	<i>4.3</i>	<i>6.0</i>	<i>8.4</i>	<i>4.0</i>	<i>2.5</i>	<i>2.2</i>	<i>0.9</i>	<i>1.0</i>	<i>1.1</i>	<i>1.6</i>	<i>1.7</i>	<i>0.8</i>	<i>1.5</i>
Currency	MAR			16.7	10.5	9.8	4.7	2.9			12.4	6.9	5.6	7.2	2.7
	Predicted			7.4	6.3	12.3	2.3	2.7			14.4	8.7	6.2	6.7	4.4
	<i>Difference/Ratio</i>			<i>9.3</i>	<i>4.2</i>	<i>-2.5</i>	<i>2.4</i>	<i>0.2</i>			<i>0.9</i>	<i>0.8</i>	<i>0.9</i>	<i>1.1</i>	<i>0.6</i>
Discretion	MAR	28.6	-0.9	11.7	14.3	6.2	7.2	15.0	8.3	6.0	5.5	5.9	5.9	4.5	6.0
	Predicted	21.5	21.2	11.2	13.0	12.5	9.5	3.9	4.4	2.4	4.0	4.0	2.6	4.4	2.3
	<i>Difference/Ratio</i>	<i>7.1</i>	<i>-22.1</i>	<i>0.4</i>	<i>1.3</i>	<i>-6.3</i>	<i>-2.3</i>	<i>11.1</i>	<i>1.9</i>	<i>2.5</i>	<i>1.4</i>	<i>1.5</i>	<i>2.2</i>	<i>1.0</i>	<i>2.6</i>
Diversified	MAR	20.5	5.8	14.9	12.9	7.3	11.8	6.6	9.1	12.2	13.7	13.8	9.9	13.3	7.9
	Predicted	6.8	-1.7	7.1	4.5	9.4	6.7	-3.1	10.6	5.7	7.2	7.5	7.8	17.5	6.0
	<i>Difference/Ratio</i>	<i>13.8</i>	<i>7.5</i>	<i>7.8</i>	<i>8.4</i>	<i>-2.1</i>	<i>5.1</i>	<i>9.7</i>	<i>0.9</i>	<i>2.1</i>	<i>1.9</i>	<i>1.8</i>	<i>1.3</i>	<i>0.8</i>	<i>1.3</i>
Financial	MAR	22.7	-3.1	16.6	20.1	14.9	10.1	0.9	9.7	7.4	11.2	15.5	12.6	13.9	8.0
	Predicted	13.8	6.9	13.6	3.9	10.2	9.8	-1.2	7.0	6.8	8.3	9.9	9.0	11.9	7.2
	<i>Difference/Ratio</i>	<i>9.0</i>	<i>-10.0</i>	<i>2.9</i>	<i>16.2</i>	<i>4.7</i>	<i>0.3</i>	<i>2.1</i>	<i>1.4</i>	<i>1.1</i>	<i>1.4</i>	<i>1.6</i>	<i>1.4</i>	<i>1.2</i>	<i>1.1</i>
Systematic	MAR					9.3	9.1	0.4					9.2	8.8	6.6
	Predicted					10.3	5.5	-2.1					8.8	15.3	6.4
	<i>Difference/Ratio</i>					<i>-1.0</i>	<i>3.6</i>	<i>2.5</i>					<i>1.0</i>	<i>0.6</i>	<i>1.0</i>
Trendfollow	MAR	18.9	-5.2	19.8	13.1	14.6	9.7	-2.2	14.5	11.4	15.8	16.4	12.4	15.7	10.4
	Predicted	10.5	-4.9	7.4	4.2	10.0	11.0	-6.9	15.4	9.5	12.0	13.2	10.5	21.2	7.9
	<i>Difference/Ratio</i>	<i>8.5</i>	<i>-0.3</i>	<i>12.4</i>	<i>8.8</i>	<i>4.5</i>	<i>-1.4</i>	<i>4.7</i>	<i>0.9</i>	<i>1.2</i>	<i>1.3</i>	<i>1.2</i>	<i>1.2</i>	<i>0.7</i>	<i>1.3</i>

¹ Spurgin (1999) reports that this combination of momentum rules had the highest correlation with broad-based CTA indexes.

² L1 regression minimizes the sum of the absolute deviations rather than the sum of squared deviations. L1 was utilized because the objective is to minimize tracking error between the style benchmark and the CTA. OLS estimates of the coefficients were nearly identical to the L1 coefficients, both in in-sample and out-of-sample tests.

³ Adjusting for the mean return had almost no effect on the accuracy of style benchmark forecasts reported in this paper, which is consistent with past research that finds persistence in measures of CTA strategy, such as *beta* versus a CTA index, but no evidence of persistence in *alpha* versus a CTA index. For example, see Elton et al., 1992, Irwin et al., 1994, McCarthy et al., 1997.

⁴ Two strategies do not have complete returns covering the sample period (1988-2000) but were included in the study. Stock Index was excluded because the length of history would only have allowed for one year of out-of-sample results.

⁵ Analysis of style drift should be much more precise if daily returns for the CTA or style are available.